The Role of Offline Ties in Online Communities

The Case of Wikipedia

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Contents

List of Figures

List of Tables

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Declaration

I declare that the contents of this thesis are my own work and that it has not been submitted for a degree at any other university[1].

Some of the methodological approaches, findings and analysis within this thesis were incorporated into the following conference presentation and were shared with the Wikimedia community in the following reports and guidelines:

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- Grants: Projects/The Role of Offline Ties of Wikipedians/Midpoint. (2022, April 4). *Meta, Discussion about Wikimedia Projects*. https://meta.wikimedia.org/w/index.php?title=Grants:Project/nschwitter/The_Role_of_Offline_Ties_of_Wikipedians/Midpoint&oldid=23103116.
- Learning patterns/Collecting data on offline meetups. (2022, May 23). *Meta, Discussion about Wikimedia Projects*. https://meta.wikimedia.org/w/index.php?title=Learning_patterns/Collecting_data_on_offline_meetups&oldid=23316752.
- Learning patterns/Collecting data on requests for adminship. (2022, June 2). *Meta, Discussion about Wikimedia Projects*. https://meta.wikimedia.org/w/index.php?title=Learning_patterns/Collecting_data_on_requests_for_adminship&oldid=23356270.
- Learning patterns/Analysing effects of offline meetups. (2022, June 2). *Meta, Discussion about Wikimedia Projects*. https://meta.wikimedia.org/w/index.php?title=Learning_patterns/Analysing_effects_of_offline_meetups&oldid=23437462.

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[1] All URLs in this thesis were last accessed 2022-07-15.

Abstract

This thesis investigates the role of offline ties in online communities, taking the online encyclopaedia Wikipedia as an example. It uses publicly available data collected from the German Wikipedia to assess whether offline meeting participation affects editors' behaviour in three different domains: 1) productivity and collaboration, 2) norm-relevant behaviour, and 3) election participation. Data was collected on over 4000 meetings covering the period between the creation of the German Wikipedia in 2001 to March 2020. In the first substantive chapter of this thesis, matching meetup attendees with a comparable control group and employing a difference-in-differences design, I find positive and significant effects of meetup attendance on productivity on Wikipedia, measured as the number of edits. In the second substantive chapter, I build upon the theoretical arguments put forward by Coleman (1990) and test whether offline network density influences norm-relevant behaviour. I find only limited importance of the offline network: those attending meetups tend to both experience and conduct fewer norm violations, and they give and receive generally more rewards. However, the density of the offline network does not play a noteworthy role in explaining online norm violation and norm enforcement, except that those in high-density offline networks generally give fewer rewards. Lastly, for the third substantive chapter, I collected data on all elections for administrators on the German Wikipedia. Using hybrid multilevel random effects models, I find that offline participation measures influence whether one is successful as a candidate, and whether and how one votes. This highlights important processes in situations of public elections. This study is one of the first to bridge the gap between online and offline behaviour, using digital trace data and offline meeting data on a large scale. The findings emphasise how offline interactions in online communities can affect the community and the important role of social capital. They have implications for online communities and Wikimedia in regard to understanding the importance of meetups and (inequality in) access to meetings.

1 Introduction: Why Does Wikipedia Matter?

Since its launch in 2001, the online encyclopaedia Wikipedia[2] has become the top destination for information to many people. It is by now the backbone of many technologies and has become a key figure in the internet landscape in general. Wikipedia has grown immensely and is not only the largest and most popular reference work on the internet but one of the most visited websites overall[3] (Anderson et al. 2016; Barnett 2018). It has had a profound impact on information retrieval and lies at the core of the movement for free and open knowledge, pushed forward by the Wikimedia Foundation, the charitable organisation behind Wikipedia. The core feature of Wikipedia is that anyone with access to the internet can post and edit any article. Anyone can thus add new content and edit or delete existing one. This openness and the absence of centralised supervision have enabled the sustained growth of the site: as of 2022, Wikipedia is available in over 300 different languages and the English Wikipedia alone features almost 6 million articles of, overall, good quality—the article accuracy of Wikipedia has been shown to be comparable to other traditional printed encyclopaedias such as the *Encyclopaedia Britannica* (Giles 2005). All of this is based on the crowd-knowledge of engaged volunteers in a collaborative effort to organise and present human knowledge, giving their time without receiving anything in return. Wikipedia has been described as a real utopia; it is an example of a social economy, being fundamentally organised in an anti-capitalist fashion (Cooke 2020; Wright 2010 chapter 7). It is a prime example of how productive non-market egalitarian collaboration on a wide scale is not only viable but also sustainable. Richter (2020) states that Wikipedia encompasses the values of today's ever-changing society: values of sustainability, individualism, an orientation towards the common good and decentralisation as well as a lack of hierarchy. Taken together with its openness and transparency,

[2] See `https://www.wikipedia.org`.

[3] See `https://www.alexa.com/topsites`; *Alexa* is an Amazon-owned web tracking company.

it ticks all the boxes of digital sustainability: Wikipedia is one of the most impressive examples of what digital technologies can enable.

Wikipedia is best known through its graphical user interface shown by browsers and through the information panel presented by Google when one is searching for information, but there is a lot more information and interaction possible and accessible. Besides the displayed current version of an article page, all previous versions of an article since its initial creation are saved on Wikipedia. Through the article history, one can retrace who has changed an article in what way and at what point in time, and whether other users have accepted or rejected—by undoing—these changes. Furthermore, articles contain a talk page, allowing users to raise suggestions and discuss controversies related to the topic. Registered users on Wikipedia also have their own user page and user talk page where they can provide information about themselves and interact with others on Wikipedia-related matters. Also, there are several pages that relate to the Wikipedia project itself and help with the broader organisation and coordination. These provide, for example, tutorials and policies on contributing or essays and meta-discussions on the project. Wikipedia is thus much more than just a digitalised encyclopaedia—it is an online community of people organised around the ever-changing collective good they have been creating for over twenty years.

While the bulk of Wikipedia happens in the *online* space, Wikipedia also has a notable *offline* component. Wikipedia exists in "the real world": the Wikimedia Foundation is headquartered in San Francisco, hosts the necessary hard- and software, and employs around 550 full-time staff members and contractors worldwide. Each year, the Foundation hosts the international conference *Wikimania* which generally attracts over 500 people[4]. Topics of discussion and presentation include the Wikimedia projects such as Wikipedia but also open-source software and issues relating to free knowledge in general. Besides this annual conference, which aims at bringing together the people involved in the Wikimedia organisation and the Wikimedia projects on a global scale, any project contributor is welcome to organise local meetings to socialise and collaborate with other involved volunteers. In many cases, such meetups are publicly advertised on their own Wikipedia page allowing users to sign up and coordinate the meetup.

The online component of Wikipedia has received a lot of attention from the research community: throughout the past twenty years, Wikipedia with its specific software structure has created a rich data source, offering the oppor-

[4] See https://en.wikipedia.org/wiki/Wikimania.

tunity to study large-scale, self-organising collaboration networks. This has made Wikipedia into a popular source of data as well as into a research topic in itself (see for reviews e.g. Jullien 2012; Okoli et al. 2012): a large amount of research in computer science is informed by Wikipedia data, taking advantage of its enormous and structured body of text to develop and improve algorithms (e.g. Fogarolli 2009; Hu et al. 2009; Milne and Witten 2008), but there is also substantial research on Wikipedia as an encyclopaedia and a productive online community itself, for example on the determinants of article quality (e.g. Arazy et al. 2011; de La Robertie et al. 2015; Liu and Ram 2018; Stein and Hess 2007; Wilkinson and Huberman 2007), or on the role of gender inequality and an existing gender bias on Wikipedia (e.g. Bear and Collier 2016; Collier and Bear 2012; Graells-Garrido et al. 2015; Hargittai and Shaw 2014). Online activity in general has become increasingly important in many areas of life, and the rise of the internet and mass digitalisation have led to vast amounts of digital data in recent years. The field of computational social science is gaining attraction and popularity, and novel digital sources of data are increasingly accessed to gain new insights into old and new questions of the social sciences (Edelmann et al. 2020; Keuschnigg et al. 2017; Lazer et al. 2009; Lazer et al. 2020; Salganik 2018). Many studies have used web data to answer general social science questions and made use of digitalised contents to access a rich data source in a cost- and time-effective way, and Wikipedia is forming one of these sources.

More and more, studies using computational methods have started to combine online data with information about offline behaviour and other offline data sources. For example, web data has been used to predict the prevalence of the flu across geographical areas (Dugas et al. 2013), to assess the salience of immigrants' concerns over deportation (Chykina and Crabtree 2018), to estimate the effects of transnational protest diffusion on political interest (Barrie 2020), to estimate migrant stocks (Rampazzo et al. 2021), or to track the prevalence of lifestyle diseases in numerous countries (Araujo et al. 2017). In other studies, traditional data sources have been expanded to ask about and contrast online and offline behaviours: for example, Quirk and Campbell (2014) and Wachs et al. (2015) compared traditional bullying and cyberbullying, Moreno et al. (2012) measured the prevalence of binge drinking and made use of Facebook data, and Bosancianu et al. (2013) compared both, online and offline prosocial behaviours.

In the case of Wikipedia, data from the online encyclopaedia has also been combined with offline data. For example, Lemmerich et al. (2019) aim to better understand reader motivations across Wikipedia languages and have combined a large-scale survey of Wikipedia readers in many different language editions with a log-based analysis of user activity. Their study allowed them to characterise different behavioural patterns associated with specific use cases. They showed how specific use cases of Wikipedia are more common in countries with certain socio-economic characteristics. Mestyán et al. (2013) focused on page views of movies, trying to predict their popularity and box office success. Several studies have addressed how real-life offline events are picked up in the online community, for example, the *Black Lives Matter* movement (Twyman et al. 2017), disease outbreaks (Tamime et al. 2018), or the Sydney hostage crisis (Avieson 2019). Recently published studies have particularly focused on the onset of the Coronavirus pandemic and assessed its effect on Wikipedia. For example, Rutovic et al. (2021) found a decrease in interest in the topic of articles on neurological diseases using page views, and Ruprechter et al. (2021) identified an increase in volunteer contributions towards Wikipedia during times of mobility restrictions.

While multiple studies have combined offline and online data regarding Wikipedia, the offline component of the community itself has largely been neglected apart from a few exceptions (Farzan et al. 2016; Littlejohn et al. 2019; Stegbauer 2009). However, offline meetups between Wikipedians are important to the community: as long-term member and active Wikipedian Richter (2020: 132–136) writes, such face-to-face meetings allow users to connect to others and help in times of conflict; they can fulfil a Wikipedian's needs for social contacts, community, and personal exchange, in the same way as other local associations. Richter (2020: 148) further states that personal acquaintances are central in a project that is based on anonymous contributions. These ties allow to create a net of trust, making collaborative labour easier. Beyond Wikipedia, a number of studies have acknowledged the occurrence of offline interactions between members of online communities and discussed the interplay between the offline and the online (e.g. Angelopoulos and Merali 2015; Ganglbauer et al. 2014; Lin 2007; Sessions 2010; Shen and Cage 2013; Xie 2008). Strong ties tend to develop at such meetings, bringing advantages to the online community. Yet, these meetings can also bring along new challenges. For example, Sessions (2010) finds that having offline relationships enhances a user's engagement with the online community, strengthens ties to other attendees of offline meetings and through this, contributes to the creation of bonding social capital. However, weak ties with non-attendees dissolve to an extent. While offline meetings can thus be beneficial for the individual, they can have detrimental effects on the online community as a whole. These meetups are often considered valuable and promoted by the community, but they can exhibit negative, unintended consequences that the individuals are not aware of (see on unintended consequences generally e.g. Merton 1936). These previously analysed online communities are quite different from Wikipedia; in most cases, they are forums or web blogs based on discussions and common interests. These are only to a very limited extent comparable with the world's largest open collaboration project which aims at providing free knowledge to all.

The following PhD thesis aims to address these gaps and will focus on Wikipedia as an example of a productive online community and explore the interplay between the offline and the online components of it. It will ask to what extent offline meetups between Wikipedians influence their online behaviour, exploring three different domains of such behaviour: productivity in the form of editing and collaborating, norm enforcement in the form of reverting, and election participation. The rich database provided by Wikipedia has been used by many researchers from different disciplines to address social scientific questions. Oftentimes, sociological theories have only tangentially been used as research has more often grown out of a data-driven perspective (Schroeder and Taylor 2015). In this thesis, data from Wikipedia is embedded in the context of core sociological concepts, allowing for deeper insights into the community aspect and allowing to link previously "offline" theories with online behaviour. This study will further complement previous research which has generally focused on the online side of Wikipedia and will establish a better understanding of the relevance of offline meetings and their effects on an online community. Wikipedia has grown immensely in the past few decades, has become an integral part of the internet and is a prime example of a collective good. Findings on this topic might be useful to not only gain a better understanding of the mechanism at work in this online community, but also of the effect of network ties in the provision of (online) collective goods in general.

This thesis will focus on the German edition of Wikipedia[5] for a number of reasons[6]. Wikipedia started as an English language encyclopaedia; by now, over 300 Wikipedias in different languages exist that are of varying sizes. The

[5] See https://de.wikipedia.org.

[6] The expressions *German Wikipedia* and *German language Wikipedia* will be used interchangeably in this thesis. However, it should be noted that Wikipedia is based on languages and not on political regions or political boundaries. Thus, the term *German language Wikipedia* is technically more accurate than *German Wikipedia*.

German Wikipedia is the second oldest language version and is also still one of the largest and most active versions. This makes it a highly relevant language version which is written and read by many people. At the same time, given its smaller size, it is computationally cheaper than its English counterpart. It has also been shown to be of good quality (see for a comparison with the encyclopaedia *Brockhaus* Stern 2007). Additionally, the German Wikipedia can more strongly be identified as a community in geographic proximity, enabling face-to-face meetings in the first place. In contrast, the English Wikipedia is highly influenced by polyglot contributors from around the world. It has been stated that the German Wikipedia is one of the few with an active offline meetup culture (Merz 2019: 21). Lastly, meetups can be considered to play a special role in the German speaking Wikipedia: the very first global meeting of Wikipedians, the first Wikimania, took place in Frankfurt am Main in 2005. From large global meetings in a metropolis like Frankfurt to small friendship gatherings in Northern German towns, from barbecues in Berlin backyards with over a hundred attendees to Christmas market visits in close circles, from group-editing in front of computers to improve the encyclopaedia to grieving the loss of long-time members when attending their funerals, the community of German Wikipedians exhibits a rich culture of meetups which lends itself to research.

The thesis will take a broad view of Wikipedia, trying to make use of the twenty years of history and data produced. It will not focus on specific cases or take an in-depth look at specific users. It is located in the field of computational social sciences, a growing interdisciplinary field at the intersection of computer science and the social sciences in which theories of human behaviour are advanced by applying computational techniques to large datasets from digital sources (Edelmann et al. 2020).

1.1 Research Questions

The overarching research question of this PhD thesis asks the following: *To what extent is online behaviour on Wikipedia affected by offline meetings between Wikipedians?*

This thesis aims to assess the effects offline relationships have on a community that predominantly acts in the virtual space. Three areas will be explored: productivity, norms, and voting behaviour. Producing content lies at the core of Wikipedia and is thus a central research area. As Wikipedians rarely create and edit a single page alone but instead co-author with multiple others, emphasis will also be put on collaboration behaviour. Contributing content does not only include writing new content but also deleting inadequate existing one. The opportunity of reverting (i.e. undoing) previous changes is a central feature of Wikipedia which has previously been embedded in a context of norms. Wikipedia is not a world without laws but is governed by a set of rules and norms which set out how articles should be written and what Wikipedia should, in very broad terms, look like. These norms are enforced through this technical feature of reverting. This interplay of norms and behaviour forms the second area of interest. Lastly, voting processes are analysed as a third domain. In contrast to contributing content to Wikipedia, participating in elections and supporting other people in promotion processes are not linked to specific thematic knowledge. Even when people who meet offline do not share any areas of interest and expertise, they can still interact and support each other in the meta-space of Wikipedia such as in promotion processes. These three different domains are important to understand the sustainability of Wikipedia: only through sustained creation of good content, sustained removal of bad content, and the election of qualified and trustworthy administrators fulfilling maintenance tasks, was Wikipedia able to become and remain relevant in the dynamic internet landscape of the past twenty years.

Throughout this thesis, I will aim at answering the following sets of questions:

1. How does participation in offline meetups influence an editor's contributing behaviour to articles?
   - To what extent does participation in offline meetings influence an editor's productivity, i.e. number of contributions?
   - To what extent does participation in offline meetings influence online collaboration?
2. How does participation in offline meetups influence an editor's norm-relevant behaviour?
   - To what extent does offline meeting network density influence the extent of norm violations experienced and conducted?
   - To what extent does offline meeting network density influence the extent of norm punishments experienced and conducted?
   - To what extent does offline meeting network density influence the extent of rewards received and given?

3. How does participation in offline meetups influence an editor's voting behaviour?
    - To what extent does participation in offline meetings influence an editor's decision to run for administrator?
    - To what extent is the outcome of requests for adminship influenced by participation in offline meetings?
    - To what extent does participation in offline meetings influence an editor's decision to vote in an election?
    - To what extent does participation in offline meetings influence an editor's decision to support a candidate in an election?

This research project focuses on Wikipedia as a case study of an online community. However, the research questions it addresses have implications for any online community which relies on an active member base and their participation. With increased digitalisation and interaction on the internet as well as hybrid approaches to work and life, it is important to understand what the drivers and inhibitors of an active community are and what (unintended) dynamics might occur. In this sense, this project contributes more broadly towards sociological research on communities and network ties and aims at understanding the role of offline ties in online communities.

1.2 Structure of This Thesis

This thesis is structured as follows: this introduction explained the motivation of this research topic and Wikipedia and introduced the research questions. The next chapter will contextualise this study: in a first section, the concept of social capital as well as the interplay of the online and offline world, particularly concerning the questions of community and friendships, will be discussed. Following this, a brief history of the internet will be given which sketches the dimensions and aspects which were relevant to the development of Wikipedia. The analogue ways of collecting information will be summarised; this will then lead to a discussion of both digital and online ways of information collection. I will outline how the online world allowed movements both towards openness and towards crowd-collaboration, the basis of Wikipedia. The history of Wikipedia will be given thereafter. Also, it will be discussed what role Wikipedia has played in research so far. Section 2.4 will highlight the lack of research about meetups between Wikipedians and discuss what meetups on Wikipedia tend to entail by providing a qualitative description.

Following this, chapter 3 will present the general data and methods employed in all substantive chapters of this thesis. I will discuss how key data sources were accessed and how key variables were constructed and defined. This includes, for example, a discussion on accessing the data dump of Wikipedia and managing large amounts of data. In detail, it will be outlined how I collected and cleaned the meeting data, which decisions I took to achieve a consistent dataset and which data I included and excluded, respectively. The meetup data will then be described quantitatively. I will give credit to the software (packages) used and conclude the chapter with ethical considerations.

After that, the thesis will split into its three main substantive chapters: chapter 4 will discuss productivity, chapter 5 will focus on norm-related behaviour, and chapter 6 will analyse elections and voting behaviour on Wikipedia. In each chapter, I will introduce the corresponding topic, discuss the current state of the literature and derive testable hypotheses, present the data and methods used unique to that specific subtopic, as well as show the results and end with concluding remarks.

Both, the general methodological chapter (chapter 3) as well as the methods sections in all three substantive chapters tend to be extensive and rich in description. This should allow readers which are not immersed into Wikipedia to better understand the dynamics of the data, the project, and the general setup one is dealing with. Wikipedia and other online platforms tend to function under their own rules and dynamics; understanding their context is important. Additionally, such descriptive insights can already reveal general patterns.

Finally, in the last chapter (chapter 7), I will discuss the results in a synthesising matter and draw conclusions. A summary will be given about the findings and the research question will be answered succinctly. I will highlight the thesis' contributions towards knowledge and general impact, discuss overall limitations and present avenues for future research.

2 Context: The Online World and Wikipedia

"Das Internet ist für uns alle Neuland" (translation: "The Internet is uncharted territory [literally: new land] for all of us") was famously proclaimed by former German chancellor Angela Merkel in 2013 (Kämper 2013). This uncharted territory has its origins in the 1960s. Throughout the past sixty years, the internet and its related technologies have had a profound influence on the world. They have created new spaces and opportunities for sharing information, socialising, communicating, and connecting with others. The internet has become pervasive in many spheres of everyday life and for many people, a large part of their day is now spent online. It is thus of utmost importance to understand more of the online world and in particular its interaction and relation to what is happening offline, the "real world".

This chapter will present the context of this thesis. In section 2.1, I will introduce the concept of social capital and outline how the offline and the online intertwine in a multitude of ways. The focus lies on online communities and offline interaction between members, as this is the central theme of this thesis. In the second section, Wikipedia will be situated in its communication-historical context. The third section will give an overview on how Wikipedia has been previously used in research. Lastly, offline meetups on Wikipedia will be discussed. The gap in the previous research concerning offline meetups will be highlighted and a rich description will be provided of these meetups.

2.1 Understanding the Interplay Between the Online and the Offline

The internet has affected many realms of everyday life, but it does not exist in a separate sphere. Instead, the offline and the online intertwine in a multitude of ways; studies which have researched this connection—particularly those focusing on online communities—will be discussed in the following. In a first section, I will introduce the concept of social capital to discuss why social relationships matter in the first place, before describing how the offline and online are studied and how offline and online data is currently being used in research.

2.1.1 Why Should Social Networks Matter?

This thesis is concerned with online and offline social networks. However, why should they matter? Knowing and being connected to other people can be important to the individual. These connections—so-called ties—can hold value as they allow the individual to access new resources: this is covered by the concept of social capital. The concept of social capital has gained immense popularity both within and beyond the social sciences in the past thirty years. Considering the wide range of applications of social capital, the concept started to be understood to encompass a range of phenomena that are connected to social embeddedness. While the specific definitions of social capital vary, at its core it can be defined as resources accessed through and in social relations (Lin 2001). In other words, social capital focuses on the productive benefits of social interactions (Brunie 2009). Social capital has aspects on both the individual level, seen as additional resources for a person, and the aggregate level, seen as a collectively produced and owned good with benefits for the whole community. The classical conceptualisation of social capital is shaped in particular by the views of Pierre Bourdieu (1980, 1986), James Coleman (1988, 1990), and Robert Putnam (1993, 2000) who have emphasised different facets of the concept in their discussions and have already incorporated the dual nature of individuality and collectivity (see also Edwards and Foley 1998). As with capital in general, individual investments in social relationships can be made and the resulting benefits can be used individually (Esser 2002 chapter 8.4, 2008). Neither the success nor the use of social capital can be controlled by individual actors though, as social capital develops and exists in the structure of relationships and is embedded in one's network (Lin 2001: 55–56; Portes 1998). The core idea of the social capital theory is that networks have value (Putnam 2000).

The distinction between social capital as a property belonging to individuals and a collective asset has often been noted and discussed (e.g. Inkeles 2000: 247; Lin 2001: 21–25; Portes 1998, 2000). This distinction has been considered controversial by some (Lin 1999b), but productively used to create a typology by others (Brunie 2009; Esser 2002, 2008). In the latter, social capital is broken apart in its interconnected, yet distinct, social processes, and individual and collective social capital are distinguished.

Individual social capital then refers to access and use of resources an individual actor has through their acquaintances and friends. On this relational level, it is assumed that social capital constitutes an actor's 'personal' resource whose value depends on earlier investments in it. An actor's total endowment of relational social capital equals the sum of all the resources and benefits on which they can draw as a result of direct or indirect relations with other individual actors (Esser 2008; van der Gaag and Snijders 2004; Lin 1999a, 2001). Relational social capital refers to the network location an actor is positioned in and the embedded resources they have access to, i.e. network resources and network structures (Huang et al. 2018; Lin 2001; Portes 1998). Furthermore, the willingness of alters to make resources available to an ego (access to resources) is an important dimension of social capital (Flap 2002; Flap and Völker 2004; Lin 1999a, 2001; Lin and Erickson 2008). It is further argued that trust and obligations are key to social capital; Esser (2008) conceptualises relational social capital as also including trust capital and obligation capital, referring to the trust that other actors place in an actor and the number of obligations other actors owe towards one. This idea is also expressed by Coleman (1990) and his notion of *credit slips*, and by Putnam (2000: 20) and his *favour bank*.

Collective social capital, on the other hand, is an emerging property of aggregate collectives. It refers to the benefits a whole network offers to all its members. Collective social capital is detached from individual actors, as it only exists through the relations between actors, and cannot be intentionally created by individuals (Esser 2008). System capital, as an attribute of the social structure instead of a private property, forms a public good from which all actors in a network can profit whether they have invested in it or not (Coleman 1990: 315).

Another often made distinction is that between *bonding* and *bridging* social capital (Burt 1995, 2007; Putnam 2000; Williams 2006). Bonding social capital results from close connections and is supposed to strengthen the connections within the group, whereas bridging relations are created by associations that cut across group lines. Bridging social capital typically stems from loose ties which are based on infrequent interactions between people from dissimilar circles; this continues the thoughts of strong and weak ties as introduced by Granovetter (1973)[7]. Bridging social capital provides novel opportunities, diverse information, and is responsible for the diffusion of ideas (Rogers 2003): connected by weak ties, otherwise disconnected social groups can receive new information through such bridges. However, bridging social capital is generally not considered a well-suited source for emotional or substantive support. On the contrary, bonding social capital is based on repeated and frequent interactions with similar others; while it thus offers little diversity in information or opinions, it provides support (Putnam 2000; Shen and Cage 2013). This support refers for example to the emotional or material aid given to close family members and friends when they are suffering from socio-economic hardship, poor mental or physical health, or other difficult circumstances.

The Dark Side of Social Capital In the social science literature, research on social capital most often focuses on its positive attributes, the "bright" side of social capital. Starting with the classics, Bourdieu (1980, 1986), Coleman (1988, 1990) and Putnam (1993, 2000) tended to highlight the positive effects of social capital. Putnam (2000) identified the fall of social capital as a main driver of negative consequences in the US. Generally, social capital is seen as a positive attribute of individuals like other sources of capital which needs to be fostered. On the contextual level, higher levels of social capital have been shown to lead to positive consequences such as economic growth (Knack and Keefer 1997) or the spread of secondary education (Goldin and Katz 1998). However, increased social capital has also been shown to lead to negative consequences. Portes (1998) and Portes and Sensenbrenner (1993) note that high levels of social capital can put constraints on individual freedom and might encourage exclusionary behaviours, such as the exclusion of people who are perceived not to be part of the community (Alcorta et al. 2020). It has been shown that higher levels of social capital and high social cohesion can have negative effects and lead, for example, to increased violent behaviour (Wright and Fitzpatrick 2006), organised crime like the Mafia (Gambetta 1996), or conformity by inhibiting entrepreneurial work (Gargiulo and Benassi 1999; de Vaan et al. 2019). Overall, there are both positive and negative consequences of social capital.

[7] Granovetter (1973) stated that relationships between people are either strong or weak: they are either based on frequent meetings and deep emotional involvement or rather on sporadic interactions with low emotional commitment. The relationships within families or close friends are thus generally strong while loose acquaintances share weak ties.

To summarise: social capital and ties to others matter. While social capital is a complex concept and is based on different levels, for the following analysis the focus lies on an individual level. The focus in the upcoming chapters lies on ties single users, i.e. Wikipedia editors, have with others.

2.1.2 The Online Space and the Question of Community

The internet and the world wide web have led to the development of new communities and spaces for communication and interconnectedness. Early research about the internet was particularly interested in how people use this new space and to what extent the same rules and norms of the "real world" also govern the online space.
There were two conflicting visions of online communities and online relationships in the early days of the internet: on one hand, these online relationships were viewed as shallow, impersonal and hostile, suggesting that the internet can at best provide only an illusion of community (e.g. Beniger 1987), while, on the other hand, it was argued that computer-mediated communication liberates interpersonal relations. Whether the internet makes us lonely or more social has thus been a topic of discussion since its emergence and larger diffusion. In an experimental study which has gained notable attention in its days, Kraut et al. (1998) found that greater use of the internet decreased communication within the family, increased feelings of loneliness, and diminished the size of local social networks. However, the reliability and generality of these findings were questioned in future studies (e.g. Boase and Wellman 2006b; Franzen 2000, 2003; Valenzuela et al. 2009). Later, it has been proposed to view social interactions on the internet as embedded in daily life (Hine 2000, 2015; Miller 2000). An overview of this discussion is given by Wilson and Peterson (2002) who also point out that the changes the internet has brought forward have been less dramatic than some anticipated in the beginning: the internet is not detached from the offline world but instead embedded in existing practices and power relations of everyday life (see also Wellman and Haythornthwai 2002). DiMaggio et al. (2001) and Erhardt and Freitag (2021) further highlighted that online practices tend to complement and not substitute or displace patterns of behaviour, social engagement, and other forms of media.
A prominent question in the exploration of the online has been the question of building communities. Wellman and Leighton (1979) define community as an entity formed by interconnected individuals who are in frequent face-to-face interactions and share a sense of solidarity. Advocates of online communities

stress that a shared identity and a sense of solidarity can arise without face-to-face interactions (Baym 2000). Rainie and Wellman (2014) and Wellman (2001) argue that the internet brought new ways of socialising, characterising the changing nature of social interactions with the concept of *networked individualism*: instead of relying on closely-knit, location-based social support, people moved into more fluid social environments, unbounded by location. Within this context, a shift towards flexible membership of interest-based, digitally mediated communities can be observed.

As one of the first, Rheingold (2000) anticipated the capacities of the internet in creating *virtual communities*: groups of people linked by their participation in computer networks. Virtual communities allow the creation of social relationships across barriers of space and time. Rheingold (2000) himself belonged to the virtual community *WELL*[8], one of the oldest computer conferencing systems. He describes computer networking as decentralised, informal, eclectic, and essentially self-governing, and highlights that the online space is not a single, monolithic culture, but an ecosystem of subcultures. The quality of discourse taking place online could be compared to that taking place in cafés, community centres or other public places. Rheingold (2000) compares the virtual community in this sense to the concept of the public sphere. He further examines other online communities in depth beyond WELL, such as *MUDS* (Multi-Use Dungeons) and other role-playing fantasy games, the French *Minitel* system (the world's first national network), and Japanese networks.

Besides the study of Rheingold (2000), many in-depth ethnographies of niche subgroups have emerged, going under the terms of *netnography* or *cyber-ethnography* (see e.g. Robinson and Schulz 2011). For example, Baym (2000) studied an internet soap opera fan group and shows how communicative practices create collaborative interpretations and criticism, group humour, interpersonal relationships, group norms, and individual identity in a gendered online community. Brotsky and Giles (2007) conducted a participant observation in an online community on eating disorders, Kunert (2019) researched female football fans' behaviour on the social media platform *Tumblr*[9], Kulavuz-Onal and Vásquez (2013) researched an online community of English language teachers, Grieve (1995) explored Neo-Paganism, Waldron (2009) focused on informal music learning, Tosenberger (2008) explored the Harry Potter fandom, Tenderich et al. (2018) investigated how people with diabetes

[8]The Whole Earth 'Lectronic Link, see https://www.well.com.
[9]See https://www.tumblr.com.

use the internet and get peer-support through online channels, and Boellstorff (2008) explored the dynamics in the video game *Second Life*. Clearly, the online world works as a space for offline interests and circumstances, as the groups forming around health conditions, leisure interests, and other struggles of everyday life show. Further examples can also be found in Thanh and Kirova (2018) who explored *Tripadvisor*[10] reviews on wine tourism, exploring wine tourists' experiences in a netnographic fashion, or in Nelson and Otnes (2005) who conduct a netnography of message boards, dealing with the real-world issues of inter-cultural weddings. Focusing on more popular online social networking sites, studies like Ferrara (2012) and Reich (2010) have analysed the sense of community and the community structure on sites like *Facebook*[11] and *MySpace*[12]. As these numerous examples highlight, the opportunities to research online communities are vast (see for a review e.g. Bartl et al. 2016). The reoccurring issue of a possible dichotomy between the "virtual" and the "real" and thus detaching the online from offline events has generally been proven to be unproductive. Gruzd et al. (2011), discussing *Twitter*[13] as a community, point out that some social formations recognisable as community can happen online, but many other formations comprise online and offline interactions, intertwined in a variety of ways. How the offline and the online can be connected in research will be described in the next section.

2.1.3 Using Digital Data

The usages of digital data in research are flourishing and novel digital sources of data are becoming popular in the social sciences (Edelmann et al. 2020; Keuschnigg et al. 2017; Lazer et al. 2009; Lazer et al. 2020; Salganik 2018). Many studies have used web data to answer general social science questions and made use of digitalised contents to access a rich data source in a cost- and time-effective way. Some researchers focused on data published on the web to answer questions concerning topics in the offline world, from gender representation to language biases or ethnic violence (e.g. Dodds et al. 2015; Jia et al. 2016; Liebe and Schwitter 2021), while others investigated dynamics of the online world itself, from matters of representation to rules, norms, and affordances of online platforms (e.g. Chandrasekharan et al. 2018; Fischer et al. 2020; Munger and Phillips 2020).

[10] See `https://www.tripadvisor.com`.
[11] See `https://www.facebook.com`.
[12] See `https://myspace.com`.
[13] See `https://twitter.com`.

An increasing body of research is investigating the suitability of digital traces of human behaviour as a substitute or complement to more traditional data sources. Digital trace data can be roughly defined as records of activity undertaken through an online information system such as websites, social media platforms, smartphone apps, or other digital trackers and sensors (Howison et al. 2011; Stier et al. 2019). In this line, Google searches have been used to predict the prevalence of the flu in different geographical areas (Dugas et al. 2013), to assess the salience of immigrants' concerns over deportation (Chykina and Crabtree 2018), to estimate the effects of transnational protest diffusion on political interest (Barrie 2020), or to examine the contribution of demographic factors to violent radicalisation (Bail et al. 2018). Besides Google search data, the Facebook Advertising Platform has been used to estimate migrant stocks by Rampazzo et al. (2021), Araujo et al. (2017) used it to track the prevalence of lifestyle diseases in numerous countries, and Kashyap et al. (2020) have used Facebook and Google data to quantify the global digital gender inequality. These studies have focused on offline behaviours but make use of proxies available online. Other examples are engagement in specific forums to measure dieting choices (Choudhury et al. 2016b; Mejova et al. 2015), suicidal thoughts (Choudhury et al. 2016a), or helping behaviour (Althoff et al. 2014).

Further, there is a notable strand of research on the mobilisation of collective action through online channels. Strong correspondence between online and offline activity has been found among social movements (Castells 2015) such as the Arab Spring (Abul-Fottouh and Fetner 2018; Hanna 2013). While it is important to note that big data comes with its traps and biases (see e.g. Araujo et al. 2017; Lazer et al. 2014), particularly around representativeness due to access to the internet and/or devices, they can provide a uniquely unobtrusive way to access information from people who are in positions of marginalisation, and may be reluctant to engage with institutions and institutional players such as researchers. Studies using web data have offered rich insights to understand both the online and offline world.

While the usages of digital data are flourishing, research which connects offline and online behaviour on an individual level is still comparatively sparse. One of the few exceptions is the study of Althoff et al. (2017) who analyse on- and offline activity of a step tracking application. They researched how the social network connected with the activity tracker influences user behaviour. Analysing 791 million online and offline actions of 6 million users over the course of 5 years, they found an interplay: social networking led to a significant increase in users' online as well as offline activity. Creating new social connections in the app had causal consequences: users were not just more likely to stay part of the social network and increase their online in-application activity, but they also were more likely to increase their offline physical activity, taking on average about 400 additional steps a day. Another example forms the study of Settle et al. (2015) who used over 100 million Facebook posts to compare users' political discussions during the 2008 US presidential election, contrasting uncompetitive "blackout" states with "battleground" states. People were much more likely to discuss politics online if they were living in a battleground state and posting a political status did matter in explaining self-reported voter turnout. Grinberg et al. (2019) have linked Twitter data with public voting records to understand the effect of fake news on the platform. They found that engagement with fake news sources to be extremely concentrated (with 1 per cent of individuals accounting for 80 per cent of fake news source exposures) and those most likely to engage with fake news sources were conservative leaning, older, and highly engaged with political news. They focused on the 2016 election season in the US.

Increasingly, passively measured behavioural data from smartphones (e.g. location, movement, activity, or sleep) is combined with self-reports. While this data is generated and collected via digital measures and sensors and thus often relies on internet-based technologies, it does not necessarily entail the same impression of "being online" to the user as the other studies outlined; this is thus not further discussed here. See for a literature review on this topic Keusch and Conrad (2022).

More frequently, studies have used traditional data sources such as surveys to ask about and contrast online and offline behaviours. For example, Quirk and Campbell (2014) and Wachs et al. (2015) compare traditional bullying and cyber-bullying, Hirzalla and van Zoonen (2010) analyse online and offline activities relating to activism and politics, Sibona and Walczak (2011) aim at explaining befriending and unfriending decisions on the social network platform Facebook, Moreno et al. (2012) measure the prevalence of binge drinking and make use of Facebook data, Bosancianu et al. (2013) compare prosocial behaviours both online and offline, de Zúñiga and Valenzuela (2010) have combined online and offline social networks in the studying of civic engagement, and others contrast online and offline forms of political engagement (di Gennaro 2006), or consumer buying behaviour (Danaher et al. 2003; Rondán-Cataluña et al. 2015). Increasingly, studies have also started to combine digital trace data with survey data, such as Munzert et al. (2020) who do this in the context of voting behaviour and research the impact of voting advice applications. Particularly, there is a large body of research analysing the intertwining of offline and online social networks and how friendships exist in these two spaces. This strand of literature will be discussed in the following section.

2.1.4 Bridging Offline and Online Social Networks

The internet and the web can serve as communities and online and offline behaviours are—to some extent—interconnected. The social networks people build in the offline and in the online space are also in some ways related to each other. These ways will be discussed in the following subsection. First, I will give an overview about traditional offline friendships which can make use of digital opportunities; next, I will be discuss to what extent friendships can start online and can then transfer to the offline sphere.

2.1.4.1 Friendships: From Offline to Online

Boase and Wellman (2006a) argue that only a small minority of internet users communicate with people that they do not already know[14]. Most social network sites were originally largely used to find and contact offline friends in the online space. The first social network site recognisable as such was *SixDegrees*[15] which launched in 1997. It promoted itself as a tool to help people connect with others as it allowed the creation of profiles and a list of friends. While it attracted millions of users, it failed to become a sustainable business. With the internet still being in its early days, most people did not have extended networks of friends who were also online, and early adopters of the site complained that "most users were not interested in meeting strangers" (boyd and Ellison 2007: 214) and that there were not many usable features besides the acceptance of friend requests. Research has generally shown how Facebook and other social networking sites are used to maintain and solidify existing offline relationships but not to meet new people (Ellison et al. 2007; Kavanaugh et al. 2005; Lampe et al. 2006; Reich et al. 2012; Valkenburg et al. 2006). While online contact might be weak, there generally is at least a shared offline element among individuals who befriend

[14] This statement is based on large-scale national surveys done in 1995 and 2000 which can by now however be considered rather outdated (Katz and Rice 2002; Katz and Aspden 1997).

[15] See http://sixdegrees.com.

one another on platforms like Facebook (such as a shared class between college students). Online interaction, in this sense, is considered to extend and enhance the communication of offline relationships. This is valid for many forms of electronic communication services such as e-mails, instant messages, or social media sites; these services are structured to allow people who know each other to keep in contact (Gruzd et al. 2011; see for a review Boase and Wellman 2006a). As discussed by Ellison et al. (2007), online communities are so thought to enhance place-based communities and facilitate social capital, similar to the wired Toronto neighbourhood as studied by Hampton (2002) and Hampton and Wellman (2003)—a study about a neighbourhood in Toronto which has made use of digital technologies to connect neighbours with each other and strengthen local cohesion. Howe (2009: 29, 121) argued that the way people spend their time has changed with more time being spent online. This has implications for social capital: people might partake less in bowling associations but interact on message boards instead. In this line, it has generally been shown that computer-mediated interactions have positive effects on community interactions, involvement, and social capital (Hampton 2002; Hampton and Wellman 2003; Kavanaugh et al. 2005).
Overall, a large body of available research suggests that most online social network platforms primarily support pre-existing social relations and discuss how offline friendships are making use of online communications. However, exceptions which focus on online relationships moving to the offline sphere exist and will be discussed next.

2.1.4.2 Friendships 2.0: From Online to Offline

The previous subsection sketched how friendships can move from an offline context to the online world, thus being enhanced with an additional form of communication. However, relationships can also move the other way around: from the online to the offline space. While online communication has been shown to strengthen pre-existing local ties, online community sites also offer the opportunity to connect with others outside of one's pre-existing social group; liberating people from building communities based on shared geography and instead allowing the formation of relationships based on shared interests (Rheingold 2000; Wellman et al. 1996). This point was already highlighted in 1968 by Licklider and Taylor (1968: 40), the Defense Department researchers who had developed the original computer network: "Life will be happier for the online individual because the people with whom one interacts most strongly will be selected more by commonality of interests and goals than by accidents of proximity".

While online communication lacks certain features and social cues (see for research on negative aspects of online communication e.g. Dubrovsky et al. 1991; Lea et al. 1992; Siegel et al. 1986), the fact that relationships can form online cannot be denied, often centred around a specific kind of interest (see e.g. Brennan et al. 1992; Parks and Floyd 1996; Rheingold 2000). Those "passion-centric" social networking sites can help strangers connect and meet based on shared interests. boyd and Ellison (2007) discuss the site *Couchsurfing*[16] which connects travellers to people offering a room, or *MyChurch*[17] which connected Christian churches and their members. Dating platforms have also always aimed at introducing people to strangers with similar interests or who match otherwise[18] (boyd 2004; boyd and Ellison 2007; see for research on dating platforms generally e.g. Bruch and Newman 2018). By today, a notable proportion of couples have met through online channels (Lampard 2020; Rosenfeld and Thomas 2012).

Online relationships are considered to be the basis for multiplex relationships. Generally, if relationships are formed online, there is a desire to incorporate them into the offline world, resulting in face-to-face meetings (Hiltz and Turoff 1993: 114; McKenna et al. 2002; Parks and Floyd 1996; Rheingold 2000: 325). Parks and Floyd (1996) report that one third of their respondents recruited from internet discussion groups later met their online correspondents face-to-face: relationships that began online moved to the offline space.

Clearly, social networks in the online and the offline are not detached and separate entities. Offline friendships make use of online communication channels, and online friendships can move into the offline space. However, can such face-to-face meetings affect online communities as a whole?

Offline Meetups for Online Communities Sessions (2010: 376) stated that "the question of how the formation of offline relationships affects online communities remains seldom asked, and as a result, unanswered". Since, a number of studies have acknowledged the occurrence of offline interactions in online communities and discussed the interplay between the offline and the online (e.g. Angelopoulos and Merali 2015; Ganglbauer et al. 2014; Koh et al. 2003; Lin 2007; McCully et al. 2011; Sessions 2010; Shen and Cage 2013;

[16] See https://www.couchsurfing.com.

[17] Not accessible anymore.

[18] An exception being *Friendster* which was designed to help friends-of-friends to meet (see on Friendster e.g. Garcia et al. 2013).

Xie 2008). In the past, it has been argued that offline meetings can play a part in complementing the low social presence inherent in most computer-mediated environments (Lombard and Ditton 1997). Kiesler et al. (1984) argued that diversifying channels of communication by balancing online with offline activities is pivotal in sustaining a virtual community. Walther (1995), on the other hand, assumed no extra value through face-to-face interactions as online interactions can be just as sociable and intimate.

Researching very different communities—Angelopoulos and Merali (2015), for example, study a community of cigar smokers, while Ganglbauer et al. (2014) research a community concerned with *foodsharing*[19]—studies tend to find both positive and negative community effects of face-to-face meetups. While there are generally positive effects on the individual level as stronger ties develop, the community itself might suffer from such gatherings. Angelopoulos and Merali (2015) and Xie (2008) find increased sociability and stronger friendships in those users that have met face-to-face, but McCully et al. (2011), Sessions (2010) and Shen and Cage (2013) find that the sustainability of the community can become undermined when people start to withdraw from the people they have not met (and the community as a whole). It is an open question to what extent these results apply to the context of Wikipedia, a very different online community with the focus on creating a collective good. After this broad introduction on the link between the offline and the online sphere, the following sections will focus more strongly on the present case study: Wikipedia. A complete literature review of research on offline meetings of Wikipedians will then be given in section 2.4.3 after a detailed description of these meetups.

2.2 From Libraries to Wikipedia: A Brief Historical Overview on Information Sharing

Wikipedia developed on the shoulders of analogue libraries and encyclopaedias, within the context of an increasingly digitalised and interconnected world. The internet has sped up and improved knowledge collection and knowledge creation in many ways. It enabled people to connect with others all over the world and to exchange information quickly. It has also created new spaces for the gathering of information: multiple crowd-projects have

[19] *Food sharers* want to save food waste and collect and distribute left over food products.

been created towards which volunteers can contribute, one of them being Wikipedia. The following section will give a historical overview of the way information has been collected in human history. It will go from the analogue to the digital. With this, I will also briefly outline the history of the internet, thereby focusing on its aspect of sharing information and knowledge. This section will further outline some other online projects and predecessors of Wikipedia and important concepts that have helped Wikipedia to its popularity and paved the way. It will not offer a wider discussion of the technical and cultural developments which made it possible to connect computers all over the world (see for this e.g. Berners-Lee 1999; see for a very extensive discussion on the social history of knowledge Burke 2012).

2.2.1 Analogue Developments in Information Collection

Libraries have been established well over 2000 years ago as institutions aimed at containing all intellectual works of the world. The *Great Library of Alexandria* in Egypt was one of the largest and most significant ones of ancient times. The Great Library was part of a larger research institution and was established during the reign of Ptolemy II Philadelphus (285–246 BC) (Phillips 2010). Alexandria came to be regarded as the capital of knowledge and learning, in part because of its library (Murray 2012).

With the same idea of universal knowledge in mind, encyclopaedias—coming from the Greek word *enklyklios paideia* and roughly meaning "basic education"—form a condensed collection of knowledge. Encyclopaedias date back to ancient Greece and to the philosopher Platon who did not write an encyclopaedia himself but founded an academy which allowed the creation of a holistic idea of education (Richter 2020)[20]. Platon's student and nephew, Speusippos, continued as the head of the academy and created the first written encyclopaedia, the *Homia*. In the Homia, he systematically discussed his research on animals and plants. While mostly destroyed by now, the Homia can be considered the first encyclopaedia (370 BC) (Preece and Collison 2016).

Similar developments were also observable in ancient Rome with the *Historiae naturalis*, written by Plinius. It is a collection of the knowledge of its time, discussing a range of topics—from cosmology to art—in 37 volumes and 2493 chapters. The historiae naturalis survived its time, it was published in Venice with the just invented letterpress and was even translated

[20] This section focuses on the Western development of encyclopaedias.

into German (published in 1534), and much later also into English (published in 1847).

As for all written works, the letterpress also helped the spread of the encyclopaedia. New encyclopaedias were written and gained popularity in the 17th and 18th centuries. Notable ones are Francis Bacon's, an English philosopher, *Preparative Toward a Natural and Experimental History* from 1620, Heinrich Zedler's, a German publisher, *Grosses vollstaendiges Universal-Lexicon Aller Wissenschafften und Kuenste*, and Denis Diderot's, a French polymath, *Encyclopédie*. Zedler was the first author to include the public in the encyclopaedia: everyone who was able to write could send in articles for publication, a very early example of crowd-sourcing (a term coined much later by Howe 2006). Zedler's encyclopaedia was finished in 1750. Following Zedler's Lexicon, Diderot's Encyclopédie was published between 1751 and 1758 in 27 volumes with 71'818 articles. The Encyclopédie was not comparable to anything that has been written before in thematic and methodological breadth and width. Up until 1889, at least 25'000 copies were sold worldwide, an impressive number back in the day (Richter 2020).

In the years to come, other notable encyclopaedias have emerged, building upon the founding works. Gaining worldwide popularity, the *Encyclopedia Britannica* followed, and in the German speaking context, *Brockhaus* and *Meyers* are well-known encyclopaedias from the last century. However, as time went on, significant disadvantages of written encyclopaedias were becoming more apparent. They are difficult to update, they lack multimedia content, and their increase in volume and size makes them bulky and expensive to produce (and buy). Updating written and published encyclopaedias is a time-consuming and difficult task as older articles need to be corrected either by producing a new version of the whole encyclopaedia or through separately and regularly published errata. These problems could well be and were addressed by other contemporaneous technical developments: the increasing digitalisation and the internet.

2.2.2 Information Going Digital

Digitisation refers to taking analogue information and encoding it in a way so that computers can store, process, and transmit such information. Through these technical advances, it became possible to make information more portable, to make it available to others, to exchange it quickly, and to preserve it, leading to digitalisation: the restructuring of many domains of social life around digital communication and media infrastructures (Brennen and Kreiss 2016). Many realms of life have increasingly become digitalised since the end of the 1970s when the first commercial mainstream computers were developed, and this has continued into the following decades with the surging availability of personal computers and ubiquitous technology.

Many institutions and places followed these advances and made information available online: speeches of American presidents are published by the *Miller Center*[21], books are being scanned and are published as part of the *Project Gutenberg*[22], the oldest digital library founded in 1971, the *Library of Congress* is making much of their collection available online[23], and most governmental agencies make statistical data available for download on their website, ranging for example from British population data offered by the Office for National Statistics[24] to American FBI data[25]. *Microsoft Encarta* was the first notable attempt to digitalise an encyclopaedia. Starting in 1993, Microsoft published its encyclopaedia first on CDs and DVDs. Having a digital encyclopaedia allowed the inclusion of multimedia content such as film clips, audio recordings, or interactive maps. With regular updates which are much more easily distributable than updates for written and published books, Microsoft Encarta could be kept up to date in a simpler fashion than printed encyclopaedias. In contrast to its printed counterparts, Microsoft Encarta was also significantly cheaper—in 2005, the most extensive version of Encarta cost around 100 pounds, a fraction of the price of then published encyclopaedias which tended to cost multiple thousands.

In 2000, the full Encarta content moved to the world wide web and became available to subscribers, with a subset available for free to anyone: the next step in the distribution of knowledge.

2.2.3 Information Going Online

Digitising information makes it portable and independent from geographic location, but to share it simultaneously with multiple others, a further technology is necessary: one which connects systems to transfer pieces of information. This technology found its implementation in what we now know as the internet. Its origins date back to the 1960s when military officials on one hand and to the 1990s when particle physicists at the CERN on the other

[21] See https://millercenter.org/the-presidency/presidential-speeches.
[22] See https://www.gutenberg.org and https://www.projekt-gutenberg.org.
[23] See https://www.loc.gov.
[24] See https://www.ons.gov.uk.
[25] See https://www.fbi.gov/services/cjis/ucr/publications.

hand used the technologies of data transfer and hyperlink markup language for fast and reliable communication.

The foundation for the internet was laid through the general concept of data communication, i.e. the transmission of data between two different places through an electromagnetic medium, and was manifested in inventions like the telegraph. Evolving computer technology allowed communication between computers over longer distances or with higher speed which was necessary for the mainframe computer model[26]. Data could then be exchanged between remote computers. However, the exchange was limited as the computers required a physical link; past technology did not allow direct communication between any two arbitrary systems. While the early computers needed to be connected directly to terminals, wide area networks (WANs) emerged during the 1950s.

Much research effort was invested by the Defense Advanced Research Projects Agency (DARPA), a research and development agency of the United States Department of Defense, responsible for the development of technology for use by the military. Following ideas about networking concepts laid out by Licklider (1960) and Licklider and Clark (1962) and about packet switching by Kleinrock and Lam (1975) and Kleinrock and Tobagi (1975), an alternative to circuits for communication, Lawrence G. Roberts (1988) developed computer network concepts and planned the ARPANET, the Advanced Research Projects Agency Network. The ARPANET worked as the pioneering packet switching network but soon included other forms of networks[27].

Building upon the technologies of the internet, the English scientist Tim Berners-Lee invented the world wide web in 1989 while employed at the CERN (see for a history written by the inventor Berners-Lee 1999). He wrote the first web browser in 1990 which was then released to other research institutions and the public one year later. This allowed that documents and other resources on the internet could be accessed by users. By 1993, websites for general use started to become available. By today (July 2022), an estimated 1.9 billion websites exist[28].

[26] The mainframe computer model consists of centralised computers which end users access via "dumb terminals". This allows the mainframe computer to be in secure, climate-controlled specialised rooms, while the terminals used as interfaces can be low-cost and simple (Leaning 2017 chapter 4.4).

[27] Comparable ideas were also developed at the Massachusetts Institute of Technology (1961-1967), at the RAND Corporation (1962-1965), and at the National Physical Laboratory (1964-1967) (Leiner et al. 2009).

[28] See `https://www.internetlivestats.com/total-number-of-websites`.

With the development and expansion of the internet, the possibility of openness has grown. Better computer performance allowed for more automation; however, the internet allowed the connection of people in a way which was unimaginable before. Leiner et al. (2009: 22) described its possibilities as follows: "The internet is at once a world-wide broadcasting capability, a mechanism for information dissemination, and a medium for collaboration and interaction between individuals and their computers without regard for geographic location".

2.2.3.1 A Movement Towards Openness

A key to the rapid growth of the internet has been the free and open access to the basic documents, in particular the specification of the protocols (like the HyperText Transfer Protocol, HTTP). The internet was also widely used by research communities, as it promoted the academic tradition of open publication of ideas and results. The general idea of openness thus lies at the core of the development of the internet.

The world wide web and the digitalisation have strengthened these developments; much of the data which is digitised is not only accessible online, but often time it is accessible for free to the public such as the aforementioned speeches of politicians, books, or statistical data. This idea of more openness in the world of information and data is not new but has gained popularity and is backed by open movements such as the movements for *open-source software*, *open education*, *open access*, *open government*, *open data*, or *open science*[29].

The most prominent example for openness in terms of open-source is the operating system Linux. Before the highly successful development of Linux, it used to be believed that complex software had to be developed by a small group of people in a carefully coordinated way. Linux, on the other hand, combined the openness and the new networking capabilities of the internet. It was developed by volunteers spread over the globe with quality maintained by timely releases and instant feedback instead of rigid standards (Raymond 1999: 16). The free software movement started with the GNU[30] manifesto (Stallman 1985) and the scene around it has been described as *hacker scene* with a distinct *hacker ethic*: a new work ethic in which there is a responsibility to share knowledge through writing software and documentation, and

[29] The growth of the open movements is paralleled and contrasted by a rise in intellectual property rights, as well as institutional walls and paywalls (Kitchin 2014: 49).

[30] GNU stands for "GNU's Not Unix"; the term is a recursive acronym.

which is shaped by the guiding principles of freedom, cooperation and sharing (see e.g. Himanen 2001; Levy 2010). Due to the complex nature and expertise necessary in developing an operating system, Linux is still centred around a rather small community. Understanding the development of the much larger Wikipedia requires a further piece: world wide crowd-collaboration and contribution of the masses.

2.2.3.2 A Movement Towards Crowd-Knowledge and Crowd-Collaboration

The accessibility of things is a first necessary prerequisite to allow large amounts of people to contribute to these things. In the ideal case, not only the result—a book or an article—is publicly and openly available, but the process of creation is founded on an idea of openness.

As stated in section 2.2.1, the idea of crowd-collaboration in the context of information gathering is not unique to the online world (see also Howe 2009: 11): Heinrich Zedler's encyclopaedia considered the publication of user sent-in content. Even more crowd-sourcing was motivated by the Philological Society of London in 1857: they asked readers to look for specific words in old books and journals and report the place they found them. The goal was to create a comprehensive dictionary of the English language, covering all words with their earliest occurrence as well as their changing usage. Their calls led to a global response and thousands of people were—and still are—supporting the search for words, thus helping in making the Oxford English Dictionary one of the most important scientific dictionaries (Oxford English Dictionary 2022).

In this fashion, many other projects grew more or less successfully in the past decades, now making use of the opportunities of the world wide web. One of the first projects collecting knowledge from the masses in the online space is the *DMOZ*[31] (from directory.mozilla.org, an earlier domain name), also known as Open Directory Project (ODP). What the phone book is in the offline world is the DMOZ in the online space. It was founded in June 1998 and formed a multilingual, open content directory of world wide web links for almost twenty years, constructed and maintained by a community of volunteer editors. It offered a topical directory of the internet. By the end of 1998, the project had about 100'000 URLs indexed with contributions from around 4500 editors. One year later, a million URLs were indexed. At

[31] Not accessible anymore; see the follow-up project *Curlie* `https://curlie.org`.

the end of 2015, about 4 million sites were listed in over 1 million different categories by about 100'000 contributing editors.

While the DMOZ is just a directory, online encyclopaedias quickly followed. The static nature of encyclopaedias in contrast with the dynamic reality of knowledge made them a clear candidate to profit from a digital world which allows updates and changes more quickly and cheaply than the printed word. One of the first projects to build an online collection of information was the *h2g2* website[32], a British-based collaborative online encyclopaedia project. It describes itself as an "unconventional guide to life, the universe and everything" in the spirit of Douglas Adams' fictional publication *The Hitchhiker's Guide to the Galaxy*. It forms a collaborative guidebook, written and maintained by volunteers. It was founded in April 1999 by Douglas Adams, was run by the BBC between 2001 and 2011 and is currently still active but run by the Community Consortium and Panicking Ltd. h2g2 covers both traditional encyclopaedic subjects as well as idiosyncratic articles, often aiming for a humorous style.

A wide arrange of online encyclopaedias have developed since, from some universal knowledge collections to those covering only niche topics of interest. There is no exhaustive list of all online encyclopaedias[33]. One notable example is *Knol*, a Google project aimed at creating a collection of knowledge. Registered users were able to write articles on a range of topics. While Knol was crowd-generated, it was not inherently collaborative as single articles stemmed from single users and there could be multiple articles on the same topic, each written by a different user (Schofield 2008). While projects like h2g2 or DMOZ are collaborative and the work of many, the addition of new articles or links is generally a longer process which requires permission. These projects all lack one important feature which Wikipedia offers: the *wiki* style of collaboration discussed in the next subsection.

2.2.3.3 The Wiki Style of Collaboration

What is a wiki? Wikis—the Hawaiian word *wiki* meaning "quick"—in themselves are hypertext publications that are collaboratively edited and managed by their audience. They can be understood as the simplest form of an online database. Wikis are enabled by wiki software which works vastly different from, for example, blogs: content is created without a defined order and

[32] See www.h2g2.com.

[33] See for an overview for example https://en.wikipedia.org/wiki/List_of_online_encyclopaedias.

leader and there is little inherent structure. Wikis allow structures to emerge according to the needs of users (Leuf and Cunningham 2001).

A wiki allows anyone to edit a website, making it fundamentally open and decentralised. The point is to make it accessible to as many people as possible. Collaborative work sky-rocketed with wikis as they made work much easier and allowed the writing of so-called stubs; stubs are initial short articles which are started with the intention of having other people expand them later on. Wiki software encourages openness and decentralisation, as page changes are logged, publicly viewable, and pages can be changed by anyone without needing any assignment (Sanger 2005).

The first ever wiki site, the *WikiWikiWeb*, was created for the Portland Pattern Repository (discussing software design patterns) and launched in 1995, programmed by Ward Cunningham[34]. That pioneering site now hosts tens of thousands of pages. Other wikis have emerged since: some of them are public, while others are private and have restricted audiences and editors, for example within the context of a company.

A few noteworthy wikis are named in the following[35]. *AboutUs* is a wiki internet domain directory, listing websites and short information about their content[36]. *WikiHow* is an extensive database of how-to guides[37], the *Stadtwiki Karlsruhe* is the largest city wiki[38]. It contains information on all topics that are related to Karlsruhe and its surroundings; many of its editors are also Wikipedians (and have also attended Wikipedia meetups). *Citizendium* was launched by Larry Sanger; it is a general encyclopaedia aiming at high reliability by requiring writers to use their real names and being generally guided by expert input while still allowing edits from the public[39]. *RationalWiki* is another encyclopaedia, providing articles written from a liberal, sceptical, and secular point of view[40]. Another popular and impressive wiki-based project is *OpenStreetMap*[41]. OpenStreetMap is a collection of free geo-data, and volunteers add information to the map and update it. The most popular and best sustained wiki-based project is Wikipedia. Its history will be outlined in the next section.

[34] See http://wiki.c2.com/?WikiWikiWeb.
[35] While there is no exhaustive list of all existing wikis, see for a list of projects for example https://en.wikipedia.org/wiki/List_of_wikis.
[36] See https://aboutus.com.
[37] See https://en.wikihow.com.
[38] See https://ka.stadtwiki.net.
[39] See https://en.citizendium.org.
[40] See https://rationalwiki.org.
[41] See https://www.openstreetmap.org.

2.2.4 A Short History of Wikipedia

Against the background of information having gone both digital and online and the idea of openness flourishing, Wikipedia was developed. As Larry Sanger (2005), one of the two founders of Wikipedia, writes, the history of Wikipedia dates back to 1999 when Jimmy Wales wanted to start a free, collaborative encyclopaedia. Starting with funding from the dot-com Bomis (which Jimmy Wales co-founded) and with collaborator Larry Sanger who was hired to oversee the project, *Nupedia* was launched in March 2000. Nupedia aimed to provide highly reliable, peer-reviewed articles written by volunteer contributors with appropriate subject matter expertise. Articles had to undergo a thorough peer-review process; in the first year, only 21 articles were approved (Sanger 2005). Due to this slow productivity of Nupedia which Jimmy Wales and Larry Sanger expected to be an ongoing problem, they opted for a way in which ordinary, uncredentialed people could participate more easily, employing a less rigid system. They decided to follow the example of WikiWikiWeb and introduced a wiki format. Initially, the idea was to have a wiki as a part of Nupedia to allow the public to contribute a stream of content which later could be fed into Nupedia after undergoing necessary revisions. However, the advisory board involved in Nupedia was sceptical of the idea, fearing the loss of rigour and reliability. Therefore, the wiki was relaunched under its own domain name, Wikipedia, on January 15, 2001.

Wikipedia sky-rocketed. Its growth was not comparable with the one of Nupedia: by the end of January 2001, 600 articles were written. While Nupedia published 21 articles in its first year, there were 18'000 published articles on Wikipedia (Sanger 2005). Wikipedia started with a handful of people, many stemming from Nupedia, but grew exponentially.

The ideas of von Hayek (1945) and Raymond (1999) have worked as guiding concepts in the development of Wikipedia, as Jimmy Wales stated in interviews (Richter 2020: 26–29). In *The Use of Knowledge in Society*, von Hayek (1945) promotes a decentralised economy, stating that each person owns just a small piece of information and that information must be made on a local level. In *The Cathedral and the Bazaar*, Raymond (1999) describes and contrasts the creation of software: comparing open-source software (the bazaar) with proprietary one (the cathedral). Open-source software is a self- and not centrally organised institution. With its focus laying on the collaboration and its self-organisation, it is never finished. These manuscripts build the theoretical underpinning of Wikipedia.

In this spirit, Wikipedia began with very few policies, expecting that they would evolve out of the community. The first entry on Wikipedia's "rules to consider" page was the rule to "ignore all rules" (Sanger 2005: 318). The thought behind this was that gathering more participants was more important than strict rules that might deter users from participating. Notably, co-founder Larry Sanger left the project as he was frustrated with non-cooperative users that were strongly against any kind of authority (Cooke 2020). Wikipedia followed some cultural features typical for wikis: it was open, decentralised, featured little authority with hands-off management which also led to extremely tolerant handling of disruptive, uncooperative behaviour; it loosely followed the distinctive *wiki culture* which promotes many collective habits and principles (Sanger 2005: 315–316). While Wikipedia began as an anarchy, some policies were settled within the first six months which aimed at ensuring the creation of an encyclopaedia; for this matter, it was discussed "what Wikipedia is not" (not a dictionary, not a place to publish original research, etc.), as well a policy on the non-bias/neutrality was instituted early on. Even though these rules led to controversies, the restrictions were necessary to achieve the goal of producing an encyclopaedia. The focus on creating an encyclopaedia provided the common task and the open content licence worked as a motivating force for people to work for the good of the world, guaranteeing that their content stays free for others to read. A strong focus on openness and ease of editing allowed anyone to contribute and feel welcome. Radical collaboration was promoted, also allowing and encouraging the posting of unfinished drafts. Starting with a knowledgeable and somewhat experienced core of people coming from Nupedia and the goal of being a neutral place further encouraged the development of a functional, cooperative community. These principles as well as profiting from the large volume of traffic generated through search engines were important for the success of Wikipedia, according to co-founder Sanger (2005: 321-323). Richter (2020) bases the success of Wikipedia on three aspects. Firstly, Wikipedia is the result of a very clear, simple, and comprehensible idea: creating an encyclopaedia. Secondly, there were and are only small hurdles to contribute towards it as edits can be made anonymously and registration only requires a username and a password. Thirdly, the model of authorship is one which does not emphasise the status or name of the author, but frees the textual contribution of the creator, allowing anyone to edit it.

Wikipedia is dedicated to the building of free encyclopaedias in all languages of the world. It began on January 15, 2001 with the English language Wiki-

pedia. Two months later, it was followed by the German Wikipedia and afterwards by many other languages. The German Wikipedia is now one of the largest language versions of the site, featuring currently (July 2022) over 2.7 million article content sites and over 3 million registered users[42].
Wikipedia is one of the wiki-based projects which is funded and managed by the Wikimedia Foundation, a charitable organisation founded in 2003 by Jimmy Wales. Next to Wikipedia, Wikimedia projects also most notably include Wiktionary, a dictionary, Wikimedia Commons, a data repository of media files, or Wikidata, a knowledge graph. The Foundation lies behind the Wikimedia movement; a movement referring to the global community of contributors to the Wikimedia Foundation projects, pursuing the goal of developing and maintaining open content, wiki-based projects and making these contents accessible to all, free of charge.

2.3 Wikipedia: State of Research

The online encyclopaedia Wikipedia has become not only one of the top destinations for information to many people but also developed into a phenomenon met with strong interest by the scientific community. Throughout the past twenty years of Wikipedia's existence, the encyclopaedia and its specific software structure have created a rich and freely accessible data base, offering the opportunity to study large-scale, self-organising collaboration networks. This has made Wikipedia both a popular source of data and a research topic in itself for scholars of different disciplines. In the following section, I will outline important research in the field. Given its scope—the Web of Science citation database finds well over 6000 articles when searching for the keyword "Wikipedia"—, the section cannot aim to be an exhaustive review of what we know about Wikipedia, but instead it aims at giving a broad overview. It focuses on mapping the gap this thesis contributes towards: research about the offline component of Wikipedia.
See for earlier literature reviews Benkler et al. (2015), Martin (2011), Medelyan et al. (2009) and Okoli et al. (2012). It has also been tried to collect research

[42]See for numbers and facts about German Wikipedia: https://stats.wikimedia.org/#/de.wikipedia.org.

on Wikipedia on a designated database[43], and to keep a list on Wikipedia up to date[44].

2.3.1 Using Wikipedia for Research

The rich and freely accessible nature of Wikipedia data, particularly its structured and large body of text in multiple languages, makes it a popular data source for computer scientists to develop, improve, and showcase new algorithms, particularly in the field of natural language processing and supervised machine learning in general.

Data from Wikipedia lends itself to train algorithms performing part-of-speech-tagging (Eskander et al. 2020), named-entity recognition (Kim et al. 2012), clustering (Hu et al. 2009), or topic-modelling (Gerlach et al. 2018). Data from Wikipedia has also been used to study language complexity, making use of the Wikipedia version in simple English and comparing it with the English Wikipedia (Yasseri et al. 2012). The link structure of Wikipedia which draws a network between pages has often been used for word sense disambiguation, the task of automatically assigning the most appropriate meaning to a word within a given context (Dandala et al. 2013; Fogarolli 2009; Li et al. 2011; Mihalcea 2007), semantic similarity (Li et al. 2020), or to create dictionaries, using the intra-language links (Erdmann et al. 2008). Quack et al. (2008) use Wikipedia articles to verify automatically tagged and annotated images of, for example, touristic sights, mined from public photo databases. Also, a large body of research is concerned with detecting errors on Wikipedia and improving it as an encyclopaedia and data source, which in turn also trains better algorithms for other usages (e.g. De Melo and Weikum 2010; Gerlach et al. 2021; Milne and Witten 2008; Sorg and Cimiano 2008)—how the contents of Wikipedia are assessed in research is further the topic of subsection 2.3.2.1.

Wikipedia has been described as a “goldmine” of data for researchers (Medelyan et al. 2009: 716) and, as outlined, numerous articles have used the Wikipedia corpus (see for reviews e.g. Medelyan et al. 2009; Okoli et al. 2012). The goals or outcomes of such studies are generally not focused on Wikipedia itself but use its content as textual data source for other scientific analyses;

[43] Not maintained anymore, see `http://web.archive.org/web/20181209084549/http://wikilit.referata.com/wiki/Main_Page`.

[44] See `https://en.wikipedia.org/wiki/Wikipedia:Academic_studies_of_Wikipedia`.

they thus pursue an inherently different goal than what this thesis tries to achieve.

2.3.2 Researching Wikipedia

Very different to the studies mentioned in the previous subsection are studies which research Wikipedia as a phenomenon itself. In this case, Wikipedia is not just the data generating platform, but the contents and the community themselves become of relevance; this thesis follows such an approach. In this section, a broad overview of the different strands of research on Wikipedia will be given. Research concerning face-to-face meetings of Wikipedians will be discussed in the next section (section 2.4).

2.3.2.1 Contents of Wikipedia

A main interest regarding Wikipedia lies in studying its content and its growth, depth, breadth, validity, and reliability; such studies focus on the articles. Particularly, the quality of Wikipedia articles has been one of the main concerns of academic and user communities, asking questions about how reliable and valid information on a website can be if anyone can edit it. Such studies typically select a sample of Wikipedia articles and judge their quality compared to those in other encyclopaedias, compared to a ground truth provided by experts, or based on subjective credibility.
Overall, there is mixed evidence on the quality of Wikipedia articles, and the quality also varies substantially across articles. One of the first in studying the quality of Wikipedia was Giles (2005) who compared it to the Britannica. According to his landmark study, both encyclopaedias featured errors (Britannica around three errors per article, Wikipedia four), but Wikipedia fared (surprisingly) well. A similar comparison was undertaken by Luyt et al. (2007), focusing on articles in the field of biochemistry. Wikipedia's validity is also considered sufficient by, for example, Rosenzweig (2006) who focused on names, dates, and events in US history, or Rajagopalan et al. (2011) who are concerned with information regarding different cancers. Others, however, found that Wikipedia is of inferior quality compared to other sources: for example, Lavsa et al. (2011) compared Wikipedia articles about medication with information written in the manufacturer's package insert and found Wikipedia articles to often be incomplete and inaccurate, and some studies have mentioned a lack of reputable references in Wikipedia articles, considering those a proxy for good quality (e.g. Luyt and Tan 2010).

Other studies cover the determinants of article quality, and aim at explaining and predicting what kind of articles on Wikipedia are being "promoted", i.e. are being highlighted by the Wikipedia community as being of exceptional quality (e.g. Arazy et al. 2011; de La Robertie et al. 2015; Liu and Ram 2018; Stein and Hess 2007; Wilkinson and Huberman 2007). For example, de La Robertie et al. (2015) use the co-editing pattern of contributors to predict article quality. Focusing on the comprehensiveness of articles covered, Halavais and Lackaff (2008) found that specific categories such as the social sciences, philosophy, medicine, and law are under-represented, while others (science, music, naval studies, geography) are over-represented. Furthermore, it has become a well-stated fact that Wikipedia suffers from a gender bias favouring men (e.g. Graells-Garrido et al. 2015; Wagner et al. 2016). Overall, the contents of Wikipedia clearly depend on discipline and specific topic. There seems to be no consensus on how reliable or comprehensive Wikipedia as a whole is.

2.3.2.2 Community of Wikipedians

Wikipedia is written by volunteers—understanding who they are, why they join the platform, and why they keep editing has been of interest to many scholars. A large body of research is concerned with issues related to participation in the Wikipedia community. Considering that Wikipedia is a prime example of a collective good—a good characterised by non-excludability, jointness of supply, and non-rivalry (Hardin 1968; Olson 1974; Varian 1992)—the incentives to contribute are low as no one can be excluded from its benefits and use. Contributing to a collective good implies voluntary, extra effort without any compensation and is thus irrational. This is, in particular, the case in large, latent groups; increasing group size should lead to a crowding-out effect and individual contribution levels are suggested to fall to zero (Andreoni 1988; Olson 1974). Following this argumentation based on rational choice theory, it is not straight-forward to comprehend why people contribute towards Wikipedia. The provision of articles is costly for the authors as they need to invest time in researching and writing, and even more effort is required for users who are more strongly engaged on the platform such as administrators.

Wikipedia is based on the voluntary effort of its volunteers and there are no financial compensations for any work conducted for Wikipedia. Nevertheless, Wikipedia exists, and its scope is remarkable. Many individuals have opted against free riding and instead participate. Even though there is, of course, also extensive free riding on Wikipedia: only a fraction of users contribute regularly. A survey of American undergraduate students has shown that over 70 per cent of respondents read Wikipedia several times per week, but only 16 per cent have ever edited anything (Antin and Cheshire 2010). There is furthermore a remarkable difference in levels of productivity between different Wikipedia contributors. Ortega et al. (2008a,b) find that less than 10 per cent of authors are responsible for more than 90 per cent of the total number of contributions; this pattern has been shown to be stable over time and across different language editions. Wikipedia edits follow a power-law distribution (Kittur et al. 2007a; Panciera et al. 2009). Panciera et al. (2009) also found that those highly active Wikipedia users are inherently different from the rest of the userbase from the start, and Merz (2019) and Welser et al. (2011) have developed a typology of different author types and social roles. These studies, however, focus solely on the online component of Wikipedia (while Merz (2019: 7) explicitly acknowledges offline activities, he considers them beyond the scope of his research).

Motivations to Contribute Against this background, it has been of interest to understand why people contribute towards Wikipedia. Reasons for contributing have been given by co-founder Sanger (2005: 321-323) and long-term member and administrator Richter (2020): both base the success of Wikipedia on the aspect of having a clear goal (creating an encyclopaedia), small hurdles to overcome when wanting to contribute, and the open way of contributing content which is not strictly linked to the author. However, these aspects still do not explain why people start to invest time and effort into the project. Looking at the cost and rewards, it is difficult to theoretically explain the levels of cooperation found between Wikipedia editors which have been sustained for decades.
Several studies have tried to understand why people contribute to the online collective good Wikipedia and surveyed participants on their motivations; data is also collected through the Wikimedia Editor Survey[45] (e.g. Algan et al. 2013; Anthony et al. 2009; Balestra et al. 2016; Baytiyeh and Pfaffman 2010; Crowston and Fagnot 2018; Kuznetsov 2006; Schroer and Hertel 2009). These studies suggest that editors are motivated to a large part by

[45] Data of the Wikimedia Editor Survey are generally not publicly available, but see for motivations on contributors also the Wikimania 2006 Wikipedian Survey: https://en.wikipedia.org/wiki/User:Linuxbeak/Wikimania_2006/Wikipedian_Survey and https://commons.wikimedia.org/wiki/File:Wikipedia_Editor_Survey_2012_-_motivation_analysis.pdf.

the mission of sharing free knowledge, as well as wanting to add content and improve the quality of articles they are interested in as they see a need for contributions. Personal fulfilment and learning, as well as curiosity and altruism are other motivational factors. It is also experienced to be a "great feeling" to edit Wikipedia[46] which fits the notion of a *warm glow of giving* as introduced by Andreoni (1990). In this case, contributors receive a private benefit in form of a warm glow (moral satisfaction, joy of giving). One's own contributions can then not be perfectly substituted through the contributions of others. Editing Wikipedia is further experienced as a fun activity with addictive qualities. Economic theories are thus bound to fall short: contributing towards Wikipedia is not work but seems to be inherently fun—it has been described as a project fostered out of love (Cooke 2020). Brown (2008) also argued that online cultural production lies between leisure and labour[47].

Community Aspects As authors of Wikipedia are not working in isolation but deeply embedded in a network with other contributors, Wikipedia needs to be understood as a community and not only as a platform to share knowledge (Hara et al. 2010; Konieczny 2009; Pentzold 2010). Some studies have directly taken Wikipedia as such, analysing different community aspects. Reagle (2010) has characterised the site as offering an encouraging environment aimed at problem orientation, spontaneity, empathy, equality and provisionalism. Forte et al. (2009) have focused on the decentralised governance structure and used interviews to understand how norms develop. A cross-cultural study analysing the norms in place in different language versions has been undertaken by Hara et al. (2010). They discuss the contents of norms in relation to Hofstede's dimensions of cultural diversity and the size of the community. Goldspink (2010) examined the effect of norms and rules on editor communicative behaviour and found that social norms only play a small role in influencing editor behaviour (norms on Wikipedia will be discussed in more detail in chapter 5). How positive and negative feedback

[46] https://commons.wikimedia.org/w/index.php?title=File%3AGreat_Feeling.ogv

[47] Contributing to Wikipedia could be understood from an economic perspective, if adopting the view of Wright (2010 chapter 7) who described Wikipedia as a real utopia; it is an example of social economy, being fundamentally organised in an anti-capitalist fashion. Following Olson (1974: 161–162), utopias, considered heavens on earth, are expected to bring benefits that are incalculably large or even infinite and are thus an exception to the rule of an expected lack of cooperation regarding collective goods. If the benefit that would come from establishing a utopia is infinite, it could be rational even for the member of a large group to contribute voluntarily to the achievement of the group goal (the utopia). A minute share of an infinite benefit or a small increase in the probability of such a benefit could exceed an individual's share of the cost of the group endeavour.

towards behaviour can influence editor activity has been studied by Restivo and van de Rijt (2012, 2014) who used a field experiment to understand the effect of *barn stars*, a sort of virtual award that users can give to each other, while Halfaker et al. (2011) and Piskorski and Gorbatâi (2017) have focused on norm enforcement via reverting edits, a sort of negative feedback, and Zhu et al. (2013) analysed and compared different forms of feedback (in the form of differing messages sent to contributors).

Adopting a network perspective, Wikipedia can also be conceptualised as a web of interconnected authors who are tied to each other in some form. The network between Wikipedians is often defined as a collaborative network where ties represent actors having worked together on the same (parts of an) article (e.g. in Piskorski and Gorbatâi 2017). In some studies, the network is created with talk pages as its foundation, thus creating a network which is based on communication or discussion (in e.g. Massa 2011; Qin et al. 2015; Viégas et al. 2007b). Using such a network approach based on collaborative ties, Halatchliyski et al. (2010) have investigated the way knowledge is built regarding articles on physiology and pharmacology. They compared the work of authors who are exclusively contributing to one domain with that of authors who contributed to both domains and find that the very active and experienced users are the ones writing intersecting articles. The balance theory put forward by Heider (1958), a fundamental theoretical matter in network analysis aiming at explaining patterns of interpersonal relations, was tested with Wikipedia data by Lerner and Lomi (2020). Simply put, the theory states that there must be a balance between interpersonal relationships so that psychological harmony can be achieved. While certain network structures are considered balanced—for example, A likes B, B likes C, and A likes C—others are considered imbalanced—for example, A likes B, B likes C, but A dislikes C[48]. Balanced structures are generally preferred over imbalanced ones. Investigating the network structure of controversial articles, Lerner and Lomi (2020) find support for the balance theory. They focus on the deletion and protection of contributions.

Different community aspects have been at the centre of many research studies on Wikipedia. Another way to understand the community of Wikipedians and their ties with each other would be to move from online connections to offline relationships. This is the focus of the next section.

[48] If no or an even number of negative relations (i.e. dislikes) are present in a triadic relationship, it is thought to be balanced.

2.4 Meetups on Wikipedia

The previous section discussed different ways in which Wikipedia has been used in research. This section will specifically focus on meetups on Wikipedia. First, I will describe what the offline component of Wikipedia looks like and what role face-to-face meetings play on Wikipedia. Next, I will give a rich description of these meetings, the different types of them, why they take place and interesting dynamics that have developed. Anecdotal examples will be given to illustrate what such meetups entail to create a better understanding for the non-Wikipedian. Lastly, previous research on offline meetups between Wikipedians will summarised.

2.4.1 The Offline Organisation of Wikipedia

Wikipedia is inherently an online endeavour as laid out in subsection 2.2.3.2 but features a number of offline components. Wikipedia exists in "the real world": the Wikimedia Foundation is headquartered in San Francisco and employs around 550 full-time staff members and contractors worldwide. In 2020, the Foundation generated a revenue of $127 million US Dollars (Wikimedia Foundation 2020). Further, so-called Wikimedia chapters are independent organisations founded to support and promote the Wikimedia projects in specified geographical areas. As of July 2022, there are 38 chapters. They follow the same aim as the Wikimedia Foundation: they want to empower and engage people around the world to collect and develop educational content under a free licence or in the public domain[49]. In the German speaking area, three chapters exist: the Austrian chapter founded in 2008 with currently 150 members, the Swiss chapter with around 500 members (founded in 2006), and the very active German chapter with over 50'000 members which is the chapter with the most members worldwide (founded in 2004). This chapter model was designed for groups of engaged Wikimedians focused on a specific geographic area to better manage increased community expectations as well as activity and reporting requirements. Wikimedia chapters also function as geographically bounded points of contact to the local Wikipedians.
Each year, the Wikimedia Foundation hosts an international conference, the Wikimania, which generally attracts over 500 people but had a turnout of over 1400 attendees in some years[50]. Topics of discussion and presentation include the Wikimedia projects such as Wikipedia but also open-source soft-

[49] See https://meta.wikimedia.org/wiki/Wikimedia_chapters.
[50] See https://en.wikipedia.org/wiki/Wikimania.

ware and free knowledge in general. The very first Wikimania was held in 2005 in Frankfurt am Main, attracted about 380 attendees, and included keynote speakers like Wikipedia founder Jimmy Wales, Ward Cunningham, the developer of the first wiki, and Richard Stallman, a well-known free software movement activist and launcher of the *GNU Project*, a mass collaborative initiative for the development of free software. The Wikimania has since been repeated annually, taking place in different countries across the globe. The sixteenth edition planned to take place in 2020 was postponed due to the Coronavirus pandemic. 2021, it was then held online for the first time.

Next to this annual conference which aims at bringing together the people involved in the Wikimedia organisation and projects on a global scale, the local chapters can organise and promote offline and online activities. However, activities do not need to be organised by such institutionalised entities, but any Wikimedia contributor is welcome to organise local meetups as well. The German Wikipedia has a designated site to organise and coordinate regional and international meetings[51]. Such meetings take place in different regions with different levels of regularity. What do such meetings look like? This will be discussed next.

2.4.2 Understanding Meetups on Wikipedia

The face-to-face meetups of Wikipedians form the core of this thesis. Over 4000 offline meetings of Wikipedians took place between the launch of the German Wikipedia in 2001 and the forced stop of face-to-face meetings in March 2020 due to the outbreak of the Coronavirus pandemic. This section will paint a rich picture of these meetings to create a better understanding of what they entail. All quotes are my own translations of the German original and all usernames are anonymised[52].

2.4.2.1 Social and Work Meetups on Wikipedia

Face-to-face meetups between Wikipedians come in all shapes and sizes. The most common form is the informal *Stammtisch*, organised locally to socialise and get to know other Wikipedians. What does such an informal meetup look like? When a new user asked in 2009 what he could expect from such a meetup in Munich, a more experienced one described them like this:

[51] See https://de.wikipedia.org/wiki/Wikipedia:Treffen_der_Wikipedianer.

[52] I do not anonymise the gender pronouns. If they are unknown, I use the neutral wording of “they/them”. In cases where this is confusing due to the sentence structure, I use the male pronouns as Wikipedia is heavily male-dominated.

> "You sit around one or multiple tables, eat pizza, pasta and co., see the faces belonging to the usernames, chat about the latest news inside and outside Wikipedia. [You talk] About topics that someone is working on, sometimes even about articles. However, perhaps surprisingly for newcomers, Wikipedia does not play such a big role in the conversations. Some people have known each other for a long time, others are new. Some mostly listen, others tell history and stories. Working on Wikipedia can be a lonely activity—through meetups, you get to know a few faces of people who also find Wikipedia amazing. And often times, you find colleagues with whom you can work better online after getting to know them personally. Just drop by, you are welcome to come."[53]

When a newly registered user asked in 2013 what the agenda of these meetings are and whether they provide good opportunities for new Wikipedians—like him—to get basic information on how to contribute to Wikipedia, he was informed by an experienced user that these meetings as organised by the portal for Southern Germany are not meetings to work, but rather serve to get to know each other personally and talk, but they warmly welcomed him and new users in general[54]. These meetups bring together editors of Wikipedia, giving the anonymous usernames a face. In one case, a meetup has even brought long-lost friends together: in a meetup in a large West German city, two users met again, twenty years after their time at vocational school, at a Wikipedia meetup of all places[55]. It has also been common practice to bring one's partner, children, or dog to meetups. In some cases, they have later on also joined Wikipedia and created their own accounts (or, in case of dogs, an account has been created for them[56]).

While such informal *Stammtische* are not meetings intended to work on Wikipedia, other forms of meetups consider exactly this their main goal. So-called editathons and open editing events are events where (potential) editors of Wikipedia meet to edit and often focus on improving a specific topic or type of content (such as adding new pictures, working specifically on (female) biographies, etc.). Meetings organised by WikiProjects and task forces (*Redaktionen*)—self-organised divisions on Wikipedia related to specific topics—also tend to be more work-focused and generally create project-related content. Such project-oriented meetings can come in different forms:

[53] https://de.wikipedia.org/wiki/Wikipedia_Diskussion:Stammtisch_M%C3%BCnchen/Archiv/2009.

[54] See https://de.wikipedia.org/wiki/Wikipedia:S%C3%BCddeutschland/Archiv/2013-10-11.

[55] See https://de.wikipedia.org/wiki/Wikipedia_Diskussion:M%C3%BCnster/Archiv/2013.

[56] See for example user WikiWuff https://de.wikipedia.org/wiki/Benutzer:WikiWuff.

they can entail collaborative walks through urban areas to take pictures of buildings and monuments for Wikipedia, guided tours in churches for which a Wikipedia article was lacking in quality, meetings in office spaces to edit together, or even a flight with a booked pilot over specific areas to take aerial images. While some task forces regularly organise meetings, others do not; for example, because some members of the task force tend to be sceptical about the level of productivity and inclusiveness at such meetings. When one highly active user and meetup goer suggested a meeting of the task force Egyptology, it was not well received:

> "What still bothers me in general is the focus of the meeting. First and foremost—if I have understood correctly—the meeting is about the Roman Limes, right? Well, I do not know anything about that topic. I would feel like a useless ornament at a meeting where I would neither have a say nor have anything to contribute. I hope this does not sound too selfish. However, I somehow suspect that only experts and archaeologists with a focus on ancient Rome will be there. And I would not be a good listener to them, let alone a helper."[57]

Meetings between contributors around the topic of Egyptology never took off. There are also social meetups that have never gotten successfully established. An example is the meeting in Hildesheim[58]. One engaged user desperately complained that they have been trying for years to set up a regular meetup in the city. Blame was finally put on user S who was responsible for removing Hildesheim from the list of cities with meetups, making the organisational page very hard to find. While some meetings never really took off in the first place, for others attendance strongly decreased over the year, for example in Munich. While there might be different reasons for this, in Munich blame was put on the fact that they stopped their archiving of meetups and keeping a list of users who were planning on attending[59]. While these are examples of unsuccessful meetings, many others have been attracting a core group of people who regularly meet up for decades.

Meetups are generally regionally based and bring people from the same area together, while project-oriented meetings tend to include users from different geographical areas sharing a topical interest. Occasionally, some more planning extensive meetups take place which are supra-regional in nature.

[57] https://de.wikipedia.org/wiki/Wikipedia_Diskussion:WikiProjekt_%C3%84gyptologie/Archiv/2013#%C3%84gyptologentreffen.

[58] See https://de.wikipedia.org/w/index.php?title=Wikipedia:Hildesheim&oldid=82056731.

[59] See https://de.wikipedia.org/wiki/Wikipedia_Diskussion:Stammtisch_M%C3%BCnchen/Archiv/2008.

An example of these are the barbecue parties organised by one very engaged Wikipedia user living in Berlin. His first barbecue took place in 2006 in his backyard as a farewell party as he was leaving for an exchange year to Portugal. He repeated his barbecue in the following two years, always attracting around one hundred Wikipedians from all over Germany, throwing the allegedly best party on Wikipedia[60].

Another example highlighting the kind of community that develops at these meetings is observable when users die. Throughout the active years of Wikipedia, a number of engaged users passed away. Generally, this leads to the setup of a public page of condolences[61]. In cases where users were active attendees of meetups, it has also been the case that Wikipedians attended the funeral of a deceased contributor. For example, in 2009, seven users attended another user's funeral in Vienna[62].

2.4.2.2 Conflict at Meetups

The point of informal meetings on Wikipedia is to socialise and, allegedly, anyone is welcome. According to the minutes recorded at meetups, most of them turn out to be friendly gatherings where users have a good time and enjoy each other's company. This subsection will discuss lines of conflict which have arisen at some meetings, but it should be kept in mind that these form the minority.

Some users were disappointed with the social and informal nature of these meetings. As Wikipedia allows for anonymous contributions, this also allows for raising critical voices about meetups in anonymity. For example, an anonymous user has given a negative review about a meeting in Tübingen, being disappointed with the lack of structure and introductions of participants. While the other users acknowledged that it can be difficult for newcomers to join established cliques as regulars at meetups are often longtime Wikipedians who have collaborated in the past, they also highlighted that it requires effort by the newcomers to join and have a good experience. The negative review of one caused numerous positive reviews to be written. Other newcomers commented on having had wonderful conversations by simply initiating them and having enjoyed a fun time[63]. Even if meet-

[60] See https://de.wikipedia.org/wiki/Wikipedia:Berlin/Gartenparties.

[61] See also https://de.wikipedia.org/wiki/Wikipedia:Gedenkseite_f%C3%BCr_verstorbene_Wikipedianer.

[62] See https://de.wikipedia.org/wiki/Wikipedia:Wien/Archiv/2010.

[63] See https://de.wikipedia.org/wiki/Wikipedia:T%C3%BCbingen/Archiv_November_2010.

ings are not appreciated by all, the regulars seem to become rather defensive about their meetup culture.

In some cases, users have not attended meetings depending on who else was attending. For example, in one city, users have mentioned that attendees seem to be a rather selective group of people, in particular made up of administrators. Users have reasoned not to come as they expected those meetups to be "meetings for administrators and insiders instead of for real authors"[64]. While this accusation was denied, the user raising this point did not attend any more meetings in the future.

Users also tend to be rather hesitant to come when journalists are present. For example, discussions have started after a press inquiry by the Axel Springer publisher in Berlin[65]. Such discussions often escalate; the aforementioned discussion in Berlin, for example, led to name-calling and debates about censoring opinionated pieces and the blocking of users[66]. It needs to be noted that the Axel Springer publishing house is famous for the lurid *Bild* which is seen critically by many. Nevertheless, overall, journalists often tend to be seen as external intruders.

There are also instances of considerable conflict between regular attendees of meetups. The most notable disputes will be discussed in the following.

User H, Vienna and Wikimedia AT A public fall-out has occurred and carried on over multiple months in Vienna[67]. User H used to go to meetups in Vienna, but declared in 2015 to stop participating at any future ones, giving the following explanation:

> "I am definitely not coming anymore. I have also already unsubscribed from the news address list. If meetup attendees have even started to log out of Wikipedia to drag me on a VM[68] (by now, this has happened multiple times, all in vain), then there is simply no basis anymore. If there is somebody who wants to see me blocked, then I do not have to come anymore. However, I must say that I have already spoken about this with this person three times in the meantime. Have fun."[69]

[64] See https://de.wikipedia.org/wiki/Wikipedia:Duisburg/Archiv.

[65] See https://de.wikipedia.org/wiki/Wikipedia_Diskussion:Berlin/Archiv/2013#Presseanfrage_Stammtisch_am_5._April.

[66] See https://de.wikipedia.org/w/index.php?title=Wikipedia:Berlin&diff=117128580&oldid=117128534 and https://de.wikipedia.org/w/index.php?title=Wikipedia:Berlin&diff=117177220&oldid=117177161.

[67] See https://de.wikipedia.org/wiki/Wikipedia:Wien/Archiv/2015 and https://de.wikipedia.org/wiki/Wikipedia:Wien/Archiv/2016.

[68] The *VM* is a designated Wikipedia page to report vandalism. Vandalism describes the practice of editing in an intentionally disruptive or malicious manner, see https://en.wikipedia.org/wiki/Vandalism_on_Wikipedia.

[69] https://de.wikipedia.org/wiki/Wikipedia:Wien/Archiv/2015.

In a later month, user H particularly criticised practices by the Austrian Wikimedia Foundation[70]:

> "I wanted to use this meetup to inform my long-standing colleagues and comrades on a larger scale about the rather unconventional activities of Wikimedia Austria, about very strange personal details reminiscent of nepotism, about letters sent to me by registered mail which included declarations of war, about threats of expulsion, hormonal confusion, and the like. It was not the first time. I can assure you all, it will be quite enjoyable in parts. [...] In the old traditional way, when meetups were still festivities and not the flag of the seven upright ones, I will organise this [next meetup in January] and announce it accordingly. Preliminary information will then be sent—also very well proven—to selected persons by personal mail. Of course, I will also put on the agenda the fact that at the last meetup, I was called a racist and sexist by a member of the board and I will raise the question of how to deal with such things in the future when those accused of such things are more easily intimidated than I am. I think it is urgent to talk about this [...].
>
> In public, they try to beat up a 'simple' member? First, slandering and shortly afterwards, a letter sent by registered mail from the association? Then there are office workers in—as I think—highly dubious roles that are worthy of clarification. A half-hearted apology, which was not really an apology, quite the contrary, was then sent to X via e-mail, in which he once again brought up the same thing, the accusations of sexism and racism. But in a format that is completely unacceptable, even almost absurd, and therefore had to be explicitly rejected. I will also report that a long-time active member was stripped of the reimbursement for Wikipedia activities, but in return, external persons are paid for expensive trips. There is a lot to report. [...]"[71]

In this fall-out, it was also important for Wikimedia to step in. They reacted to the accusations of user H:

> "In the past year, user H has made honourable statements about employees, board members, and volunteers active at Wikimedia Austria, which are demonstrably untrue, on various Wikimedia pages, on mailing lists as well as in semi-public emails to partners and employees. In addition, user H's behaviour on the Wikimedia projects causes lasting damage to the association by removing the note on WMAT-support on projects for which he received financial and organisational support. Due to the seriousness of the attempts of discreditation and the refusal to withdraw these accusations, we consider it necessary in the interest of the association and its members to take a stand on this matter here.

[70] The broader context of his reasoning, for example why user H was called a sexist and racist, is unfortunately not clear from reading meetup minutes.

[71] https://de.wikipedia.org/wiki/Wikipedia:Wien/Archiv/2016.

> We are happy to publish the anonymised contents of the warning letter sent to user H by the board. However, the prerequisite for this is the consent of the addressee.
>
> Concerning the allegations made on Friday, we would like to state: there is no 'nepotism' at Wikimedia Austria, also nothing that 'reminds' one of it. 'Office workers' are not in any 'highly dubious roles that are worthy of clarification'. Nothing could justify such an assessment. No 'long-time active member' was 'stripped' of their 'reimbursement for Wikipedia activities'. Not even to 'pay expensive travel to external persons'. No 'expensive travel for external persons' was paid.
>
> We appeal once again to user H to fulfil his duties as a member of the community and association in the sense of constructive cooperation."[72]

While some were supporting user H and tried to deescalate the situation in the beginning, others wanted to avoid meetups which were attended by user H. One user offered appreciative words for user H:

> "Dear user H, I understand you very well, because I also would not come to a meetup a certain person is planning to attend, but to turn your back on all the other people you are friends with is a bit over the top. Please reconsider the announced 'general' non-participation in meetups. Please!!!"[73]

Other users criticised the fact that user H and others tended to show up as surprise guests or signed up with a different username, making it difficult to avoid them. It is not clear how the conflicts between Wikimedia Austria and user H were resolved. However, overall, the meetups in Vienna were branded by these disputes for many years.

Recording Meetups and Being Public Another point of discussion has been the way users write minutes and reports after meetups. While it is common that a report is published after the meeting containing a list of attendees and topics talked about, this practice is not appreciated by everyone. For example, some users were against the practice of mentioning which specific topics have been talked about at meetings in the Kurpfalz[74]. One user wrote:

> "For me, such a meetup is an informal meeting, where I do not have to be aware (in contrast to every use of the keyboard as a user) about everything being public forever, in case someone gets the idea to take part in the stenography without consultation and without announcement and to document here what he wants to communicate to mankind [...]."[75]

[72] https://de.wikipedia.org/wiki/Wikipedia:Wien/Archiv/2016.
[73] https://de.wikipedia.org/wiki/Wikipedia:Wien/Archiv/2016.
[74] See https://de.wikipedia.org/wiki/Wikipedia_Diskussion:Kurpfalz/Archiv.
[75] https://de.wikipedia.org/wiki/Wikipedia_Diskussion:Kurpfalz/Archiv.

Other users find the listing of discussed topics helpful and appreciate the effort. In the ongoing discussion, the initial poster further explained their situation and conflicts they are involved in within Wikipedia causing them to be hesitant in approving detailed minutes:

> "I have been active in WP [Wikipedia] under my real name for 10 years now and have always been involved in controversial topics that have a substantially different significance than, for example, railway stations. In this context, I have been and still am subject to massive hostility, as was the case recently with a specific topic, where at first it was only about using the adjective 'Jewish' in the context of a politician who was murdered because of it ([Kurt Eisner]). Someone wanted to delete that, I was against it (as a long-time contributor to this article) and suggested that perhaps a better wording should be sought. All 3Ms (third opinions) who were consulted by the person suggesting the deletion did not see any problem in the adjective either, and finally, someone worded it differently, and everyone could have gone their own ways with satisfaction. But then it started: the advocate of the deletion added 'final words', in which he confirmed his previously expressed accusation that I had represented 'Nazi logic' and made it seem as if his deletion, which nobody supported, had now been carried out against my resistance. Okay, so far, so familiar. But my brief revision of this statement was then deleted three times, and one or two more of those guys showed up who had never been interested in the article before, but who pushed me into the Nazi corner with great passion at every opportunity. Unfortunately, our admins usually turn a blind eye to such things, and when I bring a suitable comparison, 'I' am blocked for 3 days. (Denigration as a Nazi, however, is punished with being blocked for a few hours at most)."[76]

This user was particularly concerned as the minutes about one meetup mentioned a video which got blacklisted by Wikipedia as it was against certain rules. All in all, this user did not lead a conflict-free life on Wikipedia and was thus very aware and concerned about what was and could be shared. A few years later, they again thought about joining a meetup. However, they refrained as they were an active contributor to articles regarding Donald Trump and his German grandparents which have increased in popularity. They again were worried about going public with their real name, considering they had published and worked on such articles. In this sense, being identified through a meeting can inhibit partaking.

Blocked Users How to handle blocked users is another reoccurring issue regarding meetups. In some cities like, for example, Hamburg, there were ex-

[76] https://de.wikipedia.org/wiki/Wikipedia_Diskussion:Kurpfalz/Archiv.

plicit anti-invitations of some users[77]: one user mentioned that they had been de-invited after also having been blocked on Wikipedia in general. While some agree that blocked users should not join further Wikipedia events, others did speak against this practice:

> "There are meetups where blocked users regularly appear. I am not aware of any brawls or other incidents. So let him come. Nothing worse will probably happen than the fact that maybe nobody really likes him, and he must cry alone into his beer."[78]

Another user further pointed out that being blocked from Wikipedia should not be equated with being blocked from meetups. However, they differentiated between long-time meetup goers who would still be welcomed after conflicts, and newcomers joining a meetup with different intentions such as stalking and provocation.

In Hamburg, the issue of blocked users is also discussed in the context of user S who has raised and caused controversial discussions in the past[79]. While some people highlighted that they are not in the power of disallowing others to come and people should stop bringing up their personal issues, many raised dissatisfaction if user S was to attend meetups:

> "I am too old to get involved in knick-knacks like encounter therapy. And I am too smart to turn the other cheek to him. In any case, I will spare myself an encounter with this person. After all, it is my leisure time."
>
> "I really have no interest in this person. I think that tolerance for their attacks is fundamentally wrong."
>
> "User S is one of the very few people with whom the tablecloth is cut so much [meaning with whom there were too many disputes] that I completely refuse to be in the same room with them. I am usually happy about every Wikipedian I get to know. I do not want to get to know him. There is no basis on which that could happen. And I do not want to spend an entire evening listening indirectly (let alone directly) to his legendary monologues about the evil in the world (the Foundation and all people with different opinions)."[80]

[77] See https://de.wikipedia.org/wiki/Wikipedia_Diskussion:Kontor_Hamburg/Archiv/HH.

[78] https://de.wikipedia.org/wiki/Wikipedia_Diskussion:Kontor_Hamburg/Archiv/HH.

[79] This is the same user S as noted above who removed Hildesheim from the meeting list.

[80] https://de.wikipedia.org/wiki/Wikipedia_Diskussion:Kontor_Hamburg/Archiv/HH.

On the other hand, in Heilbronn, many blocked users come to meetups or have even initiated them in the first place[81]. In the minutes of one of their meetings, they did not list the attendees but mentioned that they:

> "Appeared under cover names, with altered haircuts, by unfamiliar means of transportation, or by other means of concealment, so that alcohol-related symptoms could not be attributed to any of the well-known attendees of the other meeting. In addition, we decided to use disguise names, because for the first time at this meeting, the proportion of blocked users exceeded that of unblocked ones."[82]

Ruhrgebiet and Ruhrgebiet 2.0 A split of the meetup community has happened in the Ruhrgebiet[83] where a second meetup series *Ruhrgebiet 2.0* developed in addition to the general one in 2006. It started with a user stating that the board members of the Foundation are currently not welcome as guests at the meetup after there had been a conflict regarding whom was able to attend an award ceremony (Grimme award). This was also strongly supported by user S[84]. A number of users, including user S, were clearly offended by previous acts of the Foundation: "The meeting is by nature a Wiki**p**edia meeting and not a Wiki**m**edia in Germany meeting. Wikimedia also prefers to keep to itself on many occasions, see Grimme award." The invitation to the Grimme award ceremony was directed towards the Wikimedia Foundation, being the only tangible contact. The board members decided to take as many Wikipedians as possible to the ceremony. However, user S and some other users found the pattern of communication and the Foundation's overall behaviour regarding this issue not acceptable as they considered it not fair and transparent enough.

Many users advocated for open meetings where everyone could join as this would allow for open discussions to clear this conflict regarding the award invitation. This discussion happened in July 2005. The initial initiator of the original Ruhrgebiet meetup was one of those advocating for open meetings; he stated that the users who are complaining are not speaking in his name. He also raised the following point:

> "It is obvious that the meetup which I once founded as a friendly meeting place is to be forged into a kind of 'front' against the Foundation. I (and surely also one or more of the other previous attendees) have

[81] See https://de.wikipedia.org/wiki/Wikipedia:Heilbronn/Archiv_November_2018.

[82] https://de.wikipedia.org/wiki/Wikipedia:Heilbronn/Archiv_September_2016.

[83] Ruhr area, a polycentric urban area in North Rhine-Westphalia.

[84] This is the same user S as noted above.

> nothing to do with such ridiculous power games, which in my opinion have nothing to do with our actual goal and are mainly due to the verbal machine gun user S. The participation in this meetup is not bound to any pro / contra attitude on any topic [...]"[85]

In October 2006, an alternative meetup was founded, the *Ruhrgebiet GG* (later Ruhrgebiet x.0 and later Ruhrgebiet 2.0) which included board members of the Wikimedia Foundation (as they were considered unwelcome at the original meetup by user S and others). The meaning of "GG", their venues, as well as the clear reasoning behind their meetings was kept secret, but minutes were written after their meetups. These GG meetups led to more frustration on the side of user S who started provocative debates on the discussion page. The founding of a meetup of separatists led to a lot of negative feelings and it was difficult to track down why it was founded in the first place. For example, one user complained:

> "Oh, dear, are these fights really necessary? [...] User S's provocation here is absolutely unnecessary and totally out of line, and the secret separatist counter-meetup only contributes to the split, especially when it is demonstratively organised on the normal meetup page [...]. Why do you do this? What has actually happened since the meeting in X's backyard, where I thought that everything was still fine? Could you not all jump over your shadows and bury the miserable hatchet of war?!!! Please..."[86]

Some attendees of the GG meetup gave insights into its founding, stating that the meetup was not supposed to be a competing counter-event, but aimed at giving people who did not want to go to the regular meetup (anymore) a chance to meet, particularly giving the option to avoid user S. It was also highlighted that the Ruhrgebiet community had been split a long time ago and that the founding of GG only made this visible. It was pointed out that users were free to go to either or both Ruhrgebiet meetups and there was no deciding for or against one or the other.

There were in total ten meetups over the span of two years of Ruhrgebiet GG/2.0/x.0. Starting with their 8th meeting on February 9, 2008, they met in a more public fashion as noted in their report: "On Saturday, February 9th we finally met for the first time freely and openly in the Essen Unperfekthaus, as the reasons for the secrecy of earlier meetings had meanwhile disappeared"[87]. To the outside reader of these organisational pages, it is not known how the conflicts were resolved.

[85] https://de.wikipedia.org/wiki/Wikipedia_Diskussion:Ruhrgebiet/Archiv/1.
[86] https://de.wikipedia.org/wiki/Wikipedia_Diskussion:Ruhrgebiet/Archiv/1.
[87] https://de.wikipedia.org/wiki/Wikipedia:Ruhrgebiet_x.0.

Berlin and the Berlin Alternative Starting in 2004, the Wikipedians of Berlin had a regular meetup in place. People either met at the *c-base station* or the *IN-Berlin*. The c-base station is an event location maintained by the c-base foundation, a non-profit association which aims at increasing knowledge and skills in the context of computer software, hardware, and data networks. The c-base station functions as a hackerspace (one of the first ones in the world) that welcomes other groups and initiatives which identify with the purpose of the c-base, for example, the wireless community network freifunk.net, the Berlin Ubuntu group, the Chaos Computer Club, Android developers, and it was the place the Pirate Party of Germany was founded. The IN-Berlin is a space provided by the Individual Network Berlin foundation, a non-commercial internet service provider aiming at providing affordable access to the internet for private individuals and offering other internet-related services. Their office spaces are used in particular by the Berlin Linux User Group[88].

Both, the c-base and IN-Berlin form rather informal and peculiar spaces which provide a computer-based working environment. While this is in line with the spirit of Wikipedia, it is not how some users have imagined meetups and some thus initiated an "alternative Berlin meetup" which took place in the Resonanz, a typical Berlin pub which was in their eyes more hospitable. One user explained:

> "Well, I like the c-base as well as the IN-Berlin when our meetups should have a nerd-like working and editing atmosphere. But sometimes it is also nice to just sit inside the pub and not have to drink your beer from the bottle. And if the wine is good, why not enjoy it in nice glasses? This has something to do with, well, cosiness, sociability, and the desire to chat without looking at a monitor."[89]

The founding of this alternative meetup did not go without some feeling offended: one user was surprised that multiple people have registered for the alternative Berlin meetup who have not been to the regular meetup in the past couple of years and was wondering what users had against the c-base and the IN-Berlin as she herself did not appreciate the stiff conventions of normal restaurants. The initiator of the alternative meetup tried to conciliate: "this is not a declaration of war on the Berlin meetup in its present form, but simply an additional offer to those who like something like this more" and another user added that it was not supposed to be a competitive event but

[88] See https://de.wikipedia.org/wiki/Wikipedia:Berlin/Alternative_Stammtischorte#IN-Berlin.

[89] https://de.wikipedia.org/wiki/Wikipedia_Diskussion:Berlin/Archiv/2009.

an additional offer providing “computer freedom”[90]. The person raising the issue remained offended and further advocated for the regular meetups as she did not consider the computers as a disturbance to communication. She voiced her opinion further:

> “To bring this to a conclusion: ’is there anything against meeting somewhere where you can sit around one or multiple tables, where food and drinks are brought to you, and it is frowned upon when you start working on a computer?’ - No, there is nothing against this. Each of us can, may and should meet with one another where it is convenient for them. But there is an almost five-year-old tradition of our (!!) meetup which speaks against solving such an issue with a signature list and an undertone of ’ ’I’ find this stupid, and this is why I try to find a majority of people who also find this stupid on the discussion page’. I have always made sure and find it extremely important that we discuss such things together, when we are all sitting together. (And I am not the only one who is annoyed by this initiative in this form) Let us all discuss the matter together on Friday in the IN-Berlin, please [...].”[91]

The discussion cooled down as the initiators and attendees of the alternative meetup in the Resonanz highlighted (again) that their intention was never to replace and critique the previous meetup, but simply to offer an alternative. While the regular meetup and the alternative meetup continued to coexist for many years, there were some distinctions in how they were handled. For example, for many years, only the regular meetups were archived on Wikipedia.

The highly active meetup community of Wikipedians in Berlin started to slow down throughout the years, especially after the establishment of a community space (see also below); users visited the community space more often and it then substituted instead of complemented the informal meetups. Particularly the meetups in the c-base and IN-Berlin stopped happening while the “alternative meetup” in the Resonanz still took place regularly. Nevertheless, the “alternative meetup” was always called the “alternative”, even when there had not been any other ones for years.

The Interplay Between Community Space and Meetup Community

Some cities in the German speaking area have special community spaces for Wikipedians[92]. These spaces are generally financially supported by the

[90] See https://de.wikipedia.org/wiki/Wikipedia_Diskussion:Berlin/Archiv/2009.

[91] https://de.wikipedia.org/wiki/Wikipedia_Diskussion:Berlin/Archiv/2009.

[92] See https://de.wikipedia.org/wiki/Wikipedia:Community-Space and https://de.wikipedia.org/wiki/Wikipedia:F%C3%B6rderung/Lokale_Community-R%C3%A4ume.

Wikimedia Foundation and offer headquarters for both staff members of the Foundation as well as engaged Wikipedians. Such strongly institutionalised community spaces currently exist in Berlin, Hanover, Vienna, Hamburg, Cologne, and Munich (see for more details on community spaces also subsection 3.3.1.2).

Community spaces often grew out of an active meeting community in a city but, once established, can lead to conflicts. While the conflicts will be highlighted in the following, it needs to be noted that in most cities, the interplay between community space and general meetup community worked without issues even though they often led to a reduction in the frequency of informal *Stammtische* (for example in Berlin as mentioned above).

In Munich, a conflict started to arise based on a disagreement regarding at which restaurant users wanted to hold a meeting. While in the recent past, meetups occurred at one specific restaurant, one user who is strongly engaged in the community space suggested a different one. She wanted to start fostering a cooperation with this new restaurant as she was starting a social project directed towards collaboration with refugees in Germany (Wikipedia4Refugees). This led to stark opposition. One user raised the following points:

> “The Wikipedia4Refugees campaign is certainly a good thing, but it is still unclear to me how this relates to the meetup. If you want to help emigrants, user X, then look for other interested people in Munich who want to support you in this campaign, but please do not pull the meetup into it. Moreover, not everyone will agree, and some will probably be excluded because they are not passionate about the refugee issue.
>
> If future meetups are to be held in the Ankertorstraße [street name/location of the community space] or in social institutions, this no longer has anything to do with the most traditional community-building element of the meetup. Because some people stay away from Ankertorstraße on principle, and here too we would again have an exclusionary situation. [...] Do not destroy the last active element of the Munich Wikipedia community.”[93]

This user did not want meetings to take place at venues with an agenda as they feared that other contributors would not want to join the meetup then. The user further suggested discussing this idea at a meetup face-to-face and in a collaborative manner. The discussion which followed revolved around the division between meetups and community space. Before the establishment

[93] https://de.wikipedia.org/wiki/Wikipedia_Diskussion:Stammtisch_M%C3%BCnchen/Archiv/2017.

of the community space WikiMuc (at the Ankertorstraße) in 2016, it was said that the meetup and WikiMuc should exist side by side, but some users now got the impression that WikiMuc wanted to subordinate the meetup; a user raised his disappointment with his impression that things now seem to be decided by the WikiMuc team from above instead of the previous search for a consensus. Not everyone took these concerns seriously; it was pointed out that the decision for the new venue was made at the last WikiMuc team meeting where multiple users, who also attend the meetup, were present. In the continuing discussion, it was found "extremely strange" that attempts were made to differentiate between those active in WikiMuc and those who attend the meetup, as those overlap to a large part; these should not be categorically separated. The discussion boiled down after highlighting that the contact person of the new restaurant was not only interested in collaborating within the context of the social project, but that the restaurant was also signalling a general openness to host informal Wikipedia meetups and to collaborate on further projects.

Inequality of Meeting Access While Wikipedia meetups are generally open to all, a certain reluctance to join them is observable on the organisational pages of multiple regional portals, and skewed distributions of attendee demographics are also sometimes directly discussed (particularly skewed gender distributions). In many cases, editors who are or consider themselves to be part of a minority on Wikipedia—e.g. newcomers, young editors, women—are hesitant to join local meetups. This inequality of access to meetups reflects the inequality present on Wikipedia in general. It is well-known that women are less likely to participate on Wikipedia (Merz 2019: 115); according to a study of the Wikimedia Foundation, this holds true across different Wikimedia projects[94], and it has also been found that (the German) Wikipedia is less likely to be written by people without formal education (based on sample descriptions in Merz 2019: 115).

In the conclusions of the 33rd meeting of the meetup in Bonn[95], it was discussed that the "female quota was unfortunately only at around 11 per cent" and that "it would be good to get in touch with more young people who are editing Wikipedia or interested in it" as the average age of the meetup is also rather high. It was suggested to reach out to younger editors directly and it was discussed what kind of meetup activities would be most

[94] See https://de.wikipedia.org/wiki/Geschlechterverteilung_in_der_Wikipedia.

[95] See https://de.wikipedia.org/wiki/Wikipedia:Bonn.

interesting to the younger audience. The high average age was also mentioned at other meetings, for example, at the meetups of Southern Germany or Halle (Saale)[96].

The female quota was a reoccurring topic for the meetup in Dresden. In the minutes of the 37th and 49th meetings in Dresden, it was stated that the female quota has improved in comparison to previous meetings; in the 54th meetup, it was calculated that the female quota was at times over 20 per cent[97]. Similar observations were made in Leipzig, Munich, and Northern Germany[98]. It is a reoccurring topic to find ways to increase female participation, and it is often positively mentioned when meetups reached a higher female quota, as for example often the case in Hamburg[99].

Besides skewed demographics, it is also worth mentioning that meetups generally take place in bars and restaurants which (in the German speaking area) expect guests to consume products. It has been an issue for some Wikipedians to financially afford to attend meetups. In one case, a user further publicly shared his alcohol addiction as a reason for not being able to attend meetings:

> "I am annoyed about it right now but here I am in ... bad, bad, ... therapy centre for alcohol because everybody knows that I am a professional when it comes to beer, and I got my comeuppance now after the detox. And before I get cravings [the user used the word 'carving', but I assume this to be a typo], I better stay away. That is also the reason why I have been doing so little in the wp [Wikipedia] lately. I am sorry you have to hear it like this but it is just hard for me because I like you so much but that is my illness (I am just rattling through, forget the spelling). You gave me a lot and I took it very gladly, but I also blew myself off and you were not there then. I am an alcoholic and therefore I cannot come. It is not as easy as I thought but I think I found a good way. [...] I would appreciate it if you do not judge me right away but just think about it you sometimes kept me grounded better than anyone else. Thanks for that. I like you all a lot."[100]

[96] See https://de.wikipedia.org/wiki/Wikipedia:S%C3%BCddeutschland/Archiv/2017-04-21 and https://de.wikipedia.org/wiki/Wikipedia:Halle_(Saale), 17th meetup.

[97] See https://de.wikipedia.org/wiki/Wikipedia:Dresden/Archiv/2010 and https://de.wikipedia.org/wiki/Wikipedia:Dresden/Archiv/2011.

[98] See https://de.wikipedia.org/wiki/Wikipedia:Leipzig/Treffen-Archiv, 9th meetup, https://de.wikipedia.org/wiki/Wikipedia:Stammtisch_M%C3%BCnchen/Archiv/2004, 4th meetup, https://de.wikipedia.org/wiki/Wikipedia:Norddeutschland.

[99] See https://de.wikipedia.org/wiki/Wikipedia:Hamburg/Archiv, for example reaching 50 per cent at the 47th meetup or 67 per cent at the 63th meetup.

[100] https://de.wikipedia.org/wiki/Wikipedia:Treffen_der_Wikipedianer/K%C3%B6ln/Archiv_2009.

Users reacted positively towards this statement, with many wishing him a lot of luck.

When Covid Hit Face-to-face meetings between Wikipedians took place up until March 2020 when regulations introduced by the German, Swiss and Austrian governments forbid any public gatherings. Some of the last meetings took place at the end of February and at the beginning of March 2020 when awareness of the situation was growing but restrictions had not yet been in place. One of the larger meetings that still took place was the admin convention, a gathering of administrators which was attended by about 60 people and took place from February 21 to 23, 2020[101]. During the pandemic, some regional meetups moved to online platforms while others stopped gathering. The development of the meetup culture after the Covid-19 pandemic will not be covered in this thesis.

2.4.3 Meetups Between Wikipedians in Research

Offline meetups are a central aspect of Wikipedia, but they have rarely been addressed by the scientific community. Given this, the following review of the literature can be considered complete. A few studies have focused on editathons—concentrated editing events where people meet with the intention to work and improve Wikipedia. Such editathons are often directed at newcomers and focused on specific topics. Most often, their goal is to create more diversity on Wikipedia. For example, there have been editathons centred around female biographies, art and feminism, or women in science.

Hood and Littlejohn (2018) and Littlejohn et al. (2019) interviewed nine participants of an Edinburgh editathon to explore their experiences and used their editing behaviour to further distinguish and understand the experiences of their interviewees. They discuss how the necessary knowledge to contribute towards Wikipedia is developed through such editathons and how new editors are learning to write encyclopaedic articles. Littlejohn et al. (2019) also highlight that the personal relationships made at these events are important to some of the participants when continuing editing Wikipedia. Also using interviews of participants of an editathon with a feminist orientation, Vetter et al. (2022) found how such editathons increased (digital) critical thinking of participants. March and Dasgupta (2020) have focused on the organisers of such editing events, unravelling their motivations in 13 interviews. They

[101] See https://de.wikipedia.org/wiki/Wikipedia:AdminConvention_2020.

found that facilitators are motivated by personal and institutional values, such as wanting to promote free knowledge and aiming for more diversity on Wikipedia, as well as wanting to foster information literacy and establish community relationships. Gluza et al. (2021) focus on an online editathon event and apply an ethnomethodological perspective to better understand the experiences of editors. They find and describe a diverse set of motivational factors and moments of frustration experienced during the editing activity.

Offline and online behaviours have been linked by Farzan et al. (2016). They collected data related to 59 face-to-face editathon events and four virtual ones happening in the USA in the first quarter of 2016, collecting all attendees of the events and tracking their editing behaviour on Wikipedia in the following week. They focused on newcomers and compared editathon attendees with a random sample of users registering at the same time but independently of these events. They found that face-to-face editathons can attract more newcomers than virtual ones, but retention of them stays challenging. While only about 1 per cent of the random sample of newcomers keep editing one week after their registration date, about 9 per cent of the editathon attendees remained active.

To my knowledge, there is only one study which has focused on informal face-to-face meetings between Wikipedians. In his study, Stegbauer (2009) collected meetup data from October 2003 to November 2006 in the German Wikipedia to analyse which role the meetings play in the community. Across those three years, roughly 240 different meetups took place, attended by a total of 750 different attendees. He discussed the network which developed at those meetings and zoomed in on the meetup scene in two different German cities, Berlin and Munich. His study highlights how users who are of central importance in the meetup network—attending many meetings, spanning geographical boundaries, etc.—also tend to have an important position in the online component of Wikipedia (such as being an administrator). Focusing on the effect of the first meetup of users, he found that most tend to decrease their activity in the month after the meetup compared to the month before—except if they later become administrators (Stegbauer 2009 chapter 15).

This section has summarised previous research on face-to-face meetings on Wikipedia. With one exception, all of the studies have focused on editathons and most have employed a more qualitative approach. Given this rather sparse body of research about meetups on Wikipedia, this thesis will address an important gap by researching the offline social aspect of one of today's most important online communities and knowledge providers.

2.5 Summary: The Research Context

This chapter outlined the context within which this thesis falls. As the chapter touches on several different topics, a short summary will be given in the following. This thesis focuses on offline meetups between Wikipedians to create a better understanding of their relevance to and effects on the online community. Offline meetups between online community members are a place of interaction between the users; theoretically, the concept of social capital can be used to highlight why such ties matter in the first place. Such offline gatherings can affect online communities as previous studies have shown (predominantly) for other communities besides Wikipedia. More broadly, this thesis fits well within studies making use of digital trace and big data in the emerging field of computational social science. Unlike most previous studies, it is concerned with the online encyclopaedia Wikipedia; Wikipedia was founded in 2001 and continues a long history of the human desire to collect and gather knowledge. In the spirit of its offline predecessors like the Greek *Homia* or the Roman *Historiae naturalis* and the more recent *Britannica* and *Brockhaus*, Wikipedia aims at providing a summary of the general human knowledge. In contrast to its predecessors, it makes use of modern technologies which allow millions of people across the world to contribute towards the writing of its articles. Wikipedia has not only developed into a valuable encyclopaedia but is also regularly researched; the rich data source is used by computer scientists to inform and train their algorithms, and Wikipedia in itself is both researched in terms of its factual content and its functioning as a community. One important aspect of the community has only received little interest from the scientific community: offline meetups between Wikipedians. Following the qualitative description of meetups provided in this chapter, the next chapter will describe the methods and data used in this thesis and give a quantitative overview of the meetup data.

3 General Data and Methods

In this chapter, the general data used for all following analyses on the three topics of productivity, norms, and elections will be discussed. First, I will describe the meta data of Wikipedia which is the base of the analysis. Second, I will outline how data on users has been obtained. Following this, the collection of the meetup data as well as the data itself will be described in section 3.3. Lastly, I will give credit to the software packages used in the analyses and detail ethical considerations.

3.1 Meta Data

All online actions contributors undertake on Wikipedia are logged. Any changes made—whether it is the creation of a completely new article, the addition of a word, the deletion of a source or the restructuring of a sentence—are registered in the revision history. The revision history of an article allows to trace the contributions and reverts of authors. This data is available through the so-called *data dumps* and comes in a well-structured format[102]. It is generally possible to obtain information on all revisions of all pages. This would allow for an extremely detailed analysis of contributing behaviour. It could, for example, be traced how users have co-authored specific articles, which sentences stemming from which users have been kept in the document for how long, etc. However, as the following research aims to analyse a period of twenty years, this is not feasible. The data dump which includes all revisions of all pages expands to multiple terabytes of text and provides a computational challenge. For the following research purposes, the analysis is restricted to meta data and the text content of articles is excluded. The stub meta files[103] are the basis of this thesis as they include just the page and revision meta data (thus just the "stub" of a page/revision). They cover all namespaces of Wikipedia (see below). This meta data allows measuring productivity, collaboration networks, and norm enforcing behaviour as it

[102] See for the German Wikipedia `https://dumps.wikimedia.org/dewiki`.
[103] Called the *latest-stub-meta-history.xml.gz* on the data dump.

provides information on which users have changed what article and to what extent.

3.1.1 Namespaces

The pages meta files include meta data on revisions of pages across all of Wikipedia's namespaces. However, what are namespaces?
Wikipedia is structured in multiple namespaces which serve the system with different functions[104]. As of July 2022, there are 30 namespaces (14 subject namespaces, 14 corresponding talk namespaces, and two virtual namespaces). A Wikipedia namespace can be seen as a domain for specific pages. Wikipedia is most widely known through its encyclopaedic articles which are part of the *article namespace (mainspace)*; this is a subject namespace. In addition to the subject namespace, there is an accompanying *talk space* which is designed for communication. Articles contain a talk page, allowing users to raise suggestions and discuss controversies related to an article. Registered users on Wikipedia further have their own user page (forming another subject namespace, the *user namespace*), as well as a corresponding user talk page where they can provide information about themselves and interact with others in relation to the Wikipedia project. Also, there are several pages related to the Wikipedia project itself. These help with the broader organisation and coordination and provide, for example, information and policies about contributing, essays, or meta-discussions (the *Wikipedia namespace*).

3.1.2 Working With the Data Dump

The meta data is used to capture the productivity and collaboration behaviour of Wikipedians (see chapter 4), to measure norm violation and enforcement (see chapter 5), and in general to measure users' online activity on the platform. Overall, the data dump forms the most important data source when analysing data from Wikipedia.
Technically, the data dumps were accessed as follows: they were downloaded as extensible markup language (XML) files and then converted to a file with comma separated values (CSV) with a modified version of the Python package *wiki dump parser* (Juste 2019). The Python script copied relevant information (the name and ID of the site which was edited and of the user who edited the site, the time stamp of the edit, any accompanying comments to the edit to identify reverts) from the XML files into corresponding CSV files.

[104] See `https://en.wikipedia.org/wiki/Wikipedia:Namespace`.

Edits for which no username was given were generally skipped (except when parsing reverts) and thus excluded in the final dataset, meaning edits made by anonymous unregistered users were not included. All edits in the data dump up to the cut-off date of March 30, 2020 are considered.

3.1.2.1 Measuring Collaboration

Wikipedians rarely create and edit a page alone: a Wikipedia article is (almost) always the result of collaboration; this so evolving co-editing network has been the topic of widespread research. What constitutes collaboration has been defined in a multitude of ways. Some studies tend to investigate in detail the network structure of specific Wikipedia pages, often tracking changes on the basis of words to understand who edits the changes of whom (see e.g. Brandes et al. 2009; de La Robertie et al. 2015). As this thesis does not restrict the analysis to specific Wikipedia articles, this approach is not feasible computationally.

Others, such as Hirth et al. (2012) and Zhang and Wang (2012) try to capture the global structure of collaboration and define the collaboration network as a network in which any two editors have a tie if they ever co-edited an article. While this approach is appropriate in some contexts, it is an extremely broad view of collaboration. For the entirety of the German Wikipedia, this approach does not seem adequate: it would mean that an editor who started an article 15 years ago and has been changed by many contributors since would share a tie with an editor that now found and changed a typo. Such a definition of collaboration would result in a large amount of potentially meaningless ties. Piskorski and Gorbatâi (2017) follow a similar approach but restrict the definition of collaboration to articles which have not attracted many contributors and they also define only edits happening within a given time frame as being collaborative. Other studies define collaboration as working together on articles but also simultaneously exchanging talk messages (see e.g. Nemoto et al. 2011). Considering that users who have met offline potentially use new avenues of communication (e.g. private text messages) and subsequently might not use user talk pages extensively anymore, this approach seems too restrictive.

Taking these considerations into account, I decided to follow a modified approach. While the basic idea of defining collaboration as edits on shared articles seems the most suitable and feasible approach, some restrictions need to be employed to guarantee that editors editing an article are aware of each other's edits, i.e. the neighbourhood of an editor needs to be defined in a more meaningful way than defining the whole article editing history as a neighbourhood. One approach to accomplish this is to set an arbitrary time frame and define all editors who edited within a time frame as neighbours sharing ties (as done by Piskorski and Gorbatâi 2017). However, as the selection of a time limit is a subjective and arbitrary choice, I decided to restrict it simply to the edits that directly follow one another[105]. This means, node i has a directed tie to node j if i made an edit to the same article directly after j. While even with this very restricted setup it is still possible that i edits a different part of the article than j and does not refer to j at all, it seems reasonable to assume that in most cases, i is aware of the edits j has made; at the very least, it can be said that i is directly interacting with the article version created by j.

I restrict my analysis in chapter 4 to collaboration based on edits in the article mainspace as the article mainspace represents the most productive form of editing. When measuring collaboration in chapters 5 and 6, I take any form of co-editing into account as these chapters focus less on the writing of new articles but more on contributors being in exchange with each other. Co-editing in other namespaces is reflective of not just productive collaboration, but also of forms of communication, the answering of questions, or the statement of opinions.

Every new edit can create a new tie between users. Each person that made an edit is tied to at least one other person, as long as this other person is also a registered user; users who have not made any edits at all are not part of the network. Editing ties with bots—on Wikipedia, bots are computer-controlled user accounts which perform various tasks in order to maintain the encyclopedia[106]—are ignored, while edits of non-registered users are skipped altogether (due to the way the data was parsed, see section 3.1.2). Self-ties are excluded as users do not collaborate with themselves. This data is used to assess changes in collaboration behaviour of Wikipedians (see chapter 4) and used as a network measure when analysing norm enforcement (see chapter 5) and elections (see chapter 6).

3.1.2.2 Measuring Talk Interaction

As a second measure of interaction besides collaboration, I additionally focus on talk messages (see also e.g. Nemoto et al. 2011). These are obtained from user talk pages which each registered user automatically acquires. They

[105] I am aware that this definition still entails a level of arbitrariness.
[106] See `https://en.wikipedia.org/wiki/Wikipedia:Bots`.

themselves and any other user can edit this page so it can be used as a form of personal communication. While the purpose of article talk pages is to discuss the content of articles, user talk pages can be used by others as a form of directed, but public messaging system. Guidelines of Wikipedia[107] make it clear that Wikipedia is not a social networking site, and "all discussion should ultimately be directed solely toward the improvement of the encyclopaedia": their primary purpose is to allow for better communication and collaboration among editors.

Through the data dump, all user talk page changes were extracted to create a network. In this network, nodes represent users and a direct edge from node i to node j represents that user i edited the talk page of user j. This follows approaches as discussed in Laniado et al. (2011) and Massa (2011). Self-ties and edits made by non-registered users are excluded. This data is used as a network measure when analysing norm enforcement (see chapter 5) and elections (see chapter 6).

3.2 User Data

The meta data allows the extraction of all users who have made at least one edit while being registered; these are the users of interest in this study. This section will outline how different variables of users are being constructed and measured.

Tenure Tenure is measured via the date of a user's first edit. While some data on users can also be accessed through a MediaWiki (the software powering Wikipedia) supported API (application programming interface) call[108], users' registration dates are not extractable for all. Because of this, only the meta data is used as a source and tenure is defined in terms of years passed since a user's first edit (even if the word "registration" is often used for the sake of brevity and readability).

Name Changes Users on Wikipedia can request name changes which are usually granted[109]. New names must follow the naming guidelines of Wikipedia: they cannot already be taken by another user and cannot be offensive. Additionally, it is also possible to just sign up as a new user, allowing for greater anonymity. After renaming, the old name will generally direct to the

[107] See https://en.wikipedia.org/wiki/Help:Talk_pages.
[108] See https://www.mediawiki.org/wiki/API:Allusers.
[109] See https://de.wikipedia.org/wiki/Wikipedia:Benutzernamen_%C3%A4ndern.

new name. Also, users can set up their own redirection links if they have registered multiple accounts[110].

In this thesis, I am not interested in Wikipedia user accounts, but in the people behind those accounts. Thus, I aim at consolidating these name changes. All Wikipedia users and the redirection links linking to them were collected using the API. Additionally, all renames as logged in the renaming logbook[111] were web-scraped with an automated browser using *RSelenium* (Harrison 2020). This allowed creating a list of all current users and their redirections and previous usernames, in as so far they requested an official rename or linked to other accounts using redirection lists. In cases where users created a new account, potentially to gain more anonymity, it was impossible to link them to their previous name. In some rare cases concerning users that took part in meetings and/or in elections, previous usernames were explicitly mentioned and discussed. In these cases, those changes in usernames were also noted.

This step of data preparation required substantial effort which was spent to guarantee the matching of usernames from different sources. While some usernames were collected using the meta data, others were collected manually from the site (when collecting the meetup or election data). These different approaches led to inconsistencies regarding the handling of special characters, other special encodings, and capitalisation. Resolving these issues needed careful attention.

In the end, I created a list of 1'751'808 different usernames (and variants of their encoding and spelling) belonging to 1'149'511 unique IDs (in the ideal case, this would be reflective of 1'149'511 different people). Bots were generally excluded from the analysis. A list of bots was web-scraped from Wikipedia logbooks and overview pages[112].

[110] It is worth noting that since August 2008, all user accounts are set up as global user accounts single-user-login; this reserves a username in (almost) all Wikimedia wikis. This allows having consistent and identifiable names across all projects; however, it also came with the cost of a significant renaming effort in 2008.

[111] See https://de.wikipedia.org/wiki/Spezial:Logbuch/renameuser.

[112] See https://de.wikipedia.org/w/index.php?title=Spezial:Benutzer&offset=&limit=500&group=bot, https://de.wikipedia.org/wiki/Kategorie:Benutzer:MediaWiki-Systembot, https://de.wikipedia.org/wiki/Kategorie:Benutzer:Bot_ohne_Flag, https://de.wikipedia.org/wiki/Kategorie:Benutzer:Inaktiver_Bot_ohne_Flag, and https://de.wikipedia.org/wiki/Kategorie:Benutzer:Inaktiver_Bot_mit_Flag.

Adminship Information about the potential adminship career of users was collected from overview pages on Wikipedia[113]. This allowed the collection of start and end dates of administrator careers. Administrators resign due to inactivity, for voluntary reasons, or when they are not re-elected after a request for re-election. At the time of data collection (December 2020) there were 182 normally elected administrators and 8 additional users who have been assigned administrator rights without a formal election but have gained these rights through having other functions, such as working in the arbitration committee (*Schiedsgericht*); the arbitration committee is an institution responsible for resolving conflicts[114]. 346 users have been administrators in the past. For adminship starting dates, if only the month was given the date was set to the 1st of the month. If only the year was given, it was set to January 1st of the year. If only "before 2003" was given, it was set to July 15, 2002 (roughly the middle of the year). For adminship end dates, dates lacking detail were set to the last of a month/year. Considering the timeline of my analyses, all elections taking place after March 30, 2020 are excluded.

3.3 Understanding Meetups on Wikipedia

The face-to-face meetups of Wikipedians form the core of this thesis. This section will describe how the data has been collected and provide a quantitative overview.

3.3.1 Collecting Meetup Data

This thesis makes use of the fact that meetups are organised online. Meeting data is thus publicly available on Wikipedia; however, the data is often lacking a consistent and clear structure. In contrast to the aforementioned meta data, meetup data is user-written and not process-generated. During data collection, I aimed to collect the place/venue, date, type of meetup, attendees, apologies for absences (if available), minutes (if available) of all offline meetings since the launch of Wikipedia until March 2020 organised on the German language version of Wikipedia. Obtaining data on the meetups

[113] See https://de.wikipedia.org/wiki/Wikipedia:Administratoren/%C3%9Cbersicht, https://de.wikipedia.org/wiki/Wikipedia:Liste_der_Administratoren and https://de.wikipedia.org/wiki/Wikipedia:Liste_der_ehemaligen_Administratoren.

[114] See on the arbitration committee https://de.wikipedia.org/wiki/Wikipedia:Schiedsgericht and https://en.wikipedia.org/wiki/Wikipedia:Arbitration_Committee.

required substantial manual effort. The process of collecting this data is explained in detail in the following.

3.3.1.1 Scraped Pages

The starting point of the meetup collection was an overview list of meetings between Wikipedians[115]. This list includes the links to over one hundred pages of regions and cities where Wikipedia meetups between German speaking Wikipedians are organised and archived. These regionally based meetups are most often informal meetings with the point of socialising in public spaces (the so-called *Stammtische*). Other meetings collected include all editathons and open editing events[116]. These are events where (potentially new) editors of Wikipedia meet to edit and improve a specific topic or type of content. They generally include basic editing training for new editors and are often combined with a social meetup. There are both online and in-person editathons, but this research focuses on face-to-face meetings only. Thus, virtual editathons were not collected.

Furthermore, all events listed at an overview event site were collected[117]. These events include activities such as attending and looking after stalls representing Wikipedia at different fairs, partaking in workshops about photography, and similar events. This also includes events organised as part of the *GLAM* initiative (GLAM stands for Galleries, Libraries, Archives, Museums[118]) in which cultural institutions are supported through collaborative projects with experienced Wikipedia editors, and the so-called *KulTouren*[119]—smaller-scale events where Wikipedians visit exhibitions or take part in excursions.

Lastly, all WikiProjects[120] and task forces (called *Redaktionen* in the German Wikipedia[121]) were checked for meetings. WikiProjects and task forces are central places for discussing specific content; they are used to communicate, collect sources, and provide summaries on specific topics. They form a sort of

[115] See https://de.wikipedia.org/wiki/Kategorie:Wikipedia:Treffen_der_Wikipedianer.

[116] Listed here https://de.wikipedia.org/wiki/Wikipedia:Edit-a-thon and here https://de.wikipedia.org/wiki/Wikipedia:Offenes_Editieren.

[117] See here https://de.wikipedia.org/wiki/Kategorie:Wikipedia:Archiv/Veranstaltungen and here https://de.wikipedia.org/wiki/Kategorie:Wikipedia:Versicherte_Veranstaltung.

[118] See https://de.wikipedia.org/wiki/Wikipedia:GLAM.

[119] See https://de.wikipedia.org/wiki/Wikipedia:Wikipedianische_KulTour.

[120] See https://de.wikipedia.org/wiki/Wikipedia:WikiProjekte.

[121] See https://de.wikipedia.org/wiki/Wikipedia:Redaktionen#Liste.

virtual gathering place for Wikipedia editors interested to work on a specific cluster of topics.

Throughout the scraping of all of these pages, a snowballing approach was followed. When one meetup page linked to other ones, these were web-scraped as well until no new pages were found. Still, there is no guarantee that all pages with meetups were visited and scraped.

3.3.1.2 Excluded Pages and Excluded Meetings

Some pages and meetings were excluded from the data and/or the data collection process. As mentioned, all meetups that took place only virtually were skipped. In the observation period, only a small number of editathons have taken place online (this rapidly changed after the outbreak of the Coronavirus pandemic).

Further, portals[122] were not checked for meetups unless they are covering regional entities (portals about cities or regions). Portals are somewhat similar to WikiProjects and task forces but are directed toward readers instead of editors. Portals provide well-maintained introductory landing pages into the encyclopaedia; they provide an overview of the most important articles in a certain topic area. As these are thus not places where authors are gathering, it was not expected that any meetings are organised in the context of portals.

Also, this thesis focuses on meetings organised on the German version of Wikipedia. Some meetings which are also directed towards German speaking Wikipedians are organised on other platforms maintained by Wikimedia, such as commons[123] or meta[124]. However, any meeting or event not organised on the German Wikipedia was excluded from data collection.

As this thesis is primarily interested in the effects of network ties and assumes that attendees meet all other ones, very large meetups are excluded from the analysis. It cannot be reasonably assumed that all editors attending these meetups have met each other. This includes all WikiConventions and Wikimanias with over 50 attendees. Other notably large meetups are AdminConventions and a yearly barbecue party organised by one editor on Wikipedia. Even though these events are relatively large, they are kept in the data due to their inherently social and/or collaborative nature. The AdminConventions bring together the administrators of Wikipedia which are by nature a selective and collaborative group of users. Considering both the

[122] See https://de.wikipedia.org/wiki/Wikipedia:Portale.
[123] See https://commons.wikimedia.org.
[124] See https://meta.wikimedia.org.

work nature and the longer length of those meetups, it can be assumed that most administrators got in touch with the others. The barbecue party is a regularly reoccurring event and is praised for its social component. It is reviewed as being *the* meetup of the German Wikipedia which brings friends together. It is thus not excluded from the analyses. WikiConventions and Wikimanias with less than 50 (German speaking) attendees were also kept in the data as it can reasonably be assumed that smaller German communities met beforehand/during those conventions and/or also travelled together. In total, 10 meetups are excluded due to their size.

Community Spaces Some cities in the German speaking area have special community spaces for Wikipedians which offer a headquarter for staff members and engaged volunteers. Such spaces currently exist in Berlin (WikiBär, opened in 2017; TU23, also headquarter of Wikimedia Germany), Hanover (opened in 2015, used more strongly as a local room since 2019), Vienna, Hamburg (Kontor, opened in 2014), Cologne (Lokal K, opened in 2014), and Munich (WikiMUC, opened in 2016). Further community spaces are in Ulm, Stuttgart, Lörrach, and Bremen; however, these are less institutionalised as those previously mentioned.

Community spaces are places of very high Wikipedia activity. In spaces like the WikiBär in Berlin, there happen to be multiple meetings and open editing events per week. There are thus a very high number of meetings taking place in cities with community spaces. Also, in many cases, people stop recording their attendance at these meetings as the same users tend to attend. Some meetups taking place in these spaces are excluded from the analysis given their different dynamic. Specifically, the following meetings are excluded as they are very regular events in community spaces and generally attract the same people:

- Berlin, Tempelufer bureau: exclusion of general open editing events, exclusion of open editing events for women.
- Berlin, WikiBär: exclusion of general open editing events, exclusion of open editing events for women.
- Berlin, WikiWedding: exclusion of open Sundays, office hours.
- Hamburg, Kontor: weekly events are not explicitly organised on Wikipedia and were thus not collected in the first place.

- Hanover: exclusion of Tuesday editing events, open editing events, office hours.
- Cologne, Lokal K: weekly events are not explicitly organised on Wikipedia and were thus not collected in the first place.
- Munich, WikiMUC: all regular events are excluded, such as open evenings, introductory workshops to Wikipedia, board game Fridays, monthly meetings of another organisation, monthly work meetings[125], cleaning events and other internal office events. Irregular workshops are included.
- Lörrach, technik.cafe: no events are excluded as they were still considered regular meetups by the community.
- Stuttgart, Stadtbibliothek: exclusion of monthly open editing events.
- Ulm, Verschwörhaus: exclusion of monthly open editing events.
- Vienna: exclusion of Wikipedia Tuesdays.

Other events taking place in these amenities are not excluded. These non-excluded events are irregular ones taking place in the community spaces (such as specially organised workshops), and other irregular events which make use of the location but are organised externally, such as meetings by project teams[126].

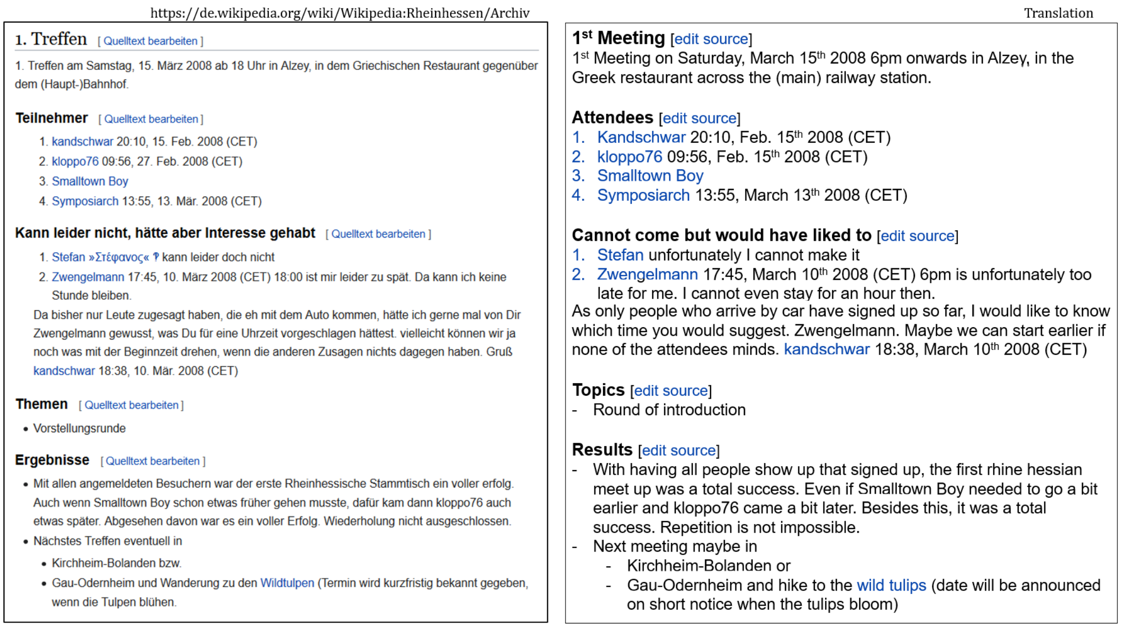
3.3.1.3 Collection of Information: Automatic Scraping and Manual Extraction

The aim of the data collection was to collect as much information as possible on all offline meetings since the launch of Wikipedia. At least, the information collected should include the date, place/venue, and attendees of a meeting to build a network with time stamps. In most cases, the data collected also included apologies for absences and minutes about the meetup. Attendance lists were collected from protocols that were published after the meeting took place, if available. If not available, attendance was recorded from the list of registration.

[125] https://de.wikipedia.org/wiki/Kategorie:Wikipedia:WikiMUC/Arbeitstreffen.

[126] Community spaces might be better understood in the context of movement organisers (Wikimedia Foundation 2019).

The way meetings were organised is depicted in figure 3.1; the example is taken from the Rhine-Hessian regional organisation page[127].


https://de.wikipedia.org/wiki/Wikipedia:Rheinhessen/Archiv

1. Treffen [Quelltext bearbeiten]

1. Treffen am Samstag, 15. März 2008 ab 18 Uhr in Alzey, in dem Griechischen Restaurant gegenüber dem (Haupt-)Bahnhof.

Teilnehmer [Quelltext bearbeiten]

1. kandschwar 20:10, 15. Feb. 2008 (CET)
2. kloppo76 09:56, 27. Feb. 2008 (CET)
3. Smalltown Boy
4. Symposiarch 13:55, 13. Mär. 2008 (CET)

Kann leider nicht, hätte aber Interesse gehabt [Quelltext bearbeiten]

1. Stefan »Στέφανος« kann leider doch nicht
2. Zwengelmann 17:45, 10. März 2008 (CET) 18:00 ist mir leider zu spät. Da kann ich keine Stunde bleiben.

Da bisher nur Leute zugesagt haben, die eh mit dem Auto kommen, hätte ich gerne mal von Dir Zwengelmann gewusst, was Du für eine Uhrzeit vorgeschlagen hättest. vielleicht können wir ja noch was mit der Beginnzeit drehen, wenn die anderen Zusagen nichts dagegen haben. Gruß kandschwar 18:38, 10. Mär. 2008 (CET)

Themen [Quelltext bearbeiten]

- Vorstellungsrunde

Ergebnisse [Quelltext bearbeiten]

- Mit allen angemeldeten Besuchern war der erste Rheinhessische Stammtisch ein voller erfolg. Auch wenn Smalltown Boy schon etwas früher gehen musste, dafür kam dann kloppo76 auch etwas später. Abgesehen davon war es ein voller Erfolg. Wiederholung nicht ausgeschlossen.
- Nächstes Treffen eventuell in
  - Kirchheim-Bolanden bzw.
  - Gau-Odernheim und Wanderung zu den Wildtulpen (Termin wird kurzfristig bekannt gegeben, wenn die Tulpen blühen.

Translation

1st Meeting [edit source]

1st Meeting on Saturday, March 15th 2008 6pm onwards in Alzey, in the Greek restaurant across the (main) railway station.

Attendees [edit source]

1. Kandschwar 20:10, Feb. 15th 2008 (CET)
2. kloppo76 09:56, Feb. 15th 2008 (CET)
3. Smalltown Boy
4. Symposiarch 13:55, March 13th 2008 (CET)

Cannot come but would have liked to [edit source]

1. Stefan unfortunately I cannot make it
2. Zwengelmann 17:45, March 10th 2008 (CET) 6pm is unfortunately too late for me. I cannot even stay for an hour then.

As only people who arrive by car have signed up so far, I would like to know which time you would suggest. Zwengelmann. Maybe we can start earlier if none of the attendees minds. kandschwar 18:38, March 10th 2008 (CET)

Topics [edit source]

- Round of introduction

Results [edit source]

- With having all people show up that signed up, the first rhine hessian meet up was a total success. Even if Smalltown Boy needed to go a bit earlier and kloppo76 came a bit later. Besides this, it was a total success. Repetition is not impossible.
- Next meeting maybe in
  - Kirchheim-Bolanden or
  - Gau-Odernheim and hike to the wild tulips (date will be announced on short notice when the tulips bloom)

Figure 3.1: Screenshot and translation of exemplar organisational page.

It varied how meetings were organised and especially archived. Generally, there were the following two approaches to how meetings have been archived:

1. An organised archive of all meetings with a consistent structure[128]. In these cases, every meetup has been recorded, and data on—at least—the attendees, date, and place/venue of the meeting are available. In terms of data collection, this was the best-case scenario as it allowed writing a simple automated script.

2. Meetings were not archived at all. The organisational pages were used to organise the most recent meeting[129]. Due to Wikipedia's technical structure, it is possible to retrieve information about past meetings using the version history. In these cases, it was necessary to scan through the complete version history to find past meetings before they had been deleted in favour of the next meeting.

These are two ideal types. In reality, they occurred in different sub- and hybrid forms. In the best version of case 1), all meetings were archived on a

[127] See https://de.wikipedia.org/wiki/Wikipedia:Rheinhessen/Archiv.
[128] See for example Zurich https://de.wikipedia.org/wiki/Wikipedia:Z%C3%BCrich/Archiv.
[129] See for example Potsdam https://de.wikipedia.org/wiki/Wikipedia:Potsdam.

single page and all meetings were recorded following a consistent structure. In a less ideal version of case 1), all meetings were recorded in archives, but there were separate archives for single years and the structure and format of the archives varied between years[130].

In some cases, organisational pages did not maintain an archive, but at least provided an overview of all meetings and linked to the respective pages in the version history[131]. In other cases, only some meetings were archived; for example, in the case of Berlin, only meetings up to 2010 and then again in 2016 were archived, but not in all other years. In Cologne, most meetings were recorded, but some were simply left out. This was the most unfortunate case, as the skipped meetings could only be noticed when the rhythm of meetings was broken (i.e. they seem to have monthly meetings but there was a month without one) and then the version history needed to be checked manually. Overall, when possible, an automatic scraper was written to extract the information. Still, most meeting data was collected manually.

3.3.2 A Quantitative Overview of the Offline Meetup Data

While section 2.4.2 gave an anecdotal impression about the meetup culture on Wikipedia, the following section will describe the data collected quantitatively.

3.3.2.1 The Where and When

Overall, 4408 meetups have been recorded that were organised on the German Wikipedia and did not meet the exclusion criteria as defined in subsection 3.3.1.2. The first meeting recorded took place on October 28, 2003 with five attendees in Munich, the last ones on March 13, 2020 (two days after the World Health Organisation declared Covid-19 a global pandemic) with three attendees in Cologne and with four attendees in Leipzig (a lot of Wikipedians interested in these meetings did send their apologies closer to the day due to the epidemiological situation).

77.2 per cent of those 4408 meetups are classified as mainly social while the other 22.8 per cent are considered work meetings. Social meetups are meetups that have an inherently social component, such as the classical informal *Stammtisch*, parties and celebrations, yearly meetings, hiking trips

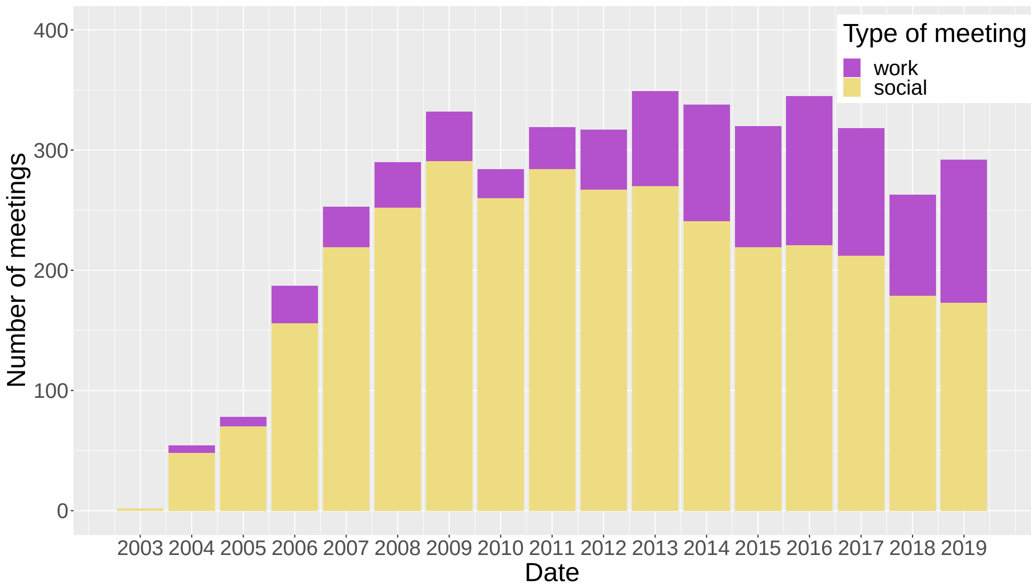
[130] See for example Hanover https://de.wikipedia.org/wiki/Wikipedia:Treffen_der_Wikipedianer/Hannover.

[131] For example Mainz https://de.wikipedia.org/wiki/Wikipedia:Mainz.

or bike tours, barbecues, visits to festivals or cinemas, common attendance at funerals, outings for breakfast, or other spontaneous meetups. Anything that is not defined to be a social meetup is considered a work meetup. These are meetups that have a substantial component of work with the intention of improving Wikipedia.

Meetings classified as work meetings cover all editathons or open editing events, field trips and guided tours (which tend to be to places which are of interest to the Wikipedia community), administrator conventions, workshops, photo tours, meetups of juries to judge on Wikipedian competitions, supporting Wikipedia booths at events and fairs, or other meetings directly oriented towards a Wikipedian initiative such as GLAM or KulTour, as well as meetings of authors collaborating within the so-called Wikipedia portals and task forces and office hours (of Wikimedia or subprojects). Also, meetups simply called "meeting" without further detail are also considered work meetups as many meetings do have an underlying motivation of working on Wikipedia and improving it. However, people can also edit during social meetups. The distinction between social and work meetups cannot be considered clear-cut and entails a subjective component.

The distribution of meetups over time is pictured in figure 3.2. Please note that meetups happening in 2020 are not plotted to allow for better comparability across years as data collection did not collect any meetups after March 2020 (sparse meetups resumed in summer 2020). For 2020, a total of 67 meetups are in the dataset with 38 being social in nature (56.7 per cent).



Note: Meetings of 2020 are not plotted.

Figure 3.2: Temporal distribution of meetups.

As seen in figure 3.2, the number of meetups increased steadily in the first years after the launch of the German Wikipedia until 2009. Numbers have remained on a relatively stable level since then, roughly counting around 300 meetups every year. The proportion of work meetups has been increasing over the years. While the meetups in 2020 are not plotted and data was only collected until March, the number of meetups is expected to have reached a new low for the year.

Spatial Distribution This thesis is concerned with meetups organised only on the German language version of Wikipedia. Therefore, it can be expected that most meetups take place in the German speaking parts of the world. The spatial global distribution of meetups is plotted in figure 3.3; figure 3.4 is restricted to meetups in the German speaking countries of Germany, Switzerland, Austria and Liechtenstein. The large majority of meetups, 88.8 per cent (3915), took place in Germany, 5.5 per cent (243) in Austria, 4.2 per cent (187) in Switzerland and 0.023 per cent (1) in Liechtenstein. Even though this captures around 99 per cent of the meetups, the remaining per cent took place in 20 different countries: Australia (5), Belgium (2), Canada (1), China (1) Czech Republic (4), Finland (6), France (3), Hungary (1), Italy (5), Japan (8), Mexico (1), the Netherlands (2), Poland (10), Slovakia (1), Slovenia (1), South Africa (1), Majorca in Spain (1), Sweden (2), the United Kingdom (6), and Ukraine (1). As mentioned in subsection 3.3.1.2, this can include the more global Wikimanias and WikiConventions, as long as a German speaking group of people of medium size (less than 50 people) organised themselves on the German Wikipedia.

Figure 3.3: Spatial distributions of meetups (world).

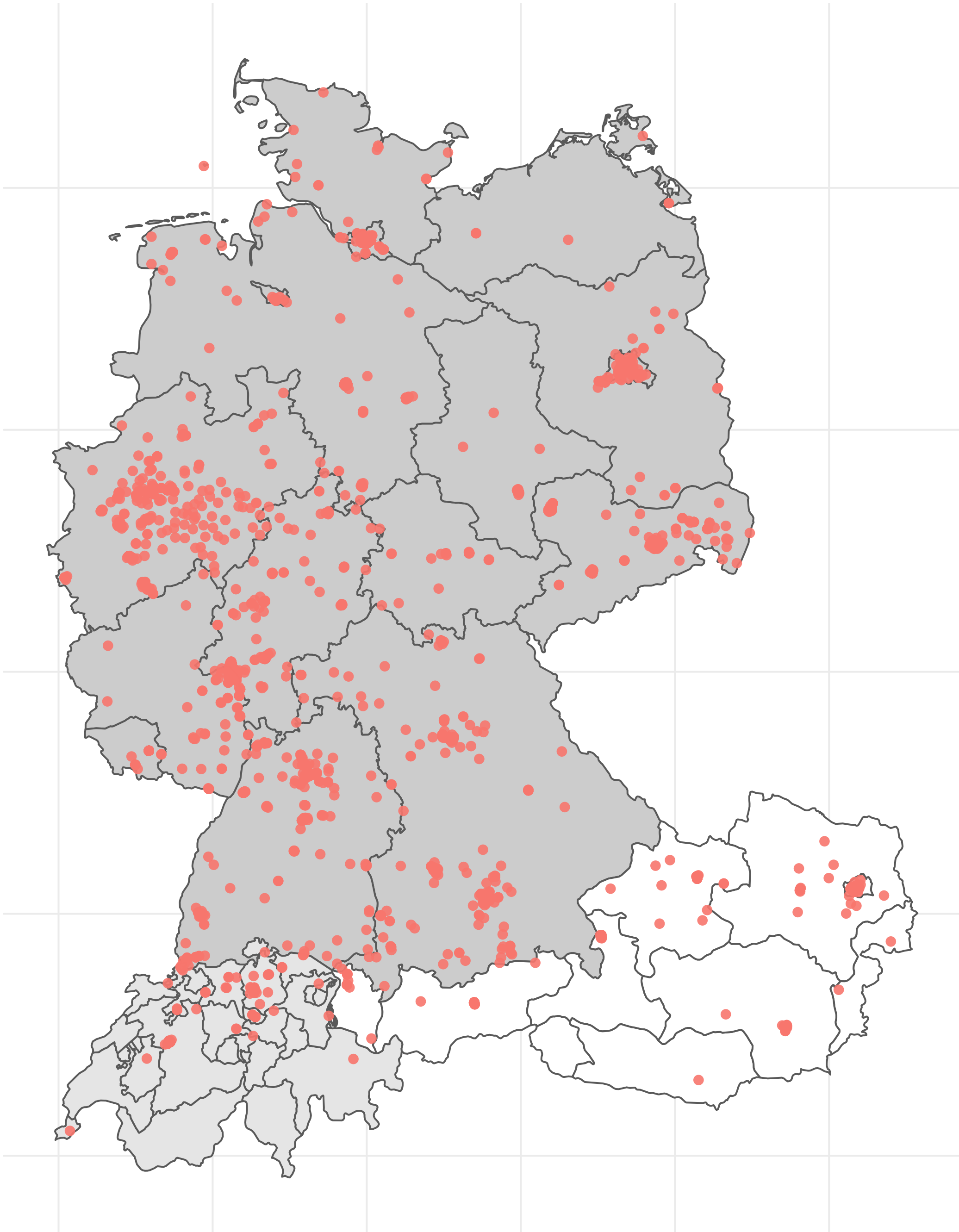


Figure 3.4: Spatial distributions of meetups (German speaking area).

3.3.2.2 The Meetup Network

While the previous subsection described the meetups in general, this subsection will focus on describing the network which has developed through them. As a first step, this leads to an affiliation network of users belonging to meetups (see Wasserman and Faust 1994 chapter 8). This is a non-dyadic, two-mode network, also known as a membership network. Using bipartite

network projection, this meeting-to-user network is transformed into a user-to-user network, connecting those users that have met.
Before 2003, a meetup network did not exist: while Wikipedians have already been editing Wikipedia for more than a year, they did not yet organise meetings with each other. Once the first meetup took place in October 2003, the first component of the network was created: five Wikipedians took part and created the first clique. By the end of data collection, the average number of attendees per meetup is 8.42 (mean; median of 7, standard deviation 6.64) with a minimum of 1—meaning there were meetups where users were alone—and a maximum of 119 (in line with the large, excluded meetups, see subsection 3.3.1.2); the distribution of attendees per meetup is displayed in figure 3.5.

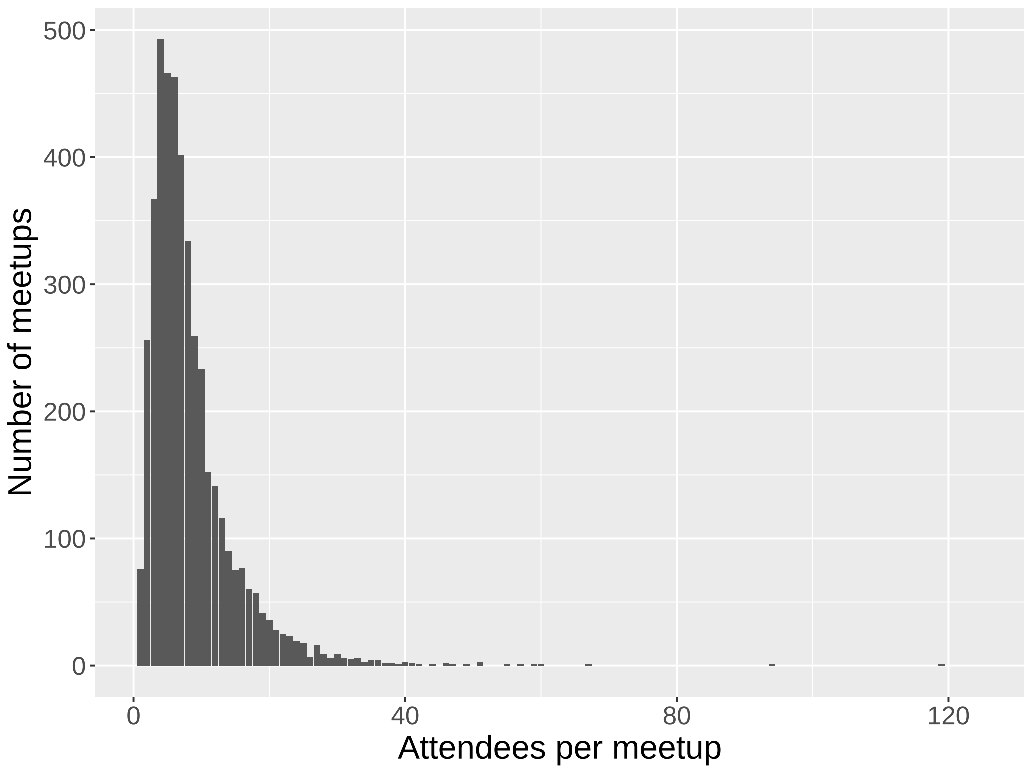
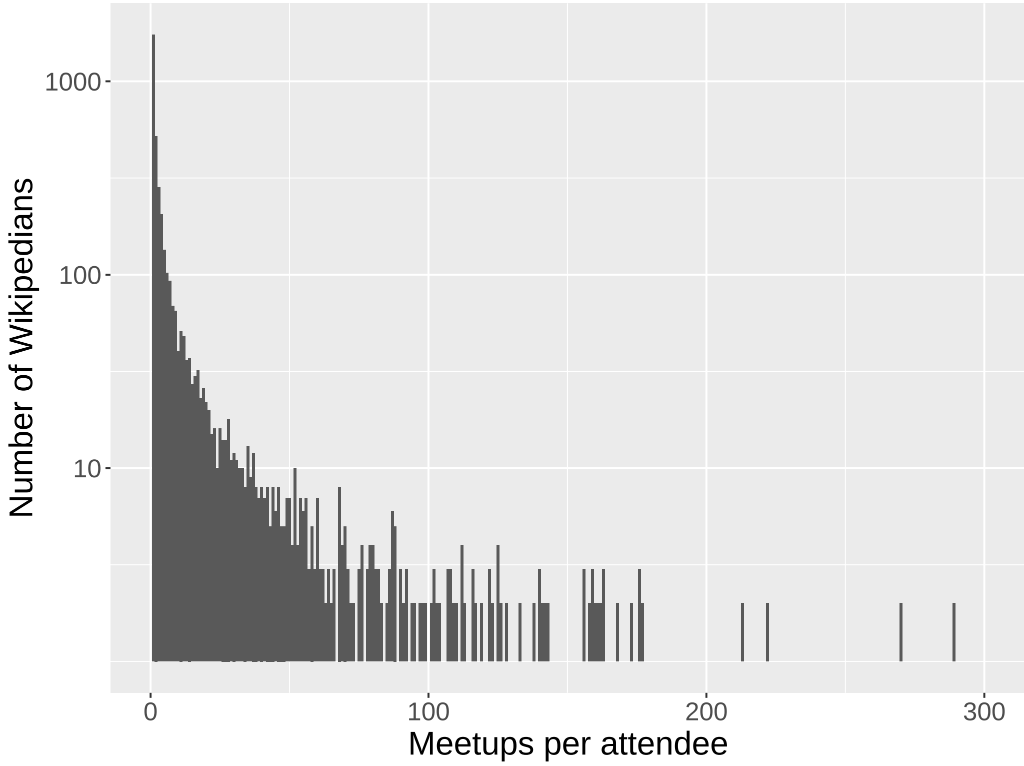


Figure 3.5: Attendees per meetup.

The average number of meetups a Wikipedian who went to at least one meetup (i.e. is a meetup goer/is in the meetup network at all) is 9.21 (mean; median of 2, standard deviation 21.08) with a minimum of 1 and a maximum of 289 meetups; the distribution is displayed in figure 3.6.
In the meetup network (network connecting users with the meetups they attended), 8421 vertices are sharing 36’949 edges (density of 0.0010). In the user network (network connecting users with other users who have attended



Note: Logarithmic scale for better legibility.

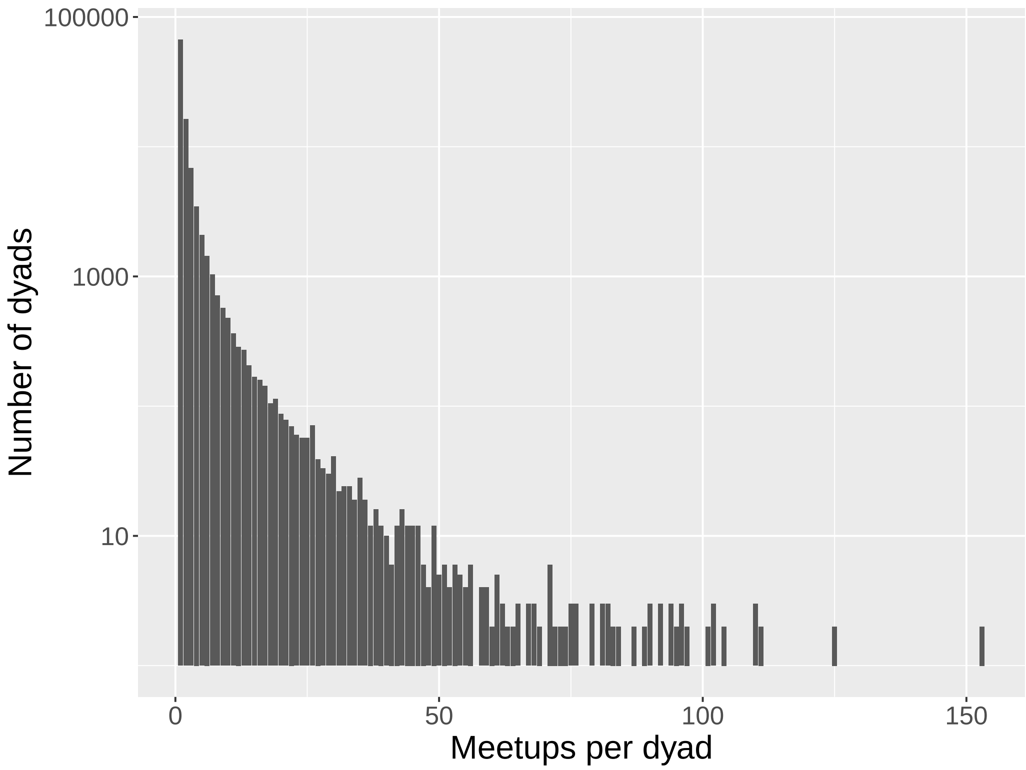
Figure 3.6: Meetups per attendee.

the same meetup) there are 4013 vertices with 102'738 edges (density of 0.013); substantially, the user network is generally of more interest in the analyses of this thesis.

Weights are assigned to the edges in the user network, measuring the number of times the edge occurs and thus capturing the strength of a dyad by counting how often the Wikipedians have met. The mean of the number of times users have met is 2.26 (median of 1, standard deviation 3.98), with a minimum of 1 and a maximum of 153 (see figure 3.7).

Degree relates to the number of other users they have met through meetups. The average degree in the user network is 51.20 (mean; median is 22, standard deviation 82.20) with a minimum of 1 and a maximum of 1141. The distribution of degree is displayed in figure 3.8.

The global, unweighted transitivity of the user network 0.29, giving the ratio of triangles and connected triples in the graph and functioning as a measure to express the extent to which nodes in a graph tend to cluster together. On the level of nodes, the transitivity is on average 0.78 (median 0.90, standard deviation 0.26) with the theoretical minimum and maximum of 0 and 1 respectively realised. Taking weights into account, the mean is 0.82 and the median 0.93 (standard deviation 0.22). The diameter of the user network,



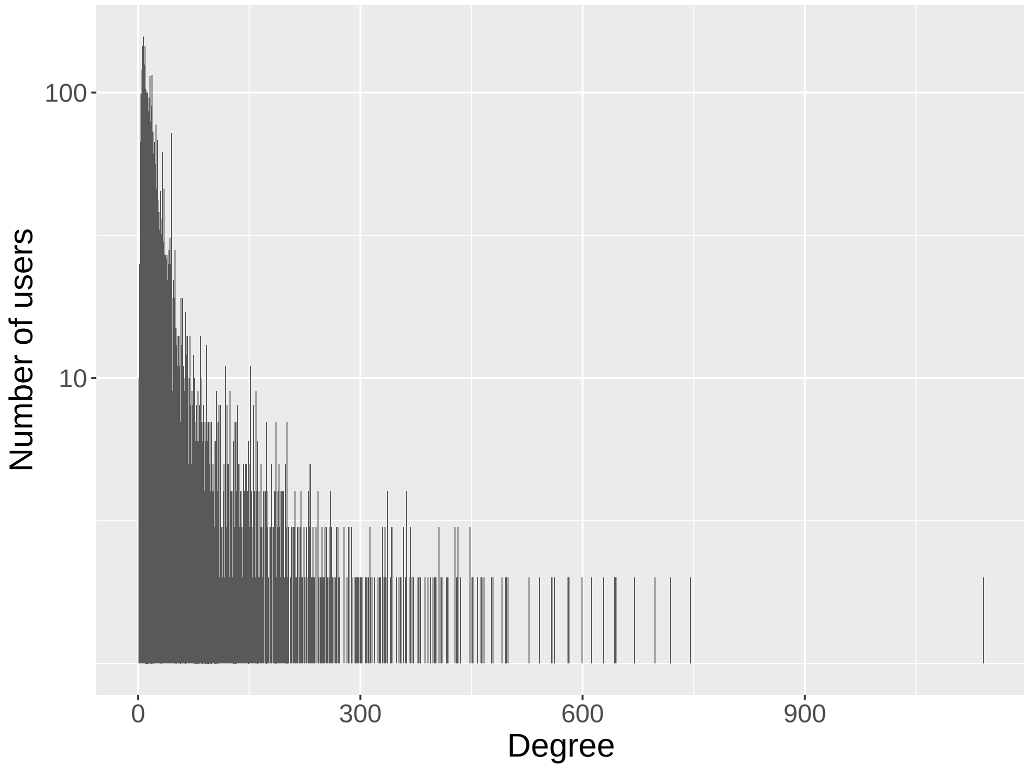
Note: Logarithmic scale for better legibility.

Figure 3.7: Meetups per dyad.

i.e. the longest path in the network and representative of the linear size of a network, is 8, with an average distance of 2.72.

Evolvement Over Time The previous paragraphs and figures have described the meetup network in its state of March 2020. The meetup network however is dynamic and changing over time as new meetups take place. As the network changes, so do the features to describe the network. The network of meetup attendees has grown across the years; by definition, it cannot decrease in size as only new nodes can enter the network but not leave the network.

The network started in October 2003 with the first meetup. It then consisted of one cluster with 5 fully connected nodes. A second meeting took place in 2003, allowing a new Wikipedian to join the meetup scene. By the end of 2004, there were 202 nodes in the network, belonging to one large component. At the end of data collection in 2020, the user network featured 5 clusters. Most nodes belong to one large component with 3996 nodes. The four other components are small, single meetups with 5, 2, 8 and 2 attendees, respectively. The user network consists mostly of one large component that has steadily grown throughout the years; each year, about 300 new Wikipe-



Note: Logarithmic scale for better legibility.

Figure 3.8: Degree of users.

dians have taken part in meetings for the first time. The development of the number of components and the size of the network is shown in table 3.1. Even though different meetups happen all across the German speaking area, they are not just visited by local Wikipedians; the large, interconnected component suggests that at least some Wikipedians must take part in meetups in different places, thus connecting potential local components to a large one. These remarks are based on the assumption that the meeting network cannot decrease in size to capture how an overarching network develops. In the substantive chapters 5 and 6, I refrain from this definition and instead assume that network ties dissolve after a year.

3.3.2.3 The Meetup Population

In the previous subsection, I described the meetups of Wikipedians: where and when they took place and how they connected the attendees with each other. But who are these attendees? The meetup population will be described in this subsection. In total, there are 36’599 observations of Wikipedians attending meetups. Considering only the first meetup a user attended, there are 4013 observations.

Table 3.1: Network components over the years.

Year	# nodes	# of edges	# of comp.	Size of components
2003	6	12	1	6
2004	202	1830	1	202
2005	413	5071	2	408; 5
2006	793	11671	4	774; 11; 5; 3
2007	1078	18839	3	1070; 5; 3
2008	1395	29874	3	1389; 5; 1
2009	1652	37788	2	1647; 5
2010	1866	43589	3	1859; 5; 2
2011	2131	50172	2	2126; 5
2012	2360	56065	2	2355; 5
2013	2618	63953	2	2613; 5
2014	2867	70674	3	2861; 5; 1
2015	3065	75956	2	3060; 5
2016	3268	82555	2	3263; 5
2017	3496	89405	2	3491; 5
2018	3661	93754	3	3648; 8; 5
2019	3956	100956	5	3939; 8; 5; 2; 2
2020	4013	102738	5	3996; 8; 5; 2; 2

Before ever taking part in a meetup, users had been active on Wikipedia on average for 921.24 days (days since their first edit; median 489.37, standard deviation 1125.16, minimum -3824.06, maximum 5968.19). This means some users partook in a meeting about 10.5 years before they made their first edit in the German Wikipedia, while others had already been on Wikipedia for over 16 years before meeting other Wikipedians face-to-face. The distribution of days since the first edit are plotted in figure 3.9.
There are 342 users who partook in a meetup before ever making an edit on Wikipedia. In some cases, users might even never edit but still attend meetings. How can this happen? There are several explanations for this:

- Users who are active in other language versions or sister projects of Wikipedia and have only signed up to the German Wikipedia to attend a meetup.
- Non-registered people who accompany an already active user (as friend, spouse, etc.) but then also decide to sign up.
- Accounts for non-humans, e.g. for dogs or other meetup mascots (for example for Sockie, the meetup sock[132]).

[132] See https://de.wikipedia.org/wiki/Benutzer:Sockie_die_echte_Stammtischsocke.

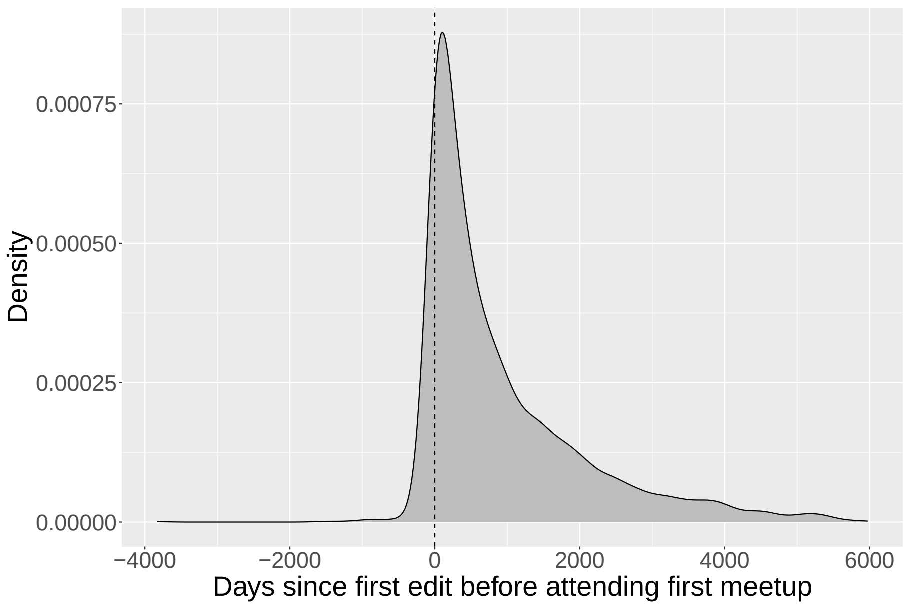


Figure 3.9: Tenure in days of first-time meetup goers.

- Users who partook in a meetup which was also advertised elsewhere (e.g. editathons), decided to sign up, but then did not continue using the account.
- A user was active in the past on Wikipedia and attended meetups. They deleted their account and after a long enough time, their account was again available for registration by new users who then also took part in meetups; this means one user is actually two different people.
- Error in the data: a user signed up for a meeting well after it happened, and this was not noticed during data collection.

As listed, one possible explanation might be that people went to a meeting which was advertised elsewhere. Social meetups are generally organised and advertised solely on Wikipedia, while work-related meetups can also be advertised elsewhere, particularly when one of their goals is attracting new editors. It could thus be the case that Wikipedians join work meetings significantly earlier in their editor career and that these work meetings work as a kick-off event for an active career.

Looking at the summary statistics of days since first edit by type of first meetup attended, there is some evidence for this (focusing on the median): users whose first meetup is of a social nature have been active for on average 907.19 days (median 557.54, standard deviation 1015.14, minimum -3824.06, maximum 5968.19), while those who have attended a work meetup have been active for on average 952.91 days (median 305.58, standard deviation 1340.50, minimum -1426.80, maximum 5929.12). Comparing the distributions of days since first edit by type of first meetup attended as shown in figure 3.10, there are some notable distributional differences. A larger part of users whose first meetup was of a work nature started editing after the meetup (263 vs. 79 users).

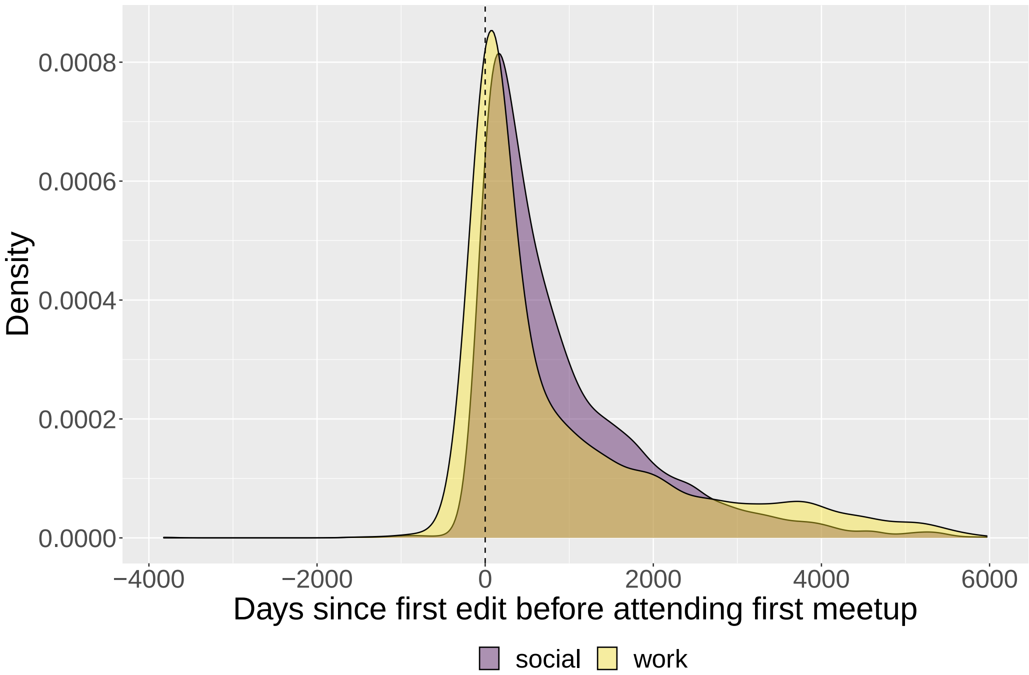
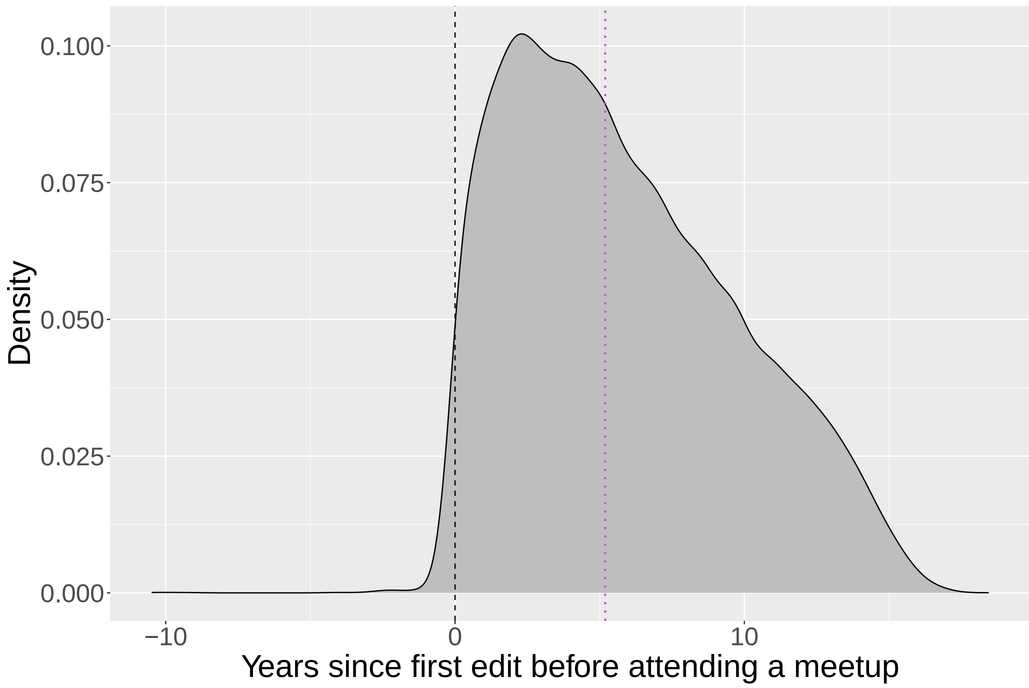


Figure 3.10: Tenure in days of first-time meetup goers, differentiating meetups with a social vs. a work orientation.

Looking at the activity level of users, users have made on average 2012 edits in the Wikipedia article namespace before attending their first meetup (median 228, standard deviation 6302.81, minimum 0, maximum 188'652). Looking at all edits (across all namespaces), the numbers are naturally higher with an average of 3005 edits (median 362, standard deviation 8343.78, minimum 0, maximum 215'717).

Looking at all meetups instead of just the first one attended, I find that Wikipedians have made on average 11'828.40 edits in the Wikipedia main namespace before attending a meetup (median 4136, standard deviation 24'527.19, minimum 0, maximum 1'986'719), and 19'608.20 edits in total (median 7759, standard deviation 34'188.75, minimum 0, maximum 2'025'450). On average, the first edit was 2126.70 days before a meeting, meaning almost 6 years (median 1895.96, standard deviation 1429.53, minimum -3824.06, maximum 6731.37). The maximum of about 18.5 years (6731 days) signifies again the long-term sustainability of Wikipedia: users who have registered and made edits almost two decades ago remain active meetup goers. It is undoubtedly quite remarkable that a Wikipedian who signed up in the very early days of the project—namely July 2001—still attends a meetup in December 2019 (see also figure 3.11).



Note: Dotted violet line marks median.

Figure 3.11: Tenure in years of meetup goers.

3.3.3 Creating a Control Group and Subsampling Data: Matching Procedure

The main goal of this thesis is to find the effects of offline meetings on the behaviour of single actors while still keeping in mind that the identification of causal effects is difficult. While exploiting the longitudinal nature of Wikipedia allows to compare changes within users, it is more insightful to also make comparisons between users. As it is computationally difficult to compare meeting attendees with all other users registered on Wikipedia, I construct a group of similar others to compare attendees to.

I make use of such comparable users in chapters 4 and 6. The "control groups" consisting of these comparable users are constructed by matching meetup attendees with similar others. Similarity is based on a selection of relevant covariates which differ between the chapters (given their differing foci). The

main logic will be described in this section, but the exact execution of the matching will be laid out in the corresponding chapters.
To create the control groups, each user who attended a specific meetup (in chapter 4) or who had attended meetups before a specific election (in chapter 6) was matched with a similar other. A popular matching approach in the social sciences is propensity score matching (see e.g. Caliendo and Kopeinig 2008; Rosenbaum and Rubin 1983). The propensity score is a balancing score; balancing scores are functions of the relevant observed covariates X such that the conditional distribution of X given $b(X)$ is independent of assignment into treatment (Rosenbaum and Rubin 1983). Calculating a propensity score is difficult in the case of Wikipedia: for example, when trying to find a control group for the causal effect of meetups on productivity, there are over 1'000'000 registered users who need to be matched to the meeting attendees at about 4000 different points in time. This would lead to an extremely large pool of observations.
As an alternative approach, I will employ covariate matching in which the control group is selected on the base of similar covariates instead of a similar propensity score (Zhao 2004). Which covariates are relevant depends on the exact analysis and will be outlined in the corresponding chapters, but they include measures like the previous level of activity or tenure. The matching procedure was coded manually. For each attendee at each meetup (in chapter 4) and for each meetup attending eligible user at elections (in chapter 6), the most similar non-attendee was searched and selected as a control user. Users were compared based on a distance measure based on ordinary least squares between Wikipedian X who attended a meetup and all those who have not attended a meetup and are not already matched to another user at the same point in time, using the relevant covariates. In case multiple users have an identical minimal distance to Wikipedian X, one of them was chosen randomly.

3.4 Statistical Software

All analyses are based on *R* versions 4.1.1/4.1.2. The large data is dealt with by making use of SQLite via the *RSQLite* package in R (Wickham et al. 2015) and using *data.table* (Dowle and Srinivasan 2021). A remote RStudio server was used to outsource computationally and time intensive tasks.
For data manipulation, the packages around the *tidyverse* were extensively used (Wickham et al. 2019), particularly *dplyr* (Wickham et al. 2021) and

magrittr (Bache and Wickham 2020). Working with dates was made easy due to *lubridate* (Grolemund and Wickham 2011), and geo-coding and -plotting was done using *tidygeocoder* (Cambon et al. 2021), *sf* (Pebesma 2018), *spData* (Bivand et al. 2021), and *maps* (Brownrigg 2021).

Network-related measures and graphs are based on the package *igraph* (Csardi and Nepusz 2006). Multilevel models are run using *lme4* (Bates et al. 2014) and its functionality was extended using *lmerTest* (Kuznetsova et al. 2017). Robust standard errors are calculated using *clubSandwich* (Pustejovsky 2021). Output tables were tidied up using *broom.mixed* (Bolker and Robinson 2021) and created using *texreg* (Leifeld 2013). Graphs were mainly created by using *ggplot2* (Wickham 2016a) and packages building upon it; these include *ggpubr* (Kassambara 2020), *dotwhisker* (Solt and Hu 2021), *hrbrthemes* (Rudis 2020), and *GGally* (Schloerke et al. 2021). Visualisations further profited from *scales* (Wickham and Seidel 2020), *tmap* (Tennekes 2018), and *viridis* (Garnier et al. 2021). Other packages used are cited in the appropriate chapters.

3.5 Ethical Considerations

This thesis is based on data collected from the world wide web. While using web data for research is becoming increasingly popular, the ethical requirements and considerations that come with it still are a somewhat grey area and a topic of ongoing debate; I follow the ethical practices as currently discussed in the literature (see e.g. Salganik 2018 chapter 6; Townsend and Wallace 2016).

In contrast to other social media sites, Wikipedia is a rewarding case for researchers. With Wikipedia, there is a general norm of public production. Content created on Wikipedia is open, there is no private space (see for notes on this regarding Twitter vs. Facebook Barberá and Steinert-Threlkeld 2020). Wikipedia offers free copies of all available content to those interested, in particular through their data dumps[133]. While private access possibilities with confidential user data exist, these were not used in this thesis. Only publicly available web data generated by Wikipedia contributors was used. However, ethical considerations can be a concern as people contribute to Wikipedia with the intention of sharing and advancing knowledge (generally), and to organise and coordinate meetings (in this special case of meetup data). They do not contribute with the intention of creating meta data for research

[133] See https://meta.wikimedia.org/wiki/Research:Data.

purposes and might not be aware of how the data is being used (see for notes on this regarding Twitter Fiesler and Proferes 2018). However, the guidelines of Wikipedia explicitly list the possibility that the setting up of a registered user account allows the linking of different edits and actions on Wikipedia to a single account/person and that anyone might investigate and analyse this data in any way[134].

Overall, and in stark contrast to other social media sites and online platforms, there is a general norm of openness that users can be assumed to be aware of when posting, and which lessens ethical concerns. Still, combining different traces of Wikipedia usage behaviour can seem intrusive to users (Geiger and Ribes 2011). However, as the generated data is publicly available with no restrictions (no registration with Wikipedia is necessary) and this research does not deal with sensitive topics, obtaining informed consent from Wikipedia contributors seems neither vital nor, considering the scale of the data, feasible. To respect users' intentions when contributing to Wikipedia, no usernames are published to diminish the possibilities for making inferences to the users. While I do not use the usernames in the text, it still needs to be acknowledged that they could be tracked down if wanted as I generally link to the sources in favour of transparency.

Ethical approval for the study with this setup was obtained in January 2020 by the ethical advisor of the Department of Sociology at the University of Warwick. Also, the Wikimedia Foundation approved of this project with this setup[135].

[134] See https://de.wikipedia.org/wiki/Hilfe:Benutzerkonto_anlegen.

[135] See https://meta.wikimedia.org/wiki/Grants:Project/nschwitter/The_Role_of_Offline_Ties_of_Wikipedians.

4 Offline Meetups of Wikipedians: Boosting or Braking Activity and Collaborations?

The following chapter focuses on the productive behaviour of Wikipedians: the writing of articles. Wikipedia's success is based on active Wikipedians who create new content and curate existing one. The following chapter will outline to what extent offline meeting participation influences contributing behaviour in terms of productivity and collaboration.

4.1 Introduction: Writing Wikipedia

Wikipedia is made up of user-written text: articles are written by knowledgeable and engaged volunteers, discussions are led to deal with controversies and disputes, public messages are exchanged, and the norms and rules of the platform are defined. It is an encyclopaedia which anyone can edit, either anonymously or after registering with a user account. Edits are the building blocks of Wikipedia, and the German Wikipedia counts over 21 million edits in total as of now (July 2022), currently counting around 25'000 edits per day[136].

Productivity on Wikipedia refers to the creation of a collective good. It refers to the quantity of contributions of editors who increase the volume of articles on Wikipedia and who thus turn it into a valuable source of information and the encyclopaedia it is today. Editors' productivity is the driver of the success of Wikipedia. Only active and productive users can create an encyclopaedia which is rich and of interest to the public. Like in other online communities, the users' contributions are necessary for Wikipedia's long-term viability (Bateman et al. 2011). However, retaining users over time,

[136] See https://stats.wikimedia.org/#/de.wikipedia.org/contributing/edits.

particularly beyond an initial trial phase, is a problem for many open-source projects and virtual communities in general (see e.g. Chen 2007; McInnis et al. 2016; Steinmacher et al. 2013; TeBlunthuis et al. 2018) and Wikipedia is no exemption to this (see e.g. Halfaker et al. 2012; Morgan and Halfaker 2018).

This chapter explores how participation in offline meetups influences an editor's contributing behaviour to Wikipedia. First, I will ask to what extent offline meetings influence an editor's productivity, i.e. number of contributions. While this analysis thus aims at identifying causal effects of meetup participation on editing activity by comparing the levels of activity of meetup attendees and a comparable control group before and after meetings, it needs to be noted that such an identification is not possible with observational digital trace data. Second, I will focus on collaboration behaviour with other users. Wikipedia is a collaborative effort and articles are generally the result of collaborations between different users. This chapter will also investigate how collaborations are influenced by creating new ties through offline meetups.

In the following theoretical section, I will outline to what extent Wikipedians are embedded in a social network with others and how offline meetup participation might influence contributing behaviour. The previous state of the literature will be discussed, and hypotheses will be derived. After the theoretical discussion, the methods and data will be described. Section 4.4 will test the hypotheses and present the results. Lastly, I will summarise the results and draw conclusions regarding the effect of offline meetup participation on productive behaviour.

4.2 Theory: Why Do People Contribute Towards and Collaborate on Wikipedia?

Understanding who Wikipedians are, why they join the platform, and why they keep editing has been of interest to many scholars. A large body of research is concerned with issues related to participation or collaboration in the Wikipedia community (see also subsection 2.3.2.2). Considering that Wikipedia is a prime example of a collective good, the incentives to contribute are low. Even though the provision of articles is costly for the authors as they need to invest time in researching and writing, Wikipedia exists and its scope is remarkable. Many individuals have opted against free riding and instead participate, sometimes staying active for years to come after joining the community.

Crowston and Fagnot (2018) have established a theoretical framework drawing on different theories to explain contributions towards user-generated content at different stages, particularly incorporating theories of helping behaviour (Schwartz and Howard 1982) and social movement theory (Klandermans 1997). They differentiate between three separate sets (initial, sustained, and meta) of motivations for participation, arguing explicitly that the motivations to make a first contribution are not the same as the motivations to make additional contributions. In this study, I do not aim at answering the question of what motivates users to *start* editing Wikipedia, but I am concerned with the (motivational) effect of meetups on (generally) already contributing Wikipedians, i.e. what role meetups play in sustaining a user's contribution (see for studies on motivational factors e.g. Algan et al. 2013; Anthony et al. 2009; Balestra et al. 2016; Crowston and Fagnot 2018; Kuznetsov 2006; Schroer and Hertel 2009). Aside from some exceptions, Wikipedians first contribute to the project and then get involved in the community.

Crowston and Fagnot (2018) understand contributions to projects such as Wikipedia as a form of voluntary participation in a voluntary organisation; Konieczny (2009) has also previously framed Wikipedia as a social movement. Crowston and Fagnot (2018) argue that three precursor conditions must be fulfilled so that helping behaviour can arise in the context of user-generated content projects: individuals must recognise the need to help, individuals must have the capabilities and feel the obligation and/or responsibility to help, and individuals must weigh their obligation and capability of helping favourably against its (social and tangible) costs.

Given my focus on sustained contribution, it can be assumed that contributors of Wikipedia are aware of the project from their initial encounter. However, Crowston and Fagnot (2018) argue that a continuing contributor must also perceive the need for further contributions. They also expect that sustained contributors who report higher domain expertise will contribute more, as well as those concluding a positive evaluation of contributing (due to learning more through contributing, due to considering it fun, or due to receiving positive feedback). More relevant for this study, Crowston and Fagnot (2018) expect that feelings of social obligations play a role in deciding whether users become sustained contributors (Schroer and Hertel 2009). Drawing on the literature on social movements, defined as an organised effort by a group of people to bring about societal change, they suggest that projects become better at retaining participants if they develop characteristics of such movements. Klandermans (1997) suggests four different areas of motivation for participation in a social movement: collective motives, identification with the group or a subgroup, reward motives, and social motives (Crowston and Fagnot 2018; Simon et al. 1998). Further, the fact that social networks matter for social movements is well documented and they are shown to be important in explaining their success (Diani and McAdam 2003; Passy and Giugni 2001).

Collective motivations come from the individual's evaluation of the group's goals or ideology. This becomes relevant as many social movements share an ideology and are organised around this shared ideology. In the case of Wikipedia, the project aims at promoting free knowledge and many contributors express feelings of agreement with this goal (Algan et al. 2013; Anthony et al. 2009; Balestra et al. 2016; Bryant et al. 2005; Kuznetsov 2006; Schroer and Hertel 2009). However, they further argue that participants who report a higher level of identification are more likely to sustain contributions and contribute more (see also González-Anta et al. 2021). Group identification can lead to feelings of obligation to the group which then provide motivations for sustained contribution. Feeling part of a group is essential to transform interests into collective actions (Gotham 1999) and generally increase commitment to it (Ren et al. 2010); commitment and self-identification can then motivate to contribute to the collective good of the group (Kramer and Brewer 1984) and work as motivating drivers of work more generally (Ellemers et al. 2004; Johnson et al. 2010), also in online communities (Bateman et al. 2011).

Following this line of argumentation, I argue that offline meetups are a measure of identification with Wikipedia and increase commitment to the project and its userbase. Face-to-face meetings offer an additional venue for interaction and thus strengthen existing online weak ties, increasing the identification and commitment to Wikipedia, which in turn increases contributions. This leads to the following hypothesis:

Hypothesis 1a: Attendees of offline meetups increase their contributions after a meetup.

Wikipedia meetups come as either social meetups or are more strongly work-related. Some meetups are specifically designed so people could learn more about how to edit Wikipedia, about gaps and missing content on Wikipedia, or about specific information which is currently lacking in the encyclopaedia. New ideas and knowledge is generated at such work meetups which—in the framework of Crowston and Fagnot (2018)—increase users' capabilities to contribute as well as their awareness of the need to contribute. I thus also expect the following:

Hypothesis 1b: Attendees of work-related offline meetups increase their contributions more than attendees of social meetups after attending.

In the context of Wikipedia, there are only a small number of previous studies which have explored the role of face-to-face meetings and their effect on users' editing behaviour (see also section 2.4.3). Stegbauer (2009) collected data on 240 different meetups with 750 different attendees. Contrary to his expectations, he finds that around 60 per cent of users, who have taken part in meetings, decrease their activity on Wikipedia, measured in the number of edits in the month after the meetup compared to activity in the month before (calculating bivariate associations). More detailed analysis shows that users who later become administrators increase their activity while only those who do not become administrators decrease it. Stegbauer (2009 chapter 15) also mentions as anecdotal evidence that users report that meetings are integral in deciding on new administrators and in suggesting who should be nominated. Analysing interview data from an editathon—a typical work-related meetup, Littlejohn et al. (2019) highlight that the personal relationships made at these events are important to some of the participants when continuing editing Wikipedia, and Farzan et al. (2016) find that Wikipedians joining the site as part of an editathon stay slightly more active (in the short time frame observed).

While offline ties have rarely been researched, the importance of online ties has been highlighted in several other studies. For example, Qin et al. (2015) have focused on discussion ties based on exchanges between users on talk pages. They find that certain properties of communication networks relate positively to project efficiency of WikiProjects. Choi et al. (2010) have shown how the socialisation of newcomers on Wikipedia via personal interaction—for example, via welcome messages or offers of assistance—can increase newcomers' commitment to the project. In a unique field experimental setup, Zhang and Wang (2012) were able to collect panel data from the Chinese language version of Wikipedia. They make use of the politically motivated blocking of Wikipedia on Mainland China as a natural field experiment which influenced, endogenously, the network structure of co-editors by blocking out and thus removing certain actors. This led to a change in the network structure for unaffected editors. They find that the centrality of the network position of a user affects both, an editor's decision about total contribution and the allocation of their effort.

More broadly, evidence has been found by other researchers studying other online platforms that the offline network matters in terms of online participation. Several studies have acknowledged the occurrence of offline interactions within online communities and discussed the interplay between the offline and the online (e.g. Angelopoulos and Merali 2015; Ganglbauer et al. 2014; Koh et al. 2003; Lin 2007; McCully et al. 2011; Sessions 2010; Shen and Cage 2013; Xie 2008); see also section 2.1 and particularly subsection 2.1.4.2. Offline meetings can play a part in complementing the low social presence inherent in most computer-mediated environments (Lombard and Ditton 1997). There is supporting evidence that stronger ties develop through offline gatherings in online communities; for example, Angelopoulos and Merali (2015) find enhanced sociability of users of an online community after meeting offline; Lin (2007) finds that offline interactions are important for the sustained success of online communities; Koh et al. (2003) state that offline activities increase the solidarity and cohesiveness of virtual communities and strengthen links between members: they expect that offline meetings facilitate virtual community activism and lead to a higher sense of virtual community, expecting positive relationships between offline activities and different dimensions of immersion into a virtual community and find some support in their analysis on Korean virtual communities. However, not all online communities show positive effects of offline meetups. McCully et al. (2011) state that meetups of a collaborative writing community strengthen online relationships but decrease the amount of participation, leading to a counter-intuitive impact on community sustainability. As previous research suggests, it thus seems to depend on the context and the specifics of the online community.

Against the background of the previous research, this study also wants to address the previous finding by Stegbauer (2009) on the activity of administrators. Stegbauer (2009 chapter 15) finds increased activity after a meetup only for administrators and argues that it might be the case that being admitted into the community within the context of the meeting has consequences for the positioning of the user within Wikipedia. If the meetup experience was negative, the user might drop out altogether and decrease their activity, while a positive experience might well lead to adminship. While the explanations cannot be tested in this project, it will be analysed whether the finding can be replicated:

Hypothesis 1c: Attendees of offline meetups who will become administrators increase their contributions after a meetup.

Next to individuals' own contributing behaviour, it is important to consider that articles are generally written through a collaboration of users. Meetups allow users to talk about their interests. Strengthening their bonds, they might realise their common interests. Meetups can lead to the creation of stronger ties and to the development of multiplex relationships. This might lead to increased collaboration between users, and thus the following hypothesis:

Hypothesis 2a: Attendees of offline meetups increase their collaboration with other attendees after a meetup.

While this reads positive, the development of stronger ties and increased social capital can lead to negative consequences: they can encourage exclusionary behaviour towards those that are perceived not to be part of the community (Alcorta et al. 2020). This falls into the notion of dark social capital as sketched out by Portes (1998) (see also section 2.1.1). In terms of online communities, such exclusionary behaviour is expected to result in a loss of ties towards those that are not attending meetups:

Hypothesis 2b: Attendees of offline meetups decrease their collaboration with non-attendees after a meetup.

Considering these hypotheses, past research has highlighted the challenges that develop within online communities engaging in offline meetups. Sessions (2010) finds that having offline relationships enhances a user's engagement with the online community, strengthens ties to other attendees of offline meetings and through this contributes to the creation of bonding social capital. However, weak ties with non-attendees dissolve to an extent. While offline meetings can thus be beneficial for the individual, they can have detrimental effects on the online community as a whole as an unintended consequence. Analysing a community of science fiction fans, Shen and Cage (2013) find that offline meetups enhance attendees' bonding social capital at the expense of bridging social capital; this reduced the opportunities for new members to join and find acceptance in the community. These results are generally in line with the findings of Zhang and Wang (2012) who focus on the (experimental) changes in the online contributor network of Wikipedians. Zhang and Wang (2012) find that the more central an editor, the smaller their total contribution but the stronger their contribution to self-written articles. This is thus a concentration on fewer articles, a more focused way of editing, leading to collaborating with fewer others.

In summary, previous research on the effect of offline meetups on online communities resulted in mixed conclusions. These previously analysed online communities are quite different from Wikipedia; most studies are concerned with forums or web blogs based on discussion and common interests. These are only to a very limited extent comparable with an open collaboration project which aims at providing free knowledge. The findings of Stegbauer (2009) who analysed meetups of Wikipedians can also be summarised as mixed: meetups can either lead to a withdrawal from the community, but they can also fuel further engagement, culminating in the promotion to an admin. Studies focusing on editathons such as the study of Farzan et al. (2016) have generally found positive effects but only focused on short time frames and new users. In the following, it will be tested how meetup participation affects sustained contributions on Wikipedia.

4.3 Methods and Data

This section will describe the data, methods, and statistical approaches used to analyse changes in productive and collaborative behaviour after a meetup. It will also provide a descriptive overview of the data used. I will refer to chapter 3 when making use of the general data which is used in all three topical chapters.

4.3.1 Measuring Productivity

The activity of Wikipedians is measured via activity logged in the meta dump (see for details section 3.1). To assess the effect of meetups on the change of editing behaviour, four different time frames are being analysed: a very short time frame of one week, two medium length time frames of one month and two months, as well as a long-term time frame of one year. In practice, this means that all edits in the week up to the meeting have been counted, all edits in the month up to the meeting, all edits in the two months up to the meeting, and all edits in the year up to the meeting, as well as the number of edits in the corresponding time frame after the meetup. Activity on the day of the meetup was counted as activity *after the meeting* as it can be considered as activity happening as a reaction to joining the meeting. These time frames are chosen as the weekly and monthly changes in editing behaviour have been used in previous research (Farzan et al. 2016; Stegbauer 2009). They represent a short and a medium time frame. The two months are chosen as some rules on Wikipedia are based on activity in the past two months (for example regarding eligibility to vote). The yearly time frame allows for a long-term perspective which previous research has ignored.

While I am looking at the total number of edits, it is important to note that this covers more than just actual articles; it also reflects activity on discussion pages and other discussions. To account for this, I separately assess edits in the mainspace as this is the driver for productivity (see on namespaces also section 3.1.1). This distinction differentiates productive edits to the encyclopaedia and any other activity in relation to the project.

Users who have not made an edit before taking part in a meetup are excluded from the following analyses. They have not been posting Wikipedians yet, even if they had taken part in meetups. They can thus not change their editing behaviour. In this case, meetups would not explain sustained contribution but initial contribution; this is beyond the scope of this study. When looking at the first meetup, 3724 users have made an edit before attending (out of 4013). In subsection 3.3.2.3, I discussed why users partook in meetups before making their first edit. Broadening the view from the first-time goers to all meetups, I find that 4013 have joined at least one meetup and 2167 users partook in more than one meetup on Wikipedia. This leads to a total of 36'364 observations, again excluding observations where a user joined a meeting before their first edit.

4.3.2 Measuring Collaboration

A Wikipedia article is (almost) always the result of collaboration; this study is interested in the way these collaborations change due to meetups. Subsection 3.1.2.1 has described how collaboration is defined.

I restrict my analysis to collaboration based on edits in the article mainspace as the article mainspace represents the most productive form of editing. Co-editing in other namespaces might not reflect collaboration but for example communication, the answering of questions, or the statement of opinions and is thus excluded.

4.3.3 Finding a Control Group

Section 3.3.3 discussed the basic idea of finding a control group for the meetup attendees. This section will explain in detail the procedure of how a comparable non-attendee was identified for each attendee when analysing productive behaviour.

This chapter is concerned with the effect of offline meetings on the behaviour of single actors. This raises questions of causality: for example, are people active on Wikipedia and then attend meetings, or do meetings work as a driver for productivity? Exploiting the longitudinal nature of Wikipedia can only partly shed light on this. To allow the identification of a *treatment effect*, a control group is needed with which the meetup attendees—the *treatment group*—can be compared to in this quasi-experimental approach. However, it needs to be noted that reverse causality and possible self-selection biases can threaten causal inferences.

To create the control group, each user that attended a specific meetup was matched with a similar other on the basis of similarity in specified covariates. The population of potential matchable non-attendees only includes users who did not take part in any meetups (and were never recorded to do so in the data). The matchable non-attendee was found by comparing users based on the following five features:

1. Days since registration
2. Sum of activity (number of edits) in the article mainspace of Wikipedia since registration up until the day of the meetup
3. Sum of activity (number of edits) anywhere but the article mainspace since registration up until the day of the meetup
4. Recent activity in the article mainspace of Wikipedia before the day of the meetup (number of edits in the last 7 days, the last month, last 2 months and last year)

5. Recent activity anywhere but the article mainspace before the day of the meetup (number of edits in the last 7 days, the last month, last 2 months and last year)

Each of these five features was assigned an equal weight of 20 per cent. The most similar other user was identified and selected as a control non-attendee. Users were compared using a distance measure based on ordinary least squares between Wikipedian X who attended a meetup and all those who have never attended a meetup and are not already a matched non-attendee for another user at that specific meetup.

Describing the Control Group: How Well Did the Matching Work?
Non-attendees who are most similar to meetup goers in terms of activity and tenure were searched. Naturally, they have never attended a meetup. There are 35'873 observations in the control group dataset, and 3724 observations (of 3319 users) when focusing on the first meetup of attendees.
Table 4.1 shows basic descriptive information on the meetup attendees (treatment group, T; see subsection 3.3.2.3) and their matched non-attendees (control group, C) for all meetings. Comparing these descriptives of non-attendees with those of the actual attendees, the matching seems successful: overall, the values of the actual meetup population and the constructed control population are very similar. In the next section, table 4.7 and table 4.8 (on pages 108 and 109) will show descriptive information on all variables included in the model estimations.

4.3.4 Description of Productivity

The level of productivity of the meetup attendees and the matched non-attendees before and after meetings is given in table 4.2 for the very first meeting, and in table 4.3 for all meetings[137].
As expected per matching process, the matched non-attendees and the attendees have a relatively similar pattern of activity before the meetup. However, overall, the non-attendees tend to be slightly less active in comparison, both before and after the meetup in any time frame. Also, comparing table

[137] The tables can be read as follows (based on the first row of table 4.2): on average, users who attend their very first meeting made about 27 edits in the Wikipedia mainspace. In the week after the meeting, they make on average 26. In the month before, they made on average 108 edits in the mainspace (112 in the month after), in the two months before 204 edits (217 in the two months after), and in the year before 893 edits (1108 in the year after).

Table 4.1: Basic descriptive information on treatment and control group.

Group	**Variable**	**Mean (SD) or %**	**Median**	**Min/Max**
T	Days since first edit (first meetup)	921.24 (1125.16)	489.37	-3824.06 / 5968.19
C		1001.46 (1127.81)	580.35	0.085 / 5955.99
T	Number of namespace edits (first meetup)	2012 (6302.81)	228	0 / 188652
C		2104.17 (6001.38)	287.50	0 / 136341
T	Number of total edits (first meetup)	3005 (8343.78)	362	0 / 215717
C		3119.29 (8175.22)	444	1 / 166770
T	Days since first edit (all meetups)	2126.70 (1429.53)	1895.96	-3824.06 / 6731.37
C		2133.46 (1409.08)	1899.47	0.085 / 6734.32
T	Number of namespace edits (all meetups)	11828.40 (24527.19)	4136	0 / 1986719
C		11487.40 (21455.73)	4308	0 / 402468
T	Number of total edits (all meetups)	19608.20 (34188.75)	7759	0 / 2025450
C		18431 (30433.88)	7622	1 / 519933
T	Observations (first meetup)	4013		
C		3724 (3319 users)		
T	Observations (all meetups)	36599		
C		35873		

T = treatment group, C = control group.

4.2 with table 4.3, we see that users are, on average, more active before joining any meetup than before joining their first one.

Table 4.2: Editing behaviour around first meetup.

Namespace	Group	7 days Before	7 days After	1 month Before	1 month After	2 months Before	2 months After	1 year Before	1 year After
Mainspace	Treatment	27.38 (81.83)	26.58 (73.14)	108.45 (270.24)	112.40 (293.23)	203.75 (476.69)	216.48 (544.47)	893.06 (2048.70)	1107.75 (2865.59)
		2	3	15	16.5	35	32	146	161
		0 / 1855	0 / 1501	0 / 5853	0 / 8179	0 / 10462	0 / 14874	0 / 27397	0 / 82460
	Control	22.33 (62.59)	20.23 (61.07)	92.45 (219.03)	82.38 (210.81)	172.07 (378.97)	157.13 (386.30)	765.48 (1650.05)	758.65 (1886.31)
		1	0	9	4	21	9	101.5	53
		0 / 1171	0 / 984	0 / 3105	0 / 2890	0 / 5455	0 / 5682	0 / 20963	0 / 27593
Total	Treatment	44.06 (106.58)	45.90 (103.67)	177.03 (376.00)	182.58 (395.79)	330.45 (673.01)	349.26 (749.37)	1387.17 (2886.70)	1781.72 (3970.32)
		6	10	33	35	66	64.5	242.5	296.5
		0 / 1943	0 / 2087	0 / 6679	0 / 8534	0 / 11851	0 / 15607	0 / 37815	0 / 86197
	Control	35.58 (83.16)	30.99 (79.68)	147.14 (307.80)	127.32 (288.17)	274.66 (552.29)	243.69 (540.28)	1181.00 (2436.09)	1170.03 (2692.68)
		4	1	20	9	39.5	18	163	87
		0 / 1353	0 / 1130	0 / 3926	0 / 3339	0 / 6356	0 / 7026	0 / 42112	0 / 39290

Given are mean (standard deviation), median, minimum / maximum for the treatment group (n=3724) and control group (n=3724).

Table 4.3: Editing behaviour around all meetups.

Namespace	Group	7 days Before	7 days After	1 month Before	1 month After	2 months Before	2 months After	1 year Before	1 year After
Mainspace	Treatment	39.37 (117.61)	37.55 (116.41)	171.03 (494.00)	167.21 (447.68)	339.99 (912.06)	330.53 (870.87)	1992.60 (5491.49)	1819.80 (4674.51)
		9	9	50	50	108	104	728	596
		0 / 7868	0 / 11822	0 / 41263	0 / 29759	0 / 74239	0 / 55575	0 / 633557	0 / 329932
	Control	32.09 (76.60)	31.82 (104.93)	139.38 (297.27)	134.47 (400.79)	277.61 (574.99)	262.99 (656.19)	1650.48 (3203.77)	1413.31 (2982.36)
		5	4	31	25	69	53	508	308
		0 / 2425	0 / 13523	0 / 9853	0 / 50276	0 / 16354	0 / 60305	0 / 73675	0 / 64619
Total	Treatment	68.20 (146.23)	67.24 (142.07)	292.76 (602.03)	287.20 (559.55)	578.84 (1126.62)	562.92 (1087.68)	3358.50 (6615.85)	3069.30 (5842.05)
		23	26	113	113	236	224	1481	1272
		0 / 7969	0 / 11893	0 / 41602	0 / 30155	0 / 75478	0 / 56272	0 / 640596	0 / 336518
	Control	52.59 (102.74)	51.43 (126.77)	227.63 (406.59)	216.73 (492.57)	451.16 (786.87)	423.46 (850.60)	2658.53 (4387.48)	2261.68 (4141.66)
		12	9	66	51	139	108	960	608
		0 / 2425	0 / 13585	0 / 9911	0 / 51422	0 / 16857	0 / 61635	0 / 83182	0 / 74567

Given are mean (standard deviation), median, minimum / maximum for the treatment group (n=37025) and control group (n=36364).

These numbers also indicate that not all meetup goers have shown activity in the German Wikipedia. Only 3654 out of 4013 users attending a meetup have shown any activity within one year before and after the meetup in any namespace of the German Wikipedia, meaning that almost 10 per cent of users have not shown any activity in the German Wikipedia even though they took part in a meetup. As mentioned, some have not made their first edit before joining a meetup (who will be excluded), while others have just not shown any recent activity. It might be the case that users are immersed in the meetup community from the past and stopped being active editors but still join the social component.

Looking at the numbers reported in tables 4.2 and 4.3, the standard deviations are very large for all time frames and groups. The range of activity levels on Wikipedia is wide, and some users invest a lot of time and effort into Wikipedia (see for research on this e.g. Ortega et al. 2008a,b). In the following analyses, I will work with the difference in activity between the time after and the time before the meetup. Given the highly skewed distribution of this measure, I will take the cube root of the values. This transformation will allow to run simpler models, sensibly account for outliers, and retain the direction of changes (in contrast to other transformations). Taking the cube root accounts for the fact that a very extreme number of changes must reflect smaller edits (such as fixing typos, reverting during an edit-war[138], etc.) as it seems rather implausible that a single user can make over 1000 substantive edits in a day. The cube root is taken from the change.

The distribution of the calculated changes is displayed in figure 4.1 for all namespaces and time frames. The distributions seem now centred around zero and the extreme outliers have been drawn closer, making it a more feasible dependent variable.

4.3.5 Description of Collaboration

In the following, the collaboration data extracted will be described. In the first part, I will describe the collaboration network (similar to the meetup network in subsection 3.3.2.2). In the second part, collaboration will be reduced to a simpler frequency measure, and this data will be described.

[138] An unconstructive repetition of contributors overriding each other, see https://en.wikipedia.org/wiki/Wikipedia:Edit_warring.

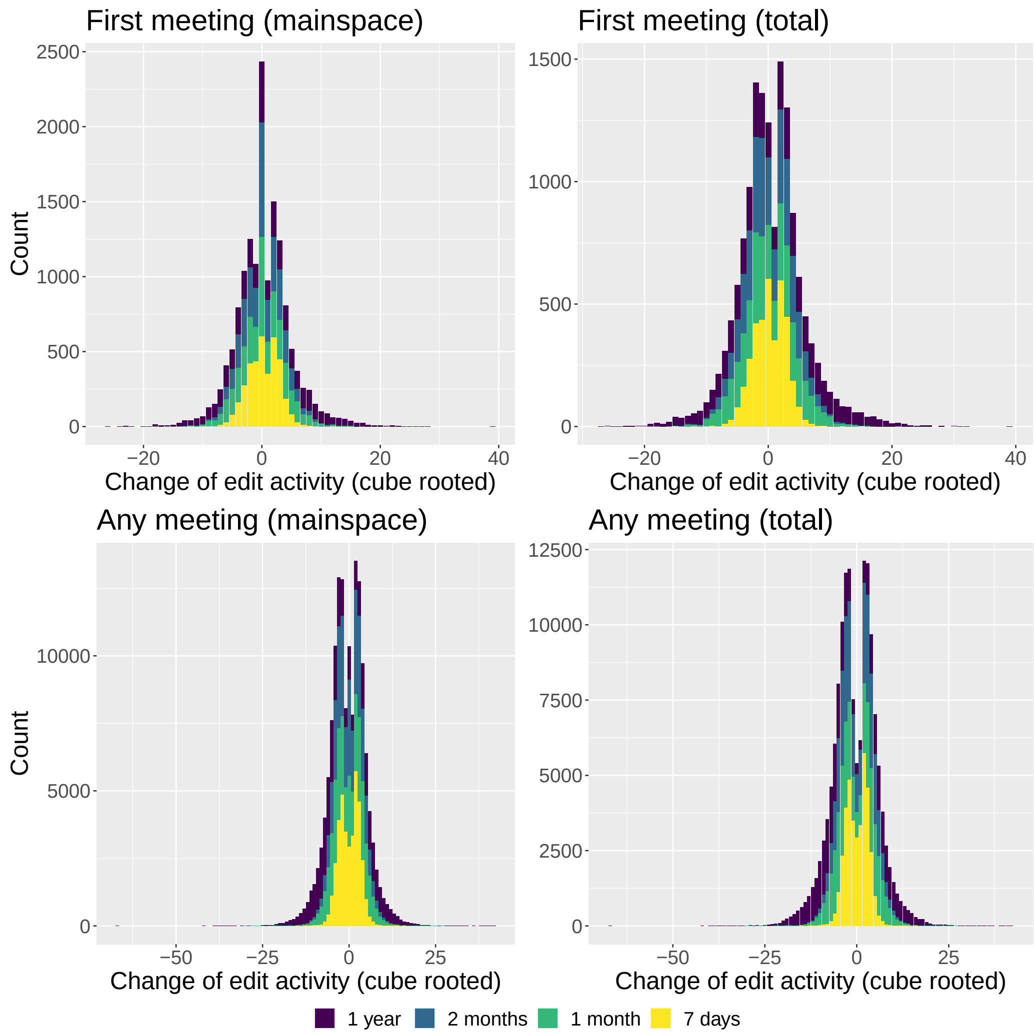


Figure 4.1: Change in editing behaviour after attending meetup.

4.3.5.1 The Collaboration Network

Understanding collaboration between users as ties sent from one to the other will result in a network. I reduce this network to users who have taken part in a meetup. Ignoring the timing of edits, this results in a directed network of 600'817 different nodes, sharing 35'490'679 edges if multiple edges are allowed. Simplifying the network, i.e. excluding multiple edges, leads to a graph with 8'823'796 edges (density of 0.000024; density is ill-defined for graphs with multiple edges). The difference in edges highlights that some users have collaborated multiple times. While the majority of ties have only occurred once with the minimum and median being 1, other user-pairs have collaborated with each other over 50'000 times (mean 4.02)[139]. The global

[139] This might not necessarily represent fruitful collaboration, but could also reflect an edit-war.

clustering coefficient of the network (ratio of triangles and connected triples) lies at 0.047. A very high share, namely 47.9 per cent, of ties are reciprocated: this means that if user A edited right after user B, in almost half the cases user B also edited after user A at some point in time.

Taking time into account, the picture becomes more complex. The network of co-authorship between meetup attendees started when the first person, who later attended a meetup, made their first edit. Later on, it is changed with every edit by users who attended meetups. In the following, the co-author network per year will be described. It is focused on all users that have taken part in a meetup up until March 2020; this means, it covers the whole before and after activity for everyone that ever took part in a meetup. It is not just focused on those who have taken part in a meetup up until that point in time. Multiple ties are taken into account as weights.

By the end of 2001, the first year of Wikipedia, the collaboration network of users who took part in meetings consisted of 32 nodes connected with 50 edges. One year later, the network grew to include 320 nodes, tied with 1410 edges. The development of the collaboration network is given in table 4.4; given are the figures by the end of the corresponding year for every other year (by March 30 for 2020).

Generally, the collaboration network is not split up into meaningful, separate components. Across the years, it is made of one large component which includes almost all vertices, and up to 19 sub-components of separate dyads. However, these separate dyads never develop into larger components but are submerged into the main component across the years. By the end of the time frame observed, the collaboration network consists of just one large component, spanning all 600'817 vertices. This suggests that the editing of articles is not done by separate groups of users that do not overlap—if this was the case, there would be separate components. Given there is only one large component does suggest that there are at least some users working on many different articles.

It is important to note that, as previously described, over 4000 Wikipedians have taken part in meetings and 3724 have made valid edits on Wikipedia, and most of them appear in the collaboration network (3498). The other ones do not share any ties to others, meaning they have not edited any Wikipedia articles right before or right after any other registered user (who is not a bot).

Table 4.4: Collaboration network over the years.

Year	# nodes (meeters)	# of edges
2001	32 (13)	50
2002	320 (100)	1410
2004	16523 (944)	238976
2006	89338 (1984)	1476893
2008	179644 (2455)	3121428
2010	264647 (2722)	4590210
2012	345380 (2969)	5804451
2014	417831 (3167)	6778083
2016	489429 (3306)	7688223
2018	559404 (3435)	8418789
2020	600817 (3498)	8823796

4.3.5.2 Frequency of Collaboration

Due to the extreme size and complexity of the collaboration network, a simpler approach will be followed to analyse the data. It is computationally not feasible to consider the detailed time structure resulting from 4000 meetings which have taken place on different days; generally, temporal network models are designed for fewer time points.

To analyse collaboration, a data frame based on collaboration activity has been created. This data frame captures the collaboration of each meetup attendee with all users they have met face-to-face. Again, the before-after collaboration pattern was collected for different time frames (one week, one month, two months, one year). This means, it was recorded to what extent user A who went to meeting Y collaborated with (meaning: edited edits by) user B whom they met at some meeting (they might have met at meeting Y, they might had met before at meeting X, or they might meet in the future at meeting Z), in the week, the month, the two months and the year before meeting Y (and all other meetings A attended), and in the week, the month, the two months and the year after. This was collected for all users that user A has ever met and summed up across all users user A has never met and will never meet, but has collaborated with. This means, the number of times users collaborated with others they have not met was added up. The information with how many others they collaborated was retained.

Collaboration behaviour between users and *the users they have met at the meeting* are given in table 4.5 for when the other user has been met for the very first time, and in table 4.6 for all meetings[140]. Comparing the figures

[140] The table can be read as follows: on average, users have collaborated 0.0014 times with other users in the week before meeting them for the first time, 0.0059 times in the

of the attendees with those of the matched non-attendees, I find that the numbers of the attendees are generally higher: even before meeting the other users, attendees collaborate with the people they meet more often.

month before meeting them for the first time, 0.012 times in the two months before, and 0.059 times in the year before (first row in table 4.5). After the meetups, these numbers did not change notably. Attendees collaborated on average 0.0022 times in the first week after taking part in a meetup with users they just met, 0.0074 times in the month after, 0.013 times in the two months after, and 0.049 times in the year after.

Table 4.5: Collaboration behaviour around meeting users for the first time.

	7 days		**1 month**		**2 months**		**1 year**	
Group	**Before**	**After**	**Before**	**After**	**Before**	**After**	**Before**	**After**
	0.0014 (0.088)	0.0022 (0.094)	0.0059 (0.26)	0.0074 (0.26)	0.012 (0.45)	0.013 (0.44)	0.059 (1.70)	0.049 (1.59)
Treatment	0	0	0	0	0	0	0	0
	0 / 19	0 / 18	0 / 72	0 / 54	0 / 94	0 / 99	0 / 250	0 / 304
	0.00034 (0.030)	0.00025 (0.020)	0.0013 (0.089)	0.0012 (0.071)	0.0025 (0.13)	0.0023 (0.13)	0.014 (0.45)	0.0097 (0.34)
Control	0	0	0	0	0	0	0	0
	0 / 8	0 / 4	0 / 24	0 / 17	0 / 30	0 / 28	0 / 61	0 / 56

Given are mean (standard deviation), median, minimum / maximum for the treatment group (n=199434) and control group (n=199433).

Table 4.6: Collaboration behaviour around all meetups.

	7 days		**1 month**		**2 months**		**1 year**	
Group	**Before**	**After**	**Before**	**After**	**Before**	**After**	**Before**	**After**
	0.0040 (0.16)	0.0051 (0.15)	0.017 (0.46)	0.020 (0.55)	0.034 (0.084)	0.035 (0.87)	0.18 (3.57)	0.16 (3.31)
Treatment	0	0	0	0	0	0	0	0
	0 / 62	0 / 45	0 / 97	0 / 132	0 / 133	0 / 167	0 / 511	0 / 500
	0.00053 (0.033)	0.00060 (0.058)	0.0023 (0.010)	0.0024 (0.12)	0.0048 (0.18)	0.0045 (0.19)	0.028 (0.83)	0.021 (0.64)
Control	0	0	0	0	0	0	0	0
	0 / 8	0 / 24	0 / 24	0 / 36	0 / 30	0 / 45	0 / 267	0 / 176

Given are mean (standard deviation), median, minimum / maximum for the treatment group (n=446574) and control group (n=446582).

In all cases, the bulk of the number of times of collaboration lies at zero as suggested by the median and very small mean values. Taken any two editors on Wikipedia, the default is not to collaborate. Given this distribution, I decided to dichotomise the values and only differentiate between *has collaborated* and *has not collaborated* for the multivariate analyses. Also, in these analyses, the focus lies on the first time users have met one another as this is the time a multiplex tie is being created. Common interests are most likely to be found at the first encounter of users.

4.3.6 Control Variables

Meetup attendees have been matched with comparable non-attendees as described; this should reconstruct an experimental setup. Further control variables are included in addition to the matching procedure as a differing treatment effect might be expected.

A differentiation will be made between the very first meetup of a user and all other meetups when assessing contribution behaviour to explore whether the first meetup has a particularly strong effect on creating an identity as a Wikipedian; this also allows for better comparison with other studies which have just assessed effects of one/the first meeting (Farzan et al. 2016; Stegbauer 2009).

Individual control variables include the previous total level of activity up to the time of the meeting as well as the recent level of activity before the meeting (previous recent activity also measures opportunity: only users who have been active before can reduce their productivity). Total activity is measured via the logged number of edits up to the meetup (see for details section 3.1), differentiating between edits across all namespaces and edits in the mainspace. In accordance with the dependent variable, the recent level of activity is measured as the cube rooted value of the number of edits in the past week, month, two months, year. When analysing collaboration behaviour, the previous level of collaboration with a user is controlled for, measured as the logged number of collaborations with a user up to the time of the meeting. Tenure is measured as years passed since a user's very first edit. As users are measured multiple times and a multilevel modelling approach is employed (see below), both within and between effects are differentiated and estimated for total activity and tenure in a mixed model (Allison 2009; Bell et al. 2018; Mundlak 1978). I also control for the year of the meetup, differentiating three equally long categories (before 2009, between 2009 and 2014, 2015 and after).

To test the hypotheses outlined, I also include an indicator of whether the meetup is of a work or social nature, and of whether a user has ever been, is, or will ever be an administrator. The career as an administrator is measured in a simple binary variable as I assume that people that have been, are, or will be administrators in the future might be inherently different to others irrespective of their current career stage.

Table 4.7 shows descriptive information on all (uncentred) independent and dependent variables included in the models on productive behaviour, while table 4.8 shows descriptive information on all (uncentred) independent and dependent variables included in the models on collaboration. The values of the meetup attendees (treatment group, T) and their matched non-attendees (control group, C) are given separately to allow for comparison. The matching procedure has worked well, but there is a notable difference in the proportion of administrators per group[141]. Values in tables 4.7 and 4.8 differ as the change in collaboration behaviour is assessed on the level of ties and only for the first meetup between two users.

4.3.7 Statistical Approach

To answer the research question on the effect of meetup participation on contributing behaviour, the treatment group of attendees was assigned a control group of non-attendees. Making use of the control group allows for a quasi-experimental design. A difference-in-differences (DiD) approach will be used to assess the effect of meetups on productive behaviour: changes in behaviour before and after the meetup will be compared across the actual attendees (= treatment group) and the matched non-attendees who have not attended the corresponding (any) meetup (= control group). With this approach, an experimental setup is replicated. A DiD estimate is the difference between the change in outcomes before (pre) and after (post) a treatment in a treatment versus a control group (Angrist and Pischke 2009; Goodman-Bacon 2021):

$$(\bar{y}_{TREAT}^{POST} - \bar{y}_{TREAT}^{PRE}) - (\bar{y}_{CONTROL}^{POST} - \bar{y}_{CONTROL}^{PRE}).$$

This measure equals the estimated coefficient on the interaction of a treatment group dummy ($treat_t$) and a post-treatment dummy ($post_t$) in a regression:

[141] Given the high number of observations, even small differences between treatment and control group in the covariates become significant according to t-test and chi-squared tests (not shown).

Table 4.7: Descriptive information on all variables included in the models on productivity.

Group	Variable	Mean (SD) or %	Min/Max
T	Change in 7 day total edits (cube root)	0.070 (2.91)	-14.62 / 15.77
C		-0.17 (2.54)	- 13.03 / 23.77
T	Change in 7 day mainspace edits (cube root)	-0.052 (2.47)	-14.29 / 15.81
C		-0.10 (2.21)	-13.03 / 23.77
T	Change in 1 month total edits (cube root)	-0.095 (4.42)	-26.32 / 21.34
C		-0.49 (3.92)	-20.14 / 35.34
T	Change in 1 month mainspace edits (cube root)	-0.077 (3.82)	-26.40 / 20.88
C		-0.34 (3.39)	-20.13 / 35.34
T	Change in 2 month total edits (cube root)	-0.27 (5.42)	-29.67 / 27.15
C		-0.69 (4.87)	-22.42 / 37.83
T	Change in 2 month mainspace edits (cube root)	-0.20 (4.70)	-29.64 / 27.11
C		-0.51 (4.20)	-22.41 / 37.83
T	Change in 1 year total year edits (cube root)	-1.75 (9.49)	-67.25 / 42.13
C		-2.71 (8.54)	-40.94 / 37.17
T	Change in 1 year mainspace edits (cube root)	-1.40 (8.14)	-67.21 / 42.02
C		-2.18 (7.31)	-40.93 / 37.49
T	Was ever admin	29.02%	
C		14.19%	
T	Total edits up to meeting (log)	8.56 (2.16)	0.69 / 14.52
C		8.45 (2.24)	0.69 / 13.16
T	Mainspace edits up to meeting (log)	7.81 (2.39)	0 / 14.50
C		7.86 (2.37)	0 / 12.91
T	Total recent 7 day edits (cube root)	3.02 (1.98)	0 / 19.97
C		2.42 (2.13)	0 / 13.44
T	Mainspace recent 7 day edits (cube root)	2.24 (1.84)	0 / 19.89
C		1.92 (1.86)	0 / 13.44
T	Total recent 1 month edits (cube root)	5.13 (3.00)	0 / 34.65
C		4.22 (3.29)	0 / 21.48
T	Mainspace recent 1 month edits (cube root)	3.96 (2.76)	0 / 34.56
C		3.42 (2.87)	0 / 21.44
T	Total recent 2 month edits (cube root)	6.53 (3.69)	0 / 42.26
C		5.39 (4.05)	0 / 25.64
T	Mainspace recent 2 month edits (cube root)	5.11 (3.37)	0 / 42.03
C		4.40 (3.54)	0 / 25.38
T	Total recent 1 year edits (cube root)	11.93 (6.44)	0 / 86.20
C		10.17 (6.96)	0 / 43.65
T	Mainspace recent 1 year edits (cube root)	9.57 (5.75)	0 / 85.89
C		8.40 (6.08)	0 / 41.92
T	Years since first edit	5.93 (3.89)	0.00024 / 18.43
C		5.23 (3.86)	0.000023 / 18.44
T	First meetup	10.22%	
T	Work meetup	23.10%	
T	Year of meetup 03-08	21.21%	
T	Year of meetup 09-14	34.17%	
T	Year of meetup 15-20	44.62%	
T	Observations	37025	
C	Observations	36364	

T = treatment group, C = control group. Variables referring to meetings (first meetup, work meetup, year of meetup) are only given for the treatment group as the values for the control group are nearly identical.

Table 4.8: Descriptive information on all variables included in the models on collaboration behaviour.

Group	**Variable**	**Mean (SD) or %**	**Min/Max**
T	Proportion collaboration 7 days before	0.069%	
C		0.021%	
T	Proportion collaboration 7 days after	0.12%	
C		0.019%	
T	Proportion collaboration 1 month before	0.22%	
C		0.072%	
T	Proportion collaboration 1 month after	0.30%	
C		0.068%	
T	Proportion collaboration 2 months before	0.34%	
C		0.13%	
T	Proportion collaboration 2 months after	0.41%	
C		0.11%	
T	Proportion collaboration 1 year before	0.90%	
C		0.42%	
T	Proportion collaboration 1 year after	0.84%	
C		0.33%	
T	Was ever admin	29.36%	
C		13.57%	
T	Total times of collaboration up to meeting (log)	0.025 (0.24)	0 / 7.43
C		0.013 (0.16)	0 / 5.80
T	Years since first edit	5.21 (3.86)	0.00024 / 18.43
C		5.18 (3.84)	0.000023 / 18.44
T	Work meetup	33.07%	
T	Year of meetup 03-08	26.24%	
T	Year of meetup 09-14	33.84%	
T	Year of meetup 15-20	39.91%	
T	Observations	204857	
C	Observations	204993	

T = treatment group, C = control group. Variables referring to meetings (first meetup, work meetup, year of meetup) are only given for the treatment group as the values for the control group are nearly identical.

$$y_it = \beta_1 + \beta_2(treat_t) + \beta_3(post_t) + \beta_4(treat_i * post_t) + \epsilon_{it}.$$

The DiD model is a special case of a two-way fixed effects (FE) model.
In addition to the DiD model, I follow the lagged dependent variable (LDV) approach to bound the causal effect (Angrist and Pischke 2009: 243–247; Ding and Li 2019; Keele et al. 2021). In these model formulations, I control for the lagged level of activity/collaboration in the period (in the week, the month, the two months, the year) before. Ding and Li (2019) show that the DiD and LDV approaches share a bracketing property and can be used to calculate bounds on the causal effect.
Both, the data on productivity and on collaboration exhibit a multilevel structure (Raudenbush and Bryk 2001). Attendance at meetups is nested in users as users can attend multiple meetups. To account for this, a mixed-effects model with a random intercept for each user is estimated and both within and between effects are differentiated and estimated for total activity and tenure (Allison 2009; Bell et al. 2018; Mundlak 1978); these models are presented in more in-depth in chapter 6 (see section 6.3.5).
For both productivity and collaboration, binary dependent variables will be used. In the case of dichotomous dependent variables, different strategies of analyses are possible, the most popular choices being the linear probability model (LPM) or logit and probit regressions. The LPM assumes that the binary outcome Y is associated with a vector of explanatory variables X in the following way:

$$E[Y|X_1, X_2, ..., X_k] = Pr(Y = 1|X_1, X_2, ..., X_k) = \beta_0 + \beta_1 * X_1 + \beta_2 * X_2 + ... + \beta_k * X_k.$$

This allows for the usage of least squares to estimate the parameters β (Cox 1970: 33-42).
The LPM is easier to compute and interpret than logit or probit models but has a number of shortcomings. The estimated probabilities may fall outside the [0,1] interval and the concept of linearity does not lend itself well to the idea of probabilities. Usage of the LPM has been discussed critically. While LPMs are not used that often in sociological research (e.g. Maddala 1983), these models have been advocated for due to their interpretability and computational speed compared to the much more complex logistic regression (Mood 2009) and they are a popular modelling choice in economics. The LPM can be employed in situations where the logit estimation fails (for

example in cases where the dependent variable is constant for one value of a categorical regressor, see Caudill 1988). Mood (2009) further argues and shows that LPM effect estimates are unbiased and consistent estimates of an independent variable's average effect (see also Wooldridge 2010: 454).

This chapter is interested in a variable's average effect on productivity and collaboration, and it deals with a very large sample size and a complex modelling strategy. Additionally, the interpretation of a DiD estimates and interactions effects are more straight-forward in linear models (Ai and Norton 2003). Non-linear DiD methods have been suggested but come with their own non-negligible complexities and challenges (Athey and Imbens 2006; Blundell and Dias 2009). Against this background, the following analyses employ LPMs. The essential issue of heteroscedasticity is addressed using robust standard errors. I employed the original form of the sandwich estimator (Liang and Zeger 1986).

Logistic regressions are included in the appendix (see sections A.1 and A.2). However, these models have in a few cases raised convergence warnings due to some large effects. Models following the LDV approach are included in sections A.1.4 (productivity) and A.2.5 (collaboration) in the appendix to bound the causal effect. For additional robustness and as Keele et al. (online appendix 2021) argue that the DiD and LDV cannot be used jointly, I further include a specification of my main DiD models in which I do not control for past activity in section A.1.5 (I generally control for centred levels of past activity). The main effect of meetups remains relatively stable across all models, except for the meeting effect on collaboration behaviour in the longest time trend which is only significant in some modelling specifications and not in the main models provided[142]. In all cases, however, the size of the effect is small. The strength and level of significance for interaction effects do vary more depending on the exact model specification. Interpretations of interaction effects in non-linear models must be done carefully and are not straight-forward (Ai and Norton 2003; Karaca-Mandic et al. 2011).

In the main text, two models per analysis will be shown: one model includes only the treatment effects, while the other model includes control variables and interactions. Models excluding the interactions are shown in the appendix (see sections A.1 and A.2).

[142]It is not significant in the main model presented in table A25, but it is significant in the GLM in table A30 and in the LDV in table A38.

Productivity Productivity is measured as number of edits in a certain time frame. Given that this is a count variable, the use of a count model regression is the obvious choice such as a Poisson or negative binomial model (see e.g. Hilbe 2017; Winkelmann 2008). Ord plots which plot the number of occurrences of a specified variable against a certain frequency ratio can be used to distinguish whether the data follows a Poisson, binomial, negative binomial, or logarithmic series distribution (Friendly 2005). In the case of edits per time frame, the Ord plot (not shown) was not able to estimate any parameters, suggesting that none of the distributions fit well. Also, given the highly skewed nature of the editing data, I decided to take the cube root of the number of edits. Looking at the Ord plot (not shown) of the transformed variable after rounding suggested the use of a negative binomial model. However, such models led to convergence problems, producing non-positive-definite Hessian matrices and false convergences using *glmmTMB* (Magnusson et al. 2017).
Instead of using a count model, I decided to break the process into two separate parts, similarly to the approach followed in hurdle models (Cragg 1971). First, I focus on all those users that have not made an edit in the week, the month, the two months, the year before the meetup and dichotomously model the decision on whether they make any edits after the meetup. A multilevel LPM is used to model this decision. In the second step, only users who have made an edit in the specified time frame before the meetup are included and the change in editing is analysed using a multilevel linear model.

Collaboration The collaboration pattern between Wikipedians can be described as a network from one user to another who has edited an article before them. The network of collaboration on Wikipedia is constantly evolving. Every new edit can create a new tie between users. Each person that made an edit is tied to at least one other person, as long as this other person is also a registered user on Wikipedia. However, due to the extreme size and complexity of the collaboration network, following a network-oriented approach does not seem fruitful. Given the circumstances, it is computationally not feasible to take into account the detailed time structure. Instead, similar to the analysis on productivity, before-levels of collaboration will be compared with the levels after a meetup. Given the rarity of events—taking any two users on Wikipedia, they are most likely *not* to collaborate—collaboration is dichotomised and LPMs are estimated. The focus lies on the first time two

users have met each other in this analysis (models referring to all meetups are in the appendix, see section A.2.4).
To test the hypothesis regarding whether users shift collaboration towards those they have met, (the rates of) collaboration with those they have met and with those they have not met will be compared. This is based on the number of edits and refers to all meetings, as it asks whether ties with those that have never been and never will be met are reduced in favour of those that have been met. The comparisons are made with those which have been met at a specific meeting.

4.4 Results on Productive Behaviour: Treatment Effect of Meetups

This section will discuss results on the influence of meetups on users' editing behaviour. First, I will discuss how the number of edits changes after users take part in meetups. In section 4.4.2, I will then discuss changes in collaborations following meetups.

4.4.1 Changing Levels of Activity

Most users of Wikipedia have been active on the platform both before and after taking part in a meetup. However, to what extent has the level of activity changed after taking part in a meetup? This will be explored in the following: first, I will compare the before and after levels of productivity around a user's first meetup, and then discuss changes in activity across all meetups. After showing bivariate relationships, I will present multilevel models.

4.4.1.1 What Happens after the First Meetup?

Based on first-time meetup goers, attendees increase their activity after taking part in the meetup both in the article mainspace as well as across all namespaces. All changes are positive, and while not all changes are significantly different from zero (which would reflect no change compared to their activity before the meetup), all changes are significantly different from the changes observed in the control group which decreased their activity (see table 4.9).

Table 4.9: Changes in editing activity after first meetup compared to activity before.

Topic	Group	7 days	1 month	2 months	1 year
Editing behaviour after first meetup: mainspace	Treatment	0.057 (2.18) 0 -11.66 / 9.19	0.10 (3.34)+ 0 -15.12 / 16.67	0.090 (4.14) 0 -18.27 / 20.79	0.89 (7.26)*** 0 -26.35 / 38.74
	Control	-0.22 (1.91)*** 0 -9.09 / 9.04	-0.56 (2.96)*** 0 -12.50 / 12.32	-0.70 (3.67)*** 0 -14.40 / 16.10	-0.99 (6.34)*** -1.26 -25.01 / 28.51
	Difference Treatment - Control	0.28***	0.66***	0.78***	1.88***
Editing behaviour after first meetup: total	Treatment	0.23 (2.58)*** 0 -11.70 / 11.57	0.10 (3.88) 0 -15.32 / 16.60	0.14 (4.76)+ 0 -18.57 / 20.65	1.43 (8.44)*** 1.44 -26.84 / 38.66
	Control	-0.40 (2.18)*** 0 -9.17 / 9.73	-0.86 (3.38)*** -1 -14.62 / 12.89	-1.03 (4.22)*** -1.26 -16.83 / 15.70	-1.22 (7.40)*** -1.82 -32.82 / 31.47
	Difference Treatment - Control	0.63***	0.96***	1.17***	2.65***

Given are mean (standard deviation), median, minimum / maximum for treatment group (n=3724) and control group (n=3724). * denotes significance on the 5 per cent level, + on 10 per cent level, ** on 1 per cent level, *** on 0.1 per cent level. Values have been cube rooted.

The Role of Adminship Stegbauer (2009) found differing effects of meetups depending on whether users have been/later became administrators. I also find some evidence supporting this when focusing on the long time frame (see table 4.10). Generally, I again see that both administrators and non-administrators increase their activity after taking part in their first meetup (this pattern is not observable in the shortest time frame for administrators). In comparison to the control group, the non-administrators tend to edit significantly more after the meeting. Administrators also increase their editing behaviour, however, due to the smaller sample size, the differences generally do not reach significance. Only in the case of the yearly change in activity, there is a strong and significant increase for administrators. The extent of change is also much larger for administrators in the yearly time frame than for non-administrators.

4.4.1.2 What Happens after Meetups?

While the previous subsection focused on users and their activity before and after joining their very first meetup, this subsection focuses on the general effect of meetups. Looking at all meetups, meetup attendees make fewer edits in the article mainspace after the meetup than before; this negative trend remains stable in any of the observed time frames. When looking across all Wikipedia namespaces, attendees make slightly more edits in the week after the meetup, but again reduce their activity in the longer time frame. However, it is important to compare these negative numbers to those

Table 4.10: Changes in editing activity after first meetup compared to activity before of administrators and non-administrators.

Topic		**Group**	**7 days**	**1 month**	**2 months**	**1 year**
Editing behaviour after first meetup: mainspace	Admin	Treatment (n = 370)	-0.37 (3.41)* -1.13 -8.98 / 9.19	0.14 (5.28) 1.13 -13.44 / 16.67	0.40 (6.58) 1.96 -18.27 / 20.79	4.56 (11.74)*** 8.31 -23.46 / 38.75
		Control (n = 154)	-0.18 (3.41) 0 -8.33 / 9.04	-0.25 (4.93) -1.26 -12.50 / 12.13	-0.030 (6.14) -0.50 -14.40 / 13.04	-0.53 (11.87) -5.92 -23.75 / 22.84
		Difference Treatment - Control	-0.19	0.38	0.43	5.11***
	¬Admin	Treatment (n = 3354)	0.10 (1.99)** 0 -11.66 / 8.89	0.097 (3.06)+ 0 -15.12 / 12.02	0.056 (3.78) 0 -17.64 / 15.29	0.48 (6.45)*** 0 -26.35 / 28.01
		Control (n = 3570)	-0.22 (1.82)*** 0 -9.09 / 7.99	-0.57 (2.84)*** 0 -12.04 / 12.32	-0.73 (3.52)*** 0 -14.40 / 16.10	-1.01 (5.99)*** -1.26 -25.01 / 28.51
		Difference Treatment - Control	0.33***	0.67***	0.79***	1.49***
Editing behaviour after first meetup: total	Admin	Treatment (n = 370)	-0.16 (3.93) -1.44 -9.33 / 11.57	0.34 (5.98) 1.90 -13.67 / 16.60	0.90 (7.41)* 3.42 -18.57 / 20.65	6.61 (13.49)*** 11.43 -24.95 / 38.66
		Control (n = 154)	-0.489 (3.85) -1.52 - 9.12 / 9.73	-0.42 (5.72) -1.70 -13.59 / 12.89	-0.18 (7.12) -1.13 -15.67 / 14.50	-0.32 (14.09) -4.95 -32.82 / 31.47
		Difference Treatment - Control	0.34	0.76	1.08	6.30***
	¬Admin	Treatment (n = 3354)	0.28 (2.38)*** 0 -11.70 / 8.95	0.077 (3.57) 0 -15.32 / 12.48	0.051 (4.37) 0 -17.70 / 16.46	0.86 (7.47)*** 1 -26.84 / 28.31
		Control (n = 3570)	-0.40 (2.08)*** 0 -9.09 / 8.45	-0.88 (3.24)*** -1 -14.62 / 12.41	-1.07 (4.04)*** -1.26 -16.83 / 15.70	-1.28 (6.96)*** -1.82 -25.23 / 28.91
		Difference Treatment - Control	0.67***	0.96***	1.12***	2.14****

Given are mean (standard deviation), median, minimum / maximum for treatment group and control group (n given in cells). * denotes significance on the 5 per cent level, + on 10 per cent level, ** on 1 per cent level, *** on 0.1 per cent level. Values have been cube rooted.

Table 4.11: Changes in editing activity after meetups compared to activity before.

Topic	Group	7 days	1 month	2 months	1 year
Editing behaviour after any meetup: mainspace	Treatment (n = 37025)	-0.052 (2.47)*** 0 -14.29 / 15.81	-0.077 (3.82)*** 0 -26.40 / 20.88	-0.20 (4.70)*** 0 -29.64 / 27.11	-1.40 (8.14)*** -2.84 -67.21 / 42.02
	Control (n = 36364)	-0.10 (2.21)*** 0 -13.03 / 23.77	-0.34 (3.39)*** 0 -20.13 / 35.34	-0.51 (4.20)*** 0 -22.41 / 37.83	-2.18 (7.31)*** -2.80 -40.93 / 37.49
	Difference Treatment - Control	0.052**	0.27***	0.30***	0.78***
Editing behaviour after any meetup: total	Treatment (n = 37025)	0.070 (2.91)*** 0 -14.62 / 15.77	-0.095 (4.42)*** 0 -26.32 / 21.34	-0.27 (5.42)*** -1 -29.67 / 27.15	-1.75 (9.49)*** -3.68 -67.25 / 42.13
	Control (n = 36364)	-0.17 (2.54)*** 0 -13.03 / 23.77	-0.49 (3.92)*** 0 -20.14 / 35.34	-0.69 (4.87)*** 0 -22.42 / 37.83	-2.71 (8.54)*** -3.53 -40.94 / 37.17
	Difference Treatment - Control	0.24***	0.40***	0.42***	0.95***

Given are mean (standard deviation), median, minimum / maximum. * denotes significance on the 5 per cent level, + on 10 per cent level, ** on 1 per cent level, *** on 0.1 per cent level. Values have been cube rooted.

of the matched non-attendees: the control group also significantly reduces their activity in the time after the meetup. Compared to the control group, the reduction in the treatment group is significantly smaller (see table 4.11).

The Role of Adminship The negative effect of attending meetups on activity also holds when distinguishing users who were past, are current, or will become administrators and those who have no past or future as administrators (see table 4.12). Both administrators and non-administrators tend to edit less after partaking in a meetup. In the short time frame, this trend is more pronounced for non-administrators; in the longer time frame, the trend is more pronounced for administrators. Comparing the effects to the matched non-attendees, it is again clear that the decrease in the control group is larger, particularly in the case of non-administrators. This highlights that decreases are not due to meetup attendance but rather developments over time.

4.4.1.3 Explaining Contribution Behaviour: Multivariate Approach

The previous subsections have explored the changing activity levels around the first and general meetups of the contribution behaviour of Wikipedians, differentiating between users that have been administrators at some point in their Wikipedia career and those who have not. This subsection will follow a multivariate multilevel modelling approach to control for relevant factors simultaneously and to consider the fact that users were observed at multiple points in time.

Table 4.12: Changes in editing activity after meetups compared to activity before administrators and non-administrators.

Topic		Group	7 days	1 month	2 months	1 year
Editing behaviour after any meetup: mainspace	Admin	Treatment (n = 10743)	-0.22 (3.06)*** 0 -12.69 / 15.81	-0.21 (4.75)*** -1.26 -26.40 / 20.88	-0.43 (5.79)*** -1.91 -29.64 / 27.11	-2.53 (10.11)*** -5.77 -67.21 / 42.02
		Control (n = 5161)	-0.065 (2.64)+ 0 -9.33 / 11.53	-0.31 (4.08)*** 0 -19.87 / 21.58	-0.51 (5.02)*** 0 -22.20 / 23.89	-3.54 (8.70)*** -5.46 -30.40 / 29.17
		Difference Treatment - Control	-0.16**	0.093	0.079	1.01***
	¬Admin	Treatment (n = 26282)	0.017 (2.19) 0 -14.29 / 14.13	-0.021 (3.36) 0 -17.74 / 19.22	-0.11 (4.16)*** 0 -20.52 / 25.40	-0.94 (7.12)*** -2.08 -37.92 / 31.82
		Control (n = 31203)	-0.11 (2.13)*** 0 -13.03 / 23.77	-0.35 (3.26)*** 0 -20.13 / 35.43	-0.51 (4.05)*** 0 -22.41 / 37.83	-1.96 (7.03)*** -2.52 -40.93 / 37.49
		Difference Treatment - Control	0.13***	0.33***	0.40***	1.02***
Editing behaviour after any meetup: total	Admin	Treatment (n = 10743)	-0.14 (3.58)*** -1 -13.13 / 15.77	-0.24 (5.50)*** -1.59 -26.32 / 21.34	-0.52 (6.69)*** -2.52 -29.67 / 27.15	-3.23 (11.87)*** -7.40 -67.25 / 42.13
		Control (n = 5161)	-0.12 (3.08)** 0 -9.64 / 12.35	-0.36 (4.77)*** 0 -19.89 / 21.70	-0.66 (5.90)*** 0 -22.20 / 24.10	-4.28 (10.32)*** -6.90 -33.36 / 32.19
		Difference Treatment - Control	-0.024	0.13	0.15	1.04***
	¬Admin	Treatment (n = 26282)	0.16 (2.58)*** 0 -14.62 / 14.21	-0.036 (3.90) 0 -17.60 / 19.38	-0.17 (4.80)*** -1 -20.95 / 25.54	-1.15 (8.26)*** -2.76 -39.03 / 32.19
		Control (n = 31203)	-0.18 (2.44) *** 0 -13.03 / 23.77	-0.51 (3.76)*** 0 -20.13 / 35.34	-0.69 (4.68)*** -1 -22.42 / 37.83	-2.45 (8.18)*** -3.21 -40.94 / 37.17
		Difference Treatment - Control	0.34***	0.48***	0.52***	1.30***

Given are mean (standard deviation), median, minimum / maximum. * denotes significance on the 5 per cent level, + on 10 per cent level, ** on 1 per cent level, *** on 0.1 per cent level. Values have been cube rooted.

For each time frame, a multilevel LPM is estimated on those users that have not made an edit in the corresponding time frame before. This means, the probability is estimated that someone who has not edited in the week (the month, the two months, the year) before the meetup makes an edit in the week (the month, the two months, the year) after the meetup. In a second step, only users who have made an edit before will be analysed. It will be checked to what extent users who have shown some activity before the meetup changed the extent of their editing behaviour.
Two models are presented in the form of coefficient plots (tables can be found in section A.1.1 in the appendix). In the first one, only a single treatment effect is estimated (statistical effect). The second model includes additional control variables and assesses whether the treatment effect depends on the type of meeting attended and whether the user is an administrator. Models excluding interaction effects are shown in the appendix in section A.1.2. Estimation results are shown in coefficient plots, differentiating binary (top) and continuous (bottom) models, as well as models concerning only the article namespace (left) or looking at activity across all namespaces (right). The effect of control variables is not depicted but can be found in the tables in the appendix (see section A.1.1).

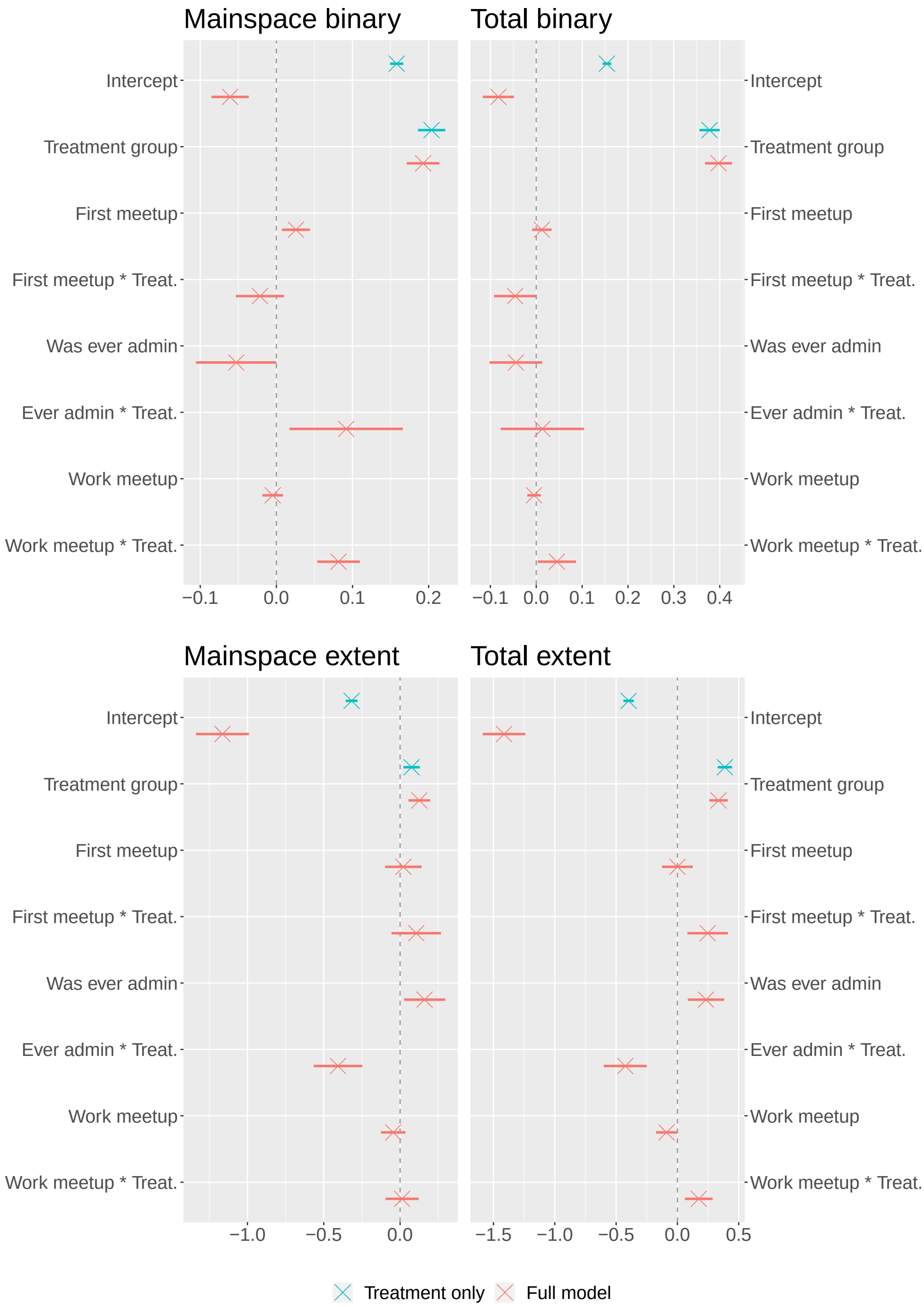
Short Term Effect: One Week Figure 4.2 shows the short term effect of meetups on editing behaviour of Wikipedians. The binary models show the estimated effects for a user who has not edited in the seven days before the meetup. The results suggest that a user is significantly more likely to contribute towards Wikipedia in the seven days after a meetup if they went to the meetup, i.e. they are in the treatment group instead of the control group. The probability for a user to make an edit in the article namespace in the week after the meetup, if they have not edited in the week before, lies at 15.8 per cent if they are in the control group and rises to 36.2 per cent if they actually took part in the meetup. Across all namespaces, the probability to edit increases from 15.4 per cent to 53.2 per cent (based on models 1 and 5 in table A1 in section A.1). These differences of 20.4 and 37.8 per cent, respectively, reflect the average treatment effect on the treated (ATT). The number of edits of users who have posted before decreases slightly for both the control group and meetup attendees, but less so for attendees. Users in the control group make on average -0.032 edits less after the meetup in the mainspace, while attendees make -0.014 edits less; across all namespaces, users in the control group make on average -0.063 edits less, while the number of contributions of attendees stays almost unchanged (-0.0000012) (based on models 3 and 7 in table A1 in section A.1). These effects represent averages across all observations.

The model results further show that users taking part in a work-related meeting become more likely to start editing in the article namespace, and that these work meetup attendees increase the extent of their editing behaviour both in the mainspace as well as across all namespaces on average more than those attending a meetup of a more social nature.

While users attending their first meetup are less likely to start editing somewhere across all namespaces, they do on average increase their editing behaviour more after their first meetup than after any other meetup. This effect cannot be found in the article mainspace. This might suggest it is not the number of actual productive edits which increases but edits in other namespaces which potentially refer to the meeting or discussions with others (i.e. the social component of Wikipedia). While administrators tend to make more edits across all namespaces—whether they have attended a meetup or not—they tend to increase their activity less both in the mainspace and across all namespaces after a meetup in this short time frame.

Medium Term Effect: One Month Looking at a longer time frame, I again find positive effects of the treatment (see figure 4.3): a user who has not edited in the month before a meetup becomes more likely to do so after the meetup if they have taken part (i.e. are in the treatment group). The predicted probability to contribute in the month after the meetup increases from 14.3 per cent to 37.3 per cent in the mainspace if the user is in the treatment instead of the control group. The predicted probability to edit any site on Wikipedia increases from 13.9 per cent to 50.0 per cent (based on models 1 and 5 in table A2 in section A.1). Comparing the month before with the month after the meeting, users in the control group make on average -0.17 edits less in the mainspace (-0.38 across all namespaces), while meetup attendees only make -0.0048 edits less (-0.0019 across all namespaces) (based on models 3 and 7 in table A2 in section A.1). Further in line with the shorter term model, there is a positive effect of work-related meetups (positive interaction effect), and administrators tend to increase their activity less after a meetup than other users.

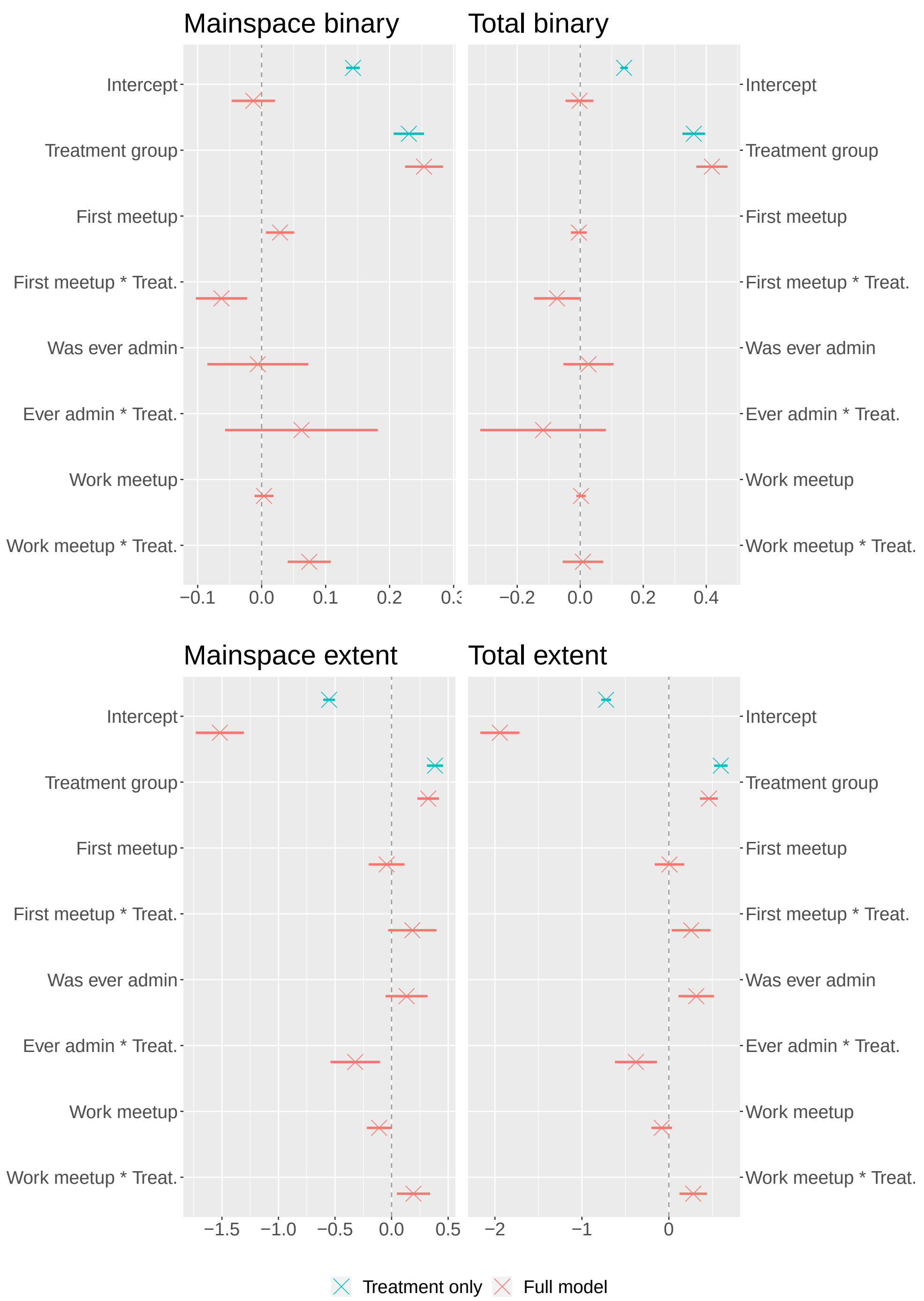
Medium Term Effect: Two Months The estimated coefficients for the change in the two-month activity is shown in figure 4.4. Again, I find a strong



Note: Horizontal line reflects 95 per cent confidence interval.

Figure 4.2: Change in editing behaviour after attending meetup (one week).

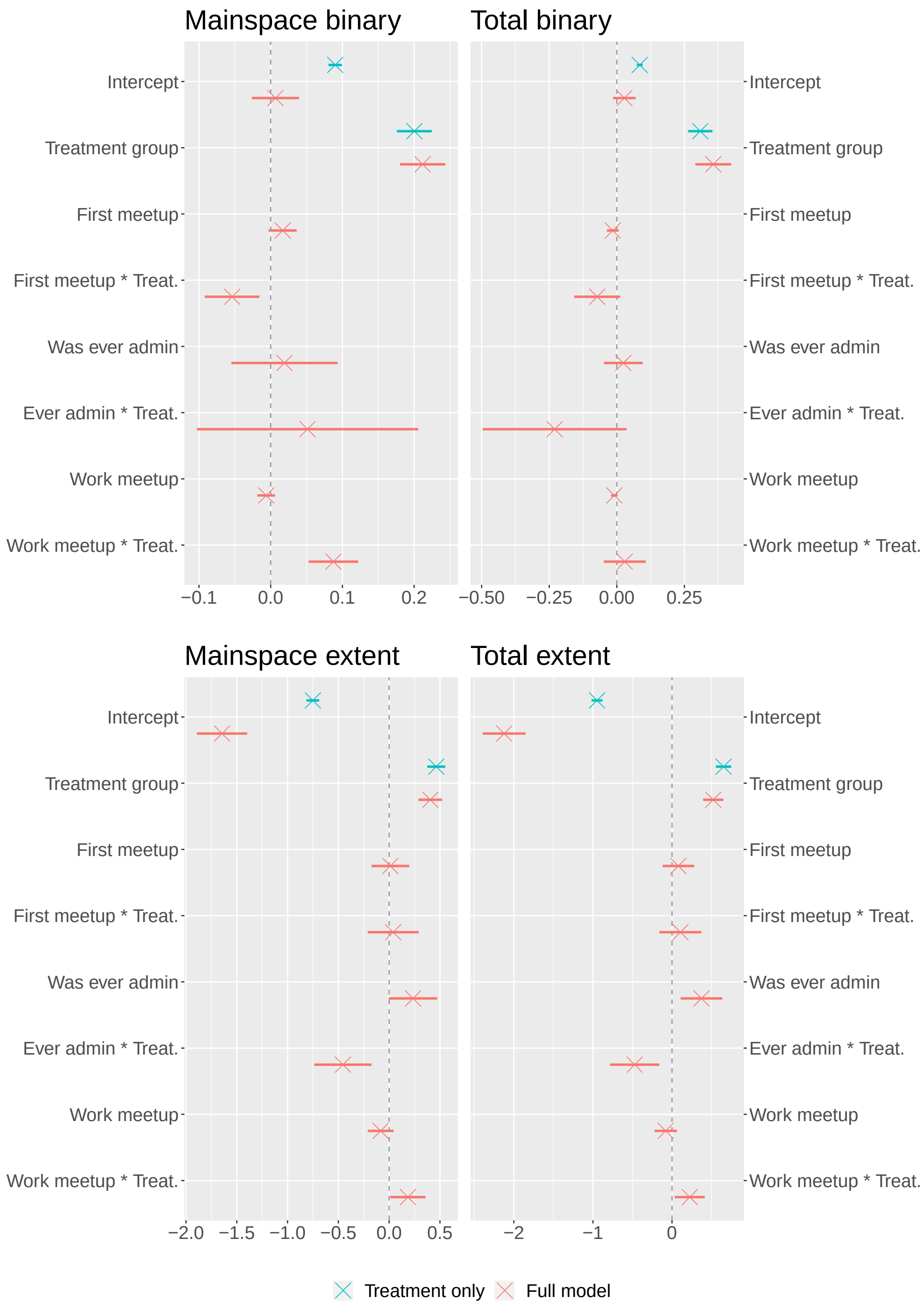
and positive effect of being in the treatment group in all models. The effect remains when including all controls. The predicted probability to contribute in the two months after the meetup increases from 9 per cent to 20 per cent in the mainspace if the user is in the treatment instead of the control group. The predicted probability to edit any site on Wikipedia increases from 8.5 per cent to 30.9 per cent (see models 1 and 5 in table A3 in section A.1).



Note: Horizontal line reflects 95 per cent confidence interval.

Figure 4.3: Change in editing behaviour after attending meetup (one month).

Users in the control group change the extent of editing by making on average -0.42 edits less in the mainspace (-0.85 across all namespaces), while editing behaviour of meetup attendees only slightly decreases over time: they make, on average -0.024 edits less in the mainspace (-0.026 across all namespaces). I find positive effects of work-related meetups (positive interaction effect) and a negative interaction effect between treatment group and administrator career. The very first meetup of users further exhibits a negative effect, meaning users are less likely to start editing in the mainspace if they have not done so in the previous two months and they are attending their first meetup (compared to any other meetup).



Note: Horizontal line reflects 95 per cent confidence interval.

Figure 4.4: Change in editing behaviour after attending meetup (two months).

Long Term Effect: One Year Lastly, how does the activity one year after a meetup compare to the activity one year before? This is the longest period that will be analysed; the estimated effects are shown in figure 4.5. In general, it is only seldom the case that users who have not made an edit in the past year will do so in the next (meaning users only rarely take such long breaks from Wikipedia). In fact, it was never the case when focusing on total edits so that no model was estimated.

Looking at the mainspace model, the predicted baseline probability to edit in the next year is 6.0 per cent if the user did not take part in a meetup and rises to 31.0 per cent if they did so. Again, there is a positive effect of taking part in a meetup, even in this very long term (see table A4 in section A.1).

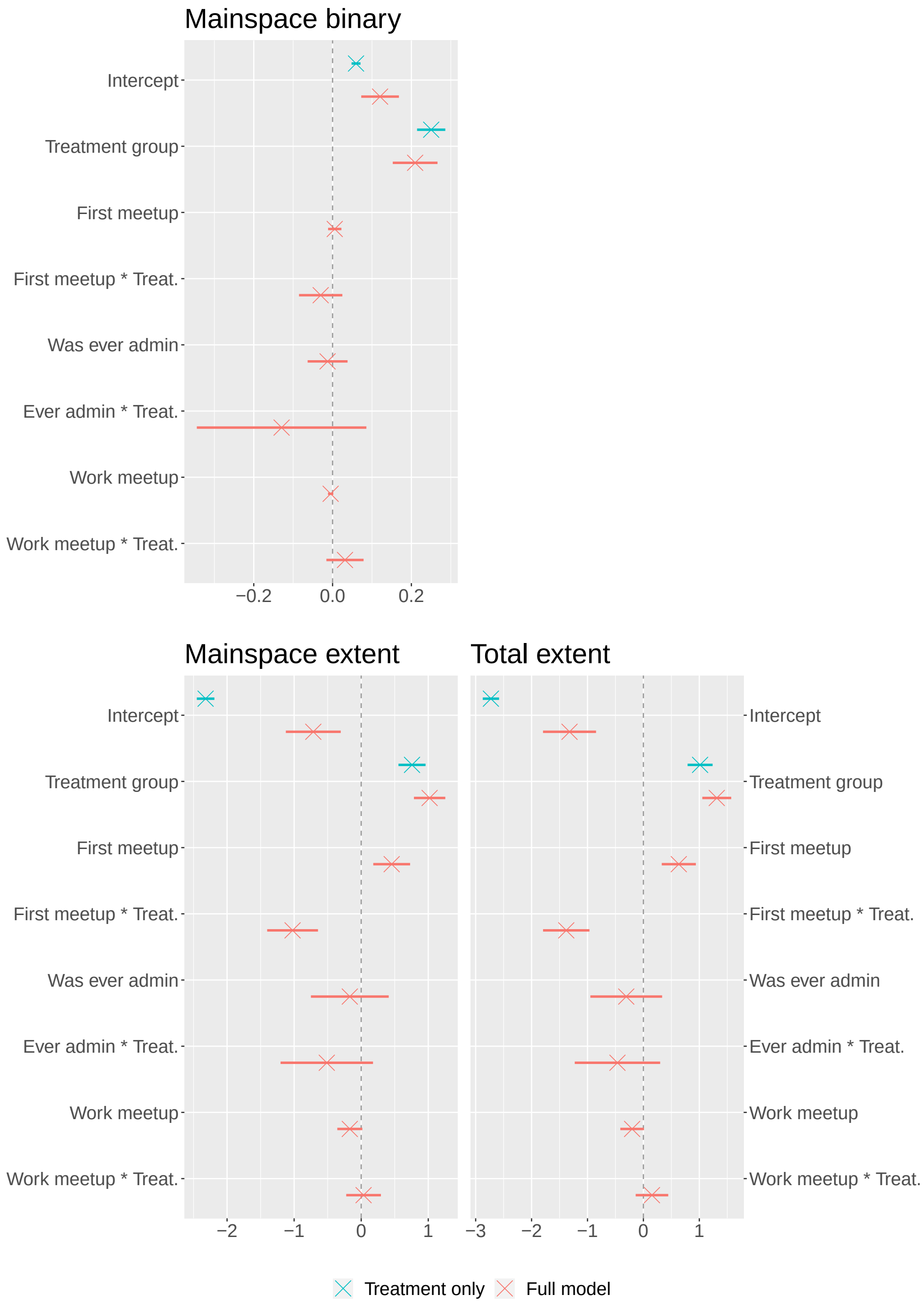
While few people start editing that have not been editing before, many more change their editing behaviour which feeds into the bottom models in figure 4.5: again, users that took part in a meetup contribute relatively more. While members of the control group make on average -12.49 edits less in the mainspace (-20.29 across all namespaces) in the year after the meetup, meetup attendees only make -3.81 edits less (-5.03 across all namespaces).

Also, there is a positive main effect of the first meetup in the models analysing the extent of changes in editing behaviour, however, it is negative for the treatment group. Users attending their first meetup have a smaller increase in activity in the long term compared to other meetups. There is no effect of adminship or the work or social nature of meetings.

In all models, the main effect of being in the treatment group is strong, positive, and highly significant. However, concerning the extent of editing behaviour, the effects are small in scope.

Model Fit To check model fit, I construct quantile-quantile (QQ) plots and conduct posterior predictive checks (Gelman et al. 2000) for the linear models on the extent of change after the meetup to assess how well they capture the distributions shown in figure 4.1. I conduct these checks on the eight models including all control variables (four time frames each with total edits and mainspace only). QQ plots are a graphical method to compare two probability distributions by plotting their quantiles against each other. Even though the data was cube rooted to account for the large range of the number of edits of some users, the QQ plots show some non-normality in the data (see plots in the appendix, subsection A.1.1.1).

To conduct posterior predictive checks, I simulate responses from my models and compare the simulated responses with the observed ones. These checks



Note: Horizontal line reflects 95 per cent confidence interval.

Figure 4.5: Change in editing behaviour after attending meetup (one year).

reveal that the models fit the mean (as expected from a linear model) and the minimum of the observed distribution well, but are unable to capture the (bimodal) distribution with its large standard deviation, as well as the high maximum values (see subsection A.1.1.2 in the appendix which demonstrates a comparison with one draw of simulated responses).

While model fit is thus not ideal, the usage of LPMs can still be justified as I am focusing on average effects in meetup attendance. Other modelling strategies should, however, be used when the goal is different. For example, when the goal is to predict changes in editing activity for specific users, other models should be used which capture the distribution of the observed data better (such as (mixed) quantile regression, see Yu et al. 2003).

4.4.2 Changes in Collaboration Behaviour

The previous section explored the (statistical) effects of meetups on the productive behaviour measured as number of edits on Wikipedia. In the following, I will focus on the collaborations that users establish through co-editing. First, the collaboration network of the attendees and of the matched non-attendees will be compared in a descriptive manner. Afterwards, the (statistical) effect of meetups will be assessed.

4.4.2.1 Comparing Collaboration Networks

Subsection 4.3.5.1 described the collaboration network of users that have taken part in meetups. How unique is it in comparison to another network in Wikipedia—the collaboration network of the meeters' matched non-attendees?

The network of meeters, up to March 2020, is a directed network of 600'817 different nodes, sharing 35'490'679 edges if multiple edges are allowed. The network of the matched non-attendees, on the other hand, is a directed network of 574'913 different nodes, sharing 37'939'074 edges. Simplifying the graph of the meeters leads to 8'823'796 edges; that of the matched non-attendees to 10'185'373. While the graph of the meetup attendees has a density of 0.000024, the graph of the matched non-attendees has a density of 0.000031. There is a significant difference (two-sided t-test, $t=15.28$, $p<0.00001$) regarding the extent of collaborations: while the mean number of times a meeter collaborated with someone else is 4.02 (median 1, standard deviation 48.04, minimum 1, maximum 51'677), the average number for a user in the control group is 3.72 (median 1, standard deviation 34.4, minimum 1, maximum 20'569). The global clustering coefficient of the meeter network lies at 0.047, the one of the control network at 0.080; 47.9 per cent of ties are reciprocated in the network of meeters and 46.6 per cent of ties are reciprocated in the network not including meetup attendees.

Table 4.13: Collaboration network of matched non-attendees (control group) over the years.

Year	# nodes (matched non-attendees)	# of edges
2001	35 (14)	38
2002	385 (113)	1947
2004	16869 (1439)	262080
2006	90613 (3706)	1640469
2008	182475 (4903)	3508262
2010	266358 (5623)	5180935
2012	342875 (6317)	6620106
2014	411475 (6909)	7799129
2016	477114 (7240)	8861489
2018	537622 (7476)	9705221
2020	574913 (7557)	10185373

Even though due to the very large sample size significant differences can be found, they are small. Overall, the global properties between control and meeter network are similar, but actors in the meeter network reciprocate slightly more and collaborate more often with the same users.

Over Time The global properties of the collaboration networks of the control and treatment group are extremely similar, but did they also evolve similarly over time? The development of the collaboration network is given in table 4.13; given are the figures by the end of the corresponding year for every other year (by March 30 in the year 2020).

Just like the collaboration network of meetup goers, the network of the control group of matched users did not split up into meaningful separate components across the years. The network started with four separate components and split into 19 sub-components in 2004, consisting of one large main component and 18 otherwise unconnected dyads. By the end of the time frame observed, the collaboration network consists of one large component, spanning all 574'913 vertices. This development resembles the development of the collaboration network of the meeters (subsection 4.3.5.1). Just like the meetup attendees did not edit articles in separated groups without overlap, neither did the users in the control group.

Overall, given these descriptive results, there are no remarkable differences between the users in the control group and meetup attendees in the overall collaboration network which has evolved.

Table 4.14: Changes in collaboration after meeting others for the first time.

Group	**Proportion collaborated**	**7 days**	**1 month**	**2 months**	**1 year**
Treatment (n=199434)	Before	0.07%	0.23%	0.35%	0.92%
	After	0.12%	0.30%	0.41%	0.86%
	Difference	0.052pp***	0.077pp***	0.062pp**	-0.059pp+
Control (n=199433)	Before	0.022%	0.073%	0.13%	0.43%
	After	0.020%	0.069%	0.11%	0.33%
	Difference	-0.0020pp	-0.0040pp	-0.016pp	-0.095pp***
Difference Treatment - Control	Difference-in-differences	0.054pp***	0.081pp***	0.078pp**	0.036pp

Given are changes in proportion collaborated. * denotes significance on the 5 per cent level, + on 10 per cent level, ** on 1 per cent level, *** on 0.1 per cent level according to two-proportions z-tests. Significance in difference-in-difference was assessed using the t value given to the interaction effect in a linear regression model.

4.4.2.2 Collaborations Between Meetup Attendees

While a network approach can be employed based on the underlying data structure, this is not feasible considering the large size of the network. In the following, I will step away from a network analytical approach and shift the analysis back to the individual. The question at the centre is whether the collaboration pattern of users changes after taking part in meetups. As the descriptives in subsection 3.1.2.1 showed, most users on Wikipedia do not collaborate with each other. Because of this, collaboration is analysed as a binary variable, and it is analysed whether users collaborate with each other after meeting each other for the first time.

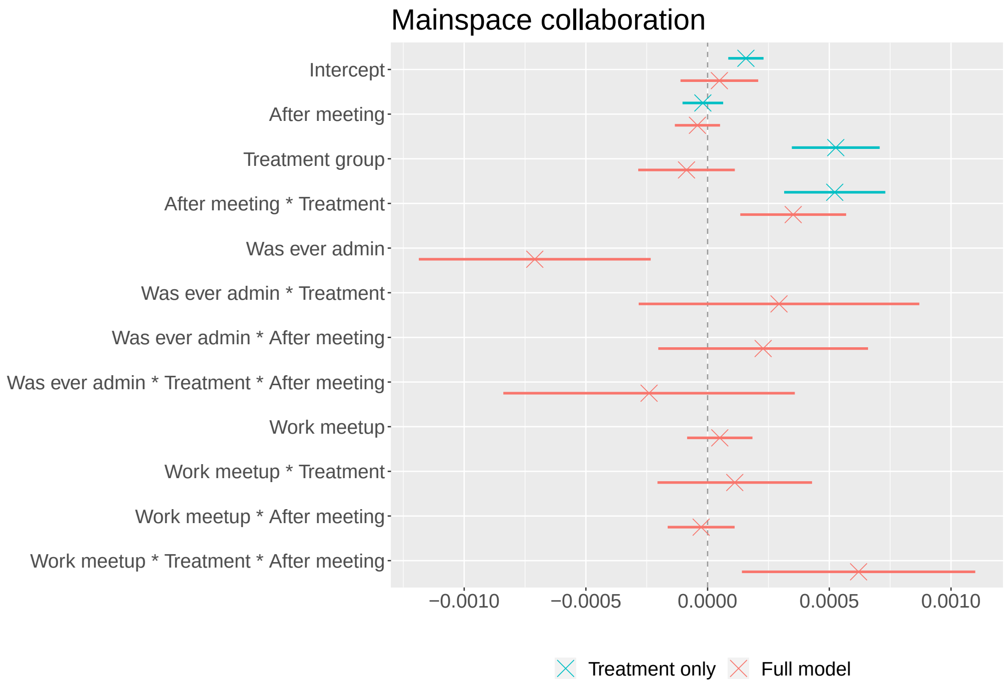
Meeting and Collaborating: Before-After Differences Table 4.14 shows how the proportion of users who collaborate with other Wikipedians changes before and after they meet them for the first time; it displays the proportion of collaborating ties existing between users and the other attendees.
After establishing a face-to-face tie, attendees tend to significantly increase collaboration across all time frames except the longest one; one year after the meeting, they are less likely to collaborate with those that they have met for the first time one year ago. However, the percentages are small in scale. Comparing their changes with the control group shows that the difference-in-differences is larger and always positive as the matched non-attendees tend to decrease collaboration behaviour (yearly difference is not significant). However, it might well be that users decrease collaborations with those they have not met in favour of collaborating with those they have met. Such dynamics will be explored in subsection 4.4.2.3.

A Multivariate Approach Next, I will present multivariate multilevel models to explore the (statistical) effect of meetups on collaboration. Do users start to collaborate more with people after having met them, and does this depend on other characteristics? The occurrence of events is rare: in the case of the one-week collaboration activity, the goal of the model is to explain the occurrence of 0.06 per cent of cases, i.e. 469 events vs. 819'231 non-events. The focus lies on the users that have been met at a specific meeting. Again, four different models are estimated to capture collaboration activity in four different time frames. The estimated coefficients are plotted in figures 4.6, 4.7, 4.8 and 4.9 (the corresponding table is shown in the appendix, see A.2.1). For all time frames except the yearly one, there is a significant interaction effect between being in the treatment group and the point in time being after the meeting, meaning that users who have met each other are significantly more likely to collaborate with one another. This effect is not significant in the very long term, meaning that a face-to-face meeting does not significantly influence long term collaboration behaviour. The positive main effect of the treatment group shows that users attending a meetup are generally more likely to collaborate with the respective others in the first place—this could suggest that users might be meeting other users exactly because they have been collaborating in the past. Nevertheless, the positive interaction effect in the difference-in-differences design suggests that meetup attendees further increase their collaboration. However, it is also important to note the very small effect sizes in all models.

4.4.2.3 Collaborating With New Friends vs. Old-Time Collaborators

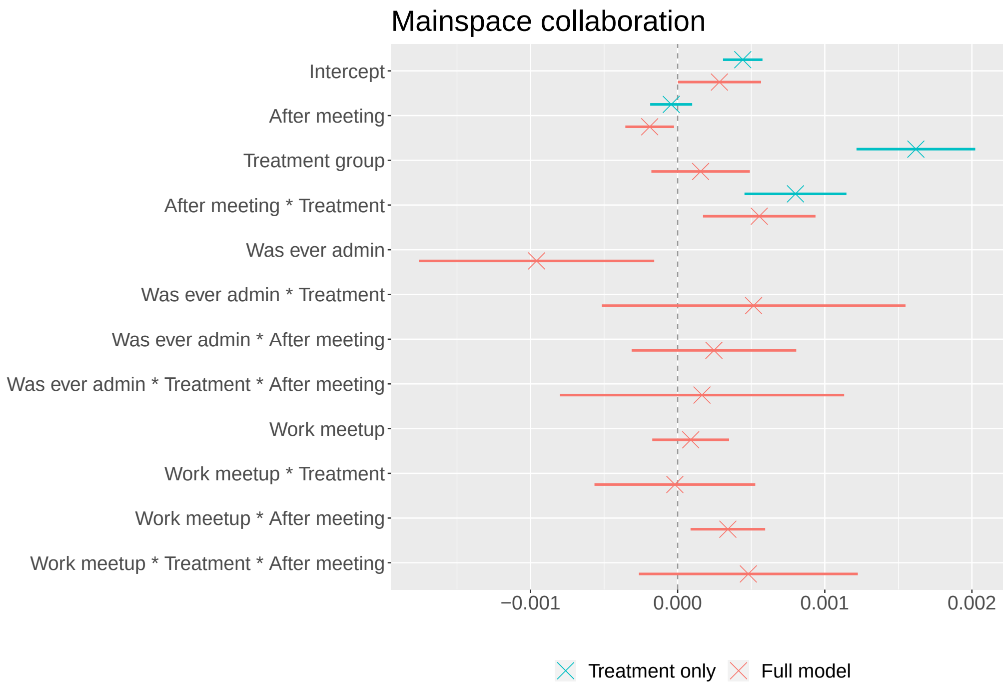
According to the previous subsection 4.4.2.2, attendees of meetups are more likely to collaborate with those they have met. Table 4.14 suggests that the users in the control group reduce collaboration with people who were met at a meetup—this might well be caused by attendees reducing their collaboration behaviour with "outsiders", the non-meetup community. Whether this is the case will be explored in the following.

Extent of Collaboration Following the hypothesis outlined in section 4.2, I expect that Wikipedians form stronger ties with the people they have met in a face-to-face setting and that they then start to collaborate more with them. Attendees might substitute some of their previous ties to online friends with those newly created stronger offline ties (increasing bonding social capital, decreasing bridging social capital). However, I find no evidence for this in



Note: Horizontal line reflects 95 per cent confidence interval.

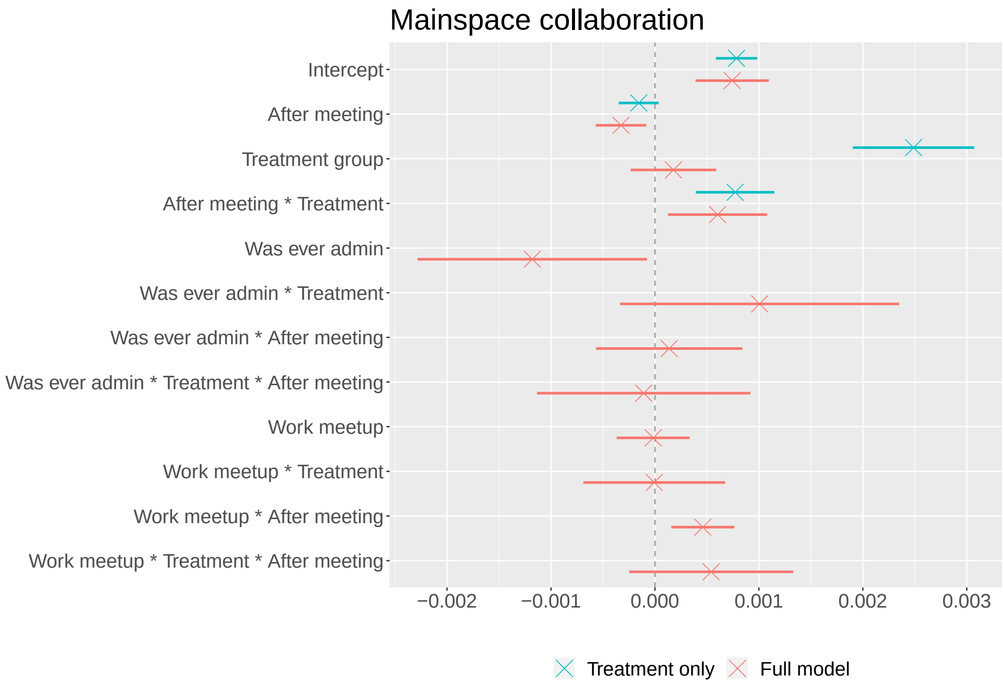
Figure 4.6: Change in collaboration behaviour after attending a meetup (7 days).



Note: Horizontal line reflects 95 per cent confidence interval.

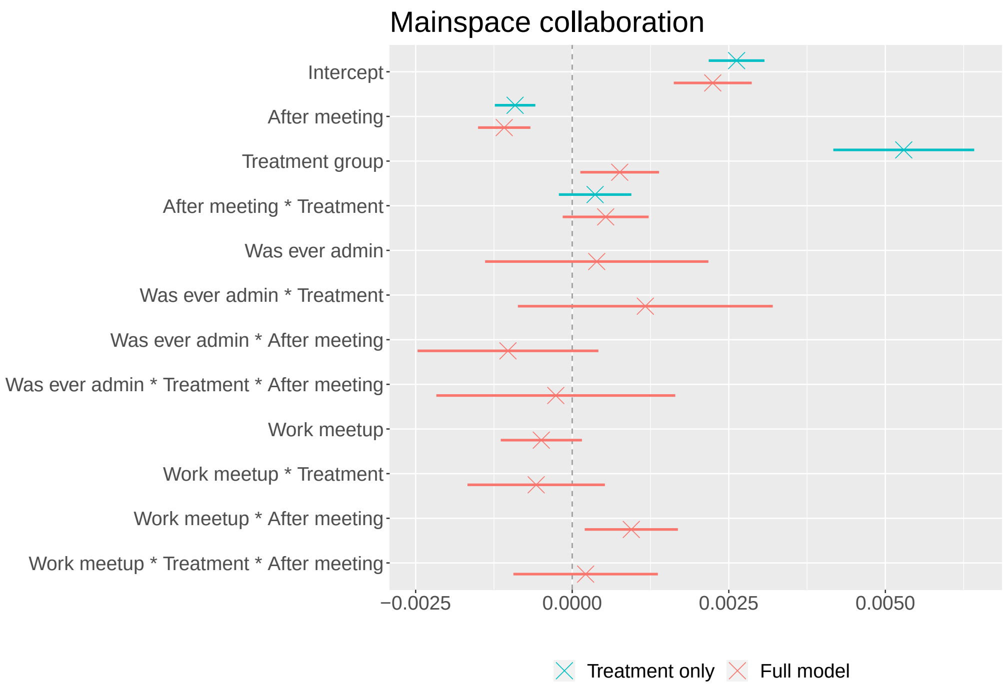
Figure 4.7: Change in collaboration behaviour after attending a meetup (1 month).

terms of collaboration, neither in the short nor in the long term. Figure 4.10 depicts the scatter plots of the before-after change of users in number of



Note: Horizontal line reflects 95 per cent confidence interval.

Figure 4.8: Change in collaboration behaviour after attending a meetup (2 months).



Note: Horizontal line reflects 95 per cent confidence interval.

Figure 4.9: Change in collaboration behaviour after attending a meetup (1 year).

collaborations with other users they have met (x-axis) or not met (y-axis). This is based on all meetings. Plots include a fitted regression line (blue).

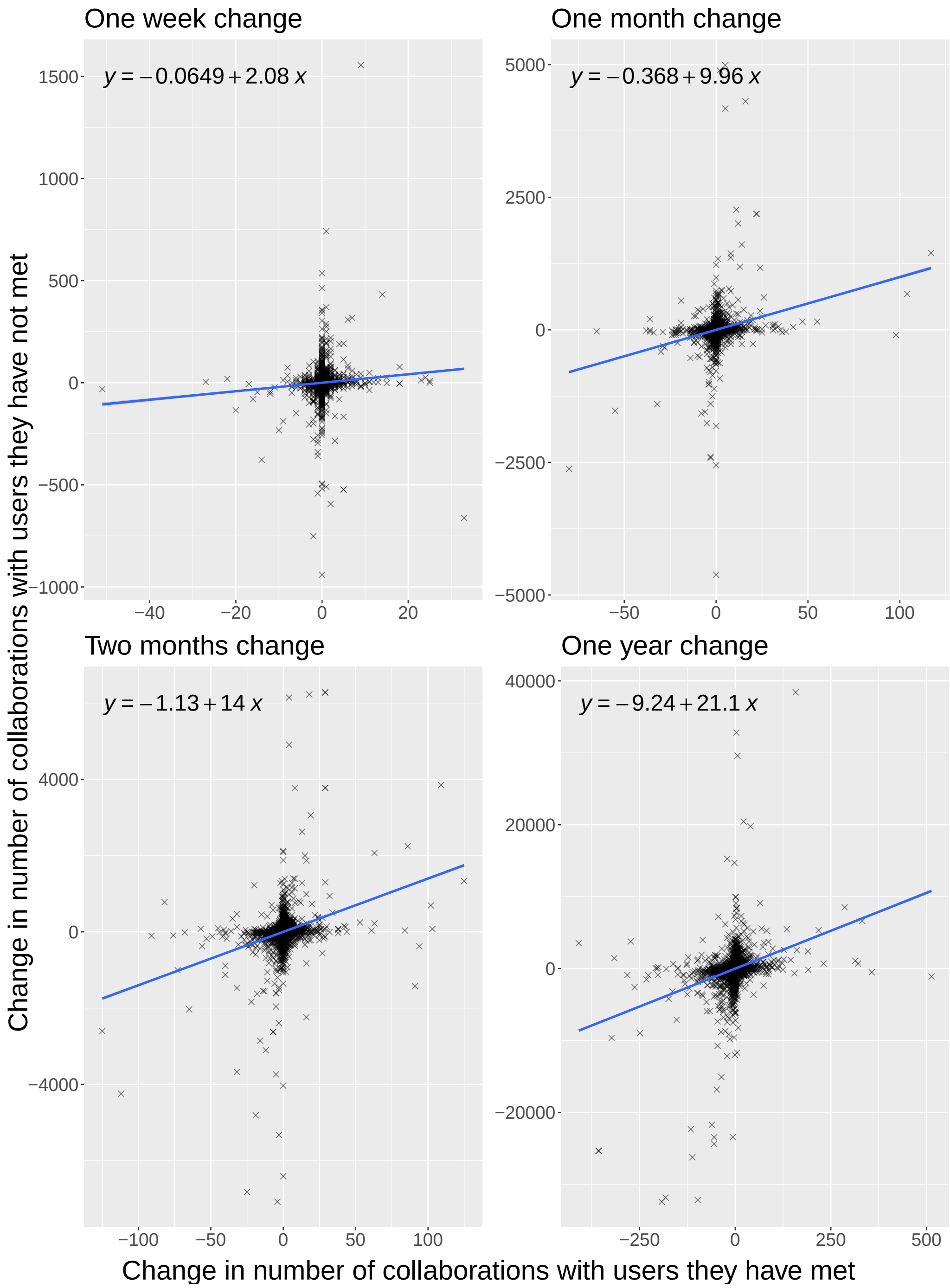


Figure 4.10: Association of change in collaboration behaviour with others a user has met and those he has not met.

According to the hypothesis, I expect that the change in number of collaborations with users a meetup goer has met is positive while the change in number of collaborations with users they have not met is negative. This would mean that most points fell into the fourth quadrant, and it would also suggest a negative association between the two variables. This is not the case: I observe a significant and positive relationship between the number of collaborations with other users a user has met and the number of collaborations with those they have not met. One additional instance of collaboration with another user that has been met leads, on average, to 2 additional collaborations with those that have not been met in the first week after the meetup, 10 in the month after, 14 in the two months after the meeting, and 21 in the year after the meeting.

Also, there is no accumulation of observations in the fourth quadrant. Looking at the short term change, 286 of 1197 observations fall into the fourth quadrant. This is not any different from chance ($\frac{1}{4}$ of observations per quadrant), where 299±29 observations were expected (with a five per cent confidence interval). In the one-month change, 498 of 2335 of observations fall into the fourth quadrant. This is even significantly less than what is expected from chance (584±40). The same holds true for the two-month change (623 of 3015; chance: 754±46) and the yearly change (820 of 4734; chance: 1184±58). There is no evidence that the extent of the collaboration shifted to the users who have been met at a meetup[143].

Relative Rate It was analysed how the absolute numbers of collaborations changed for users that have been met/that have not been met. However, if attendees changed their overall editing behaviour, these numbers might not be insightful; to account for this, a relative rate of collaboration is calculated, both for the time frame before and after the meetup: the extent of collaboration with those that have been met is divided by the total number of collaborations. For example, this means when a user has collaborated 3 times with users he[144] will meet before the meetup and 7 times with other users, his before-meetup rate of collaboration with users he will meet is 0.3. If, in the week after the meetup, he collaborated 10 times with the users he has met and 10 times with all other users, his rate of collaboration with those he has met will rise to 0.5.

To calculate the rate, values are divided by the total number of collaborations. If the total number of collaborations is zero, the rate is not defined. Thus, in the following, the one-week change is based on 5409 values only,

[143] I also checked whether there is an effect on the number of collaborators. It might be that users collaborate only with specific others and there is a concentration on these specific others. However, there was no evidence for this. Both in the short and long term, users collaborated either with the same amount of people they have just met, with one additional person or with one less. This one additional/fewer user cannot be the reason for the larger changes in collaborating with non-friends. There is too little variance to conclude an effect.

[144] As previously mentioned in section 2.4.2, I use male pronouns when a neutral wording using "they/them" is confusing as Wikipedia is heavily male-dominated.

the one-month change on 6740 values, the two-month change on 7089 values, and the one-year change on 7596 values.

In figure 4.11, the relative rates of collaborating with the users a user will meet are displayed in a scatter plot, showing the association between collaborating behaviour before and after the meeting. A linear regression is calculated and fitted to the observations (blue) and the diagonal is plotted (red) which represents the line where users remain in a stable co-editing pattern with their collaborators. Observations above the diagonal represent users who increased collaborations with other meetup attendees after meeting them; observations below the diagonal show decreasing collaboration.

Expecting an increase in collaboration behaviour after the meetup would entail seeing more observations above the diagonal, as well as a regression coefficient greater than one. I do not observe this for any of the time frames[145]. The intercept of the regression line reflects how much users, who have previously not collaborated with those that they will meet, start collaborating after the meetup. This is significantly greater than zero.

Also, there is no accumulation of observations above the diagonal. Looking at the short term change, 742 of 5409 observations fall above the diagonal. This is significantly less than expected from chance ($\frac{1}{2}$ of observations per half of quadrant), where 2705$\pm$61 observations were expected. This is due to the fact that most users have not collaborated before the meetup and will not start to do so after. If I only compare users who have collaborated with others before or after at all, I find significantly more observations above the diagonal than expected by chance, namely 742 of 1321 (chance: 661$\pm$30). The same pattern holds true for the longer term changes, except for the yearly change. In the one-month change, 1415 of 6740 of observations fall above the diagonal (chance: 3370$\pm$69); excluding those which did not change their behaviour, it is more than what is expected by chance (n reduced to 2635; chance: 1318$\pm$43). In the two-month change, 1741 of 7089 fall above the diagonal (chance: 3545$\pm$70); excluding those which did not collaborate with each other at all, it is again more than what is expected by chance (n reduced to 3341; chance: 1671$\pm$48). The pattern does not hold for the yearly change. 2322 of 7596 total observations fall above the diagonal which is less than expected by chance (3798$\pm$73). However, even when only taking those into account who have previously collaborated, there are fewer cases in the

[145] I also do not see this when restricting the intercept to 0. The regression coefficient naturally increases then but remains below 1.

upper triangle than expected by chance (2322 of 5087, where chance predicts 2544±60).
This means that overall, users tend to collaborate less with users they have met after their meeting than what would be expected when the baseline was that the likelihood to collaborate and not to collaborate was the same. However, most users on Wikipedia do not collaborate, so I observe the majority of observations on the origin (no collaboration before, no collaboration after the meetup). Looking only at cases where there was some sort of collaboration, users tend to increase it after they met (except in the longest time frame).

4.5 Conclusions

This chapter has investigated to what extent offline meetups influence the productive online behaviour of Wikipedians. It was assessed how users change their editing behaviour after a meetup in comparison to before, looking on one hand at the number of edits and on the other hand at collaborations with others. The analyses allowed to test the hypotheses derived.
In comparison to a control group, I found that across all time frames observed (one week, one month, two months, one year), attending an offline meetup exhibits a positive statistical effect on the contribution behaviour of users, partly supporting hypothesis 1a. It is not necessarily the case that users increase their contributions after a meetup in comparison to before the meetup—while, bivariately, this holds true on average for the very first meetup a user attends, it is not the case when looking at all meetups—their reduction in contributions is less than the reduction users of the control group experience. The difference-in-differences design was able to reveal that even though there is a general trend to decrease editing activity across time, this decrease is significantly smaller for the treatment group of meetup attendees. Generally, users attending a meetup are much more likely to start contributing again if they have not done so in the recent past. This finding thus provides some support for the theoretical framework presented by Crowston and Fagnot (2018): after attending an offline meetup, which reflects an increased commitment to the project and the people, users increase their contributions and effort spent. Making users identify with the community—and one of the ways for identification being offline interactions—is important for sustained contribution to the online public good (Klandermans 1997).

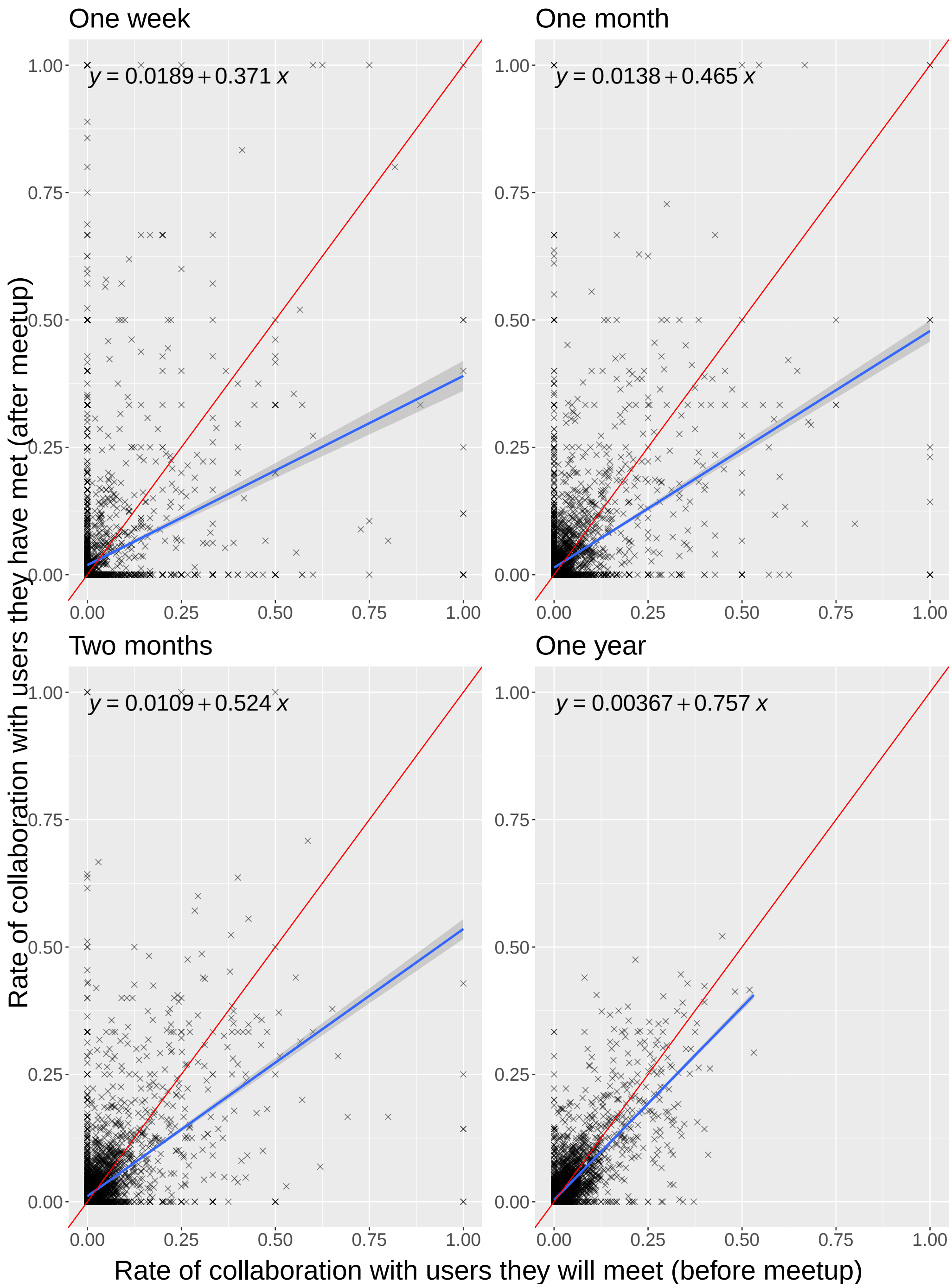


Figure 4.11: Association of change in collaboration behaviour with users a user will meet before and after meetup.

Concerning the comparison of work-related meetings with social meetings, hypothesis 1b can be supported for all except the yearly time frame: attending a work-related offline meetup has a stronger, positive effect on editing behaviour than social meetings. When looking at the long time frame of one year, it does not significantly matter whether the meetup attended was of a social or work nature. Following the framework of Crowston and Fagnot

(2018), there is thus evidence for short- and medium-term effects of improving a person's capabilities to contribute towards user-generated content.

I find only partial evidence for the finding by Stegbauer (2009) as expressed in hypothesis 1c. While his result suggests increased editing activity particularly for administrators, I find that administrators tend to make more edits—whether they have attended a meetup or not—but that they tend to increase their activity less after a meetup than other users. Only in the bivariate tables when assessing the effect of the first meetup, I found some evidence for this in the long term when administrators tend to increase their activity much more than non-administrators. Differences in the results might be caused either by the fact that Stegbauer (2009) has only taken a user's first meeting into account, by the different transformations applied to the data (he categorises to what extent activity has changed, expressed in percentages), or other reasons.

Concerning collaboration, I find that the default given any two users is to not collaborate. Still, there is support for hypothesis 2a: after a meeting, attendees become more likely to collaborate with each other (in all time frames except the longest one). This suggests that, while small, there is some impact of meeting other users face-to-face on subsequent collaboration behaviour. There is no evidence that the extent of the collaboration is shifted towards users who have co-attended a meetup to the detriment of those that have not been met (rejection of hypothesis 2b). Theoretically, these findings support the positive effects of social capital: the strengthening of bonds between meetup attendees increases their collaboration, and even though stronger ties develop, there is no observable tendency that exclusionary cliques develop as users continue to collaborate with others; in other terms, and in contrast to Shen and Cage (2013), I do not observe that bridging social capital is reduced in favour of bonding one after offline meetings in an online community.

In summary, there are positive effects for the community of Wikipedians after face-to-face meetings. In comparison to a comparable control group, those attending a meeting become or remain more active in the project. While collaboration becomes more likely with those who have been met, these new collaborative ties do not lead to other ties being dissolved. In contrast to other online communities (like those studied by McCully et al. 2011; Shen and Cage 2013), offline gatherings do seem to support the community. These results suggest that users might feel more attached to the project after taking part in meetings and that the development of offline social capital is advantageous.

Limitations and Future Research This study has several limitations which must be discussed, and which also offer future research opportunities. This passage will review limitations regarding editing and collaboration. Other aspects going beyond productive behaviour are discussed in the final chapter in section 7.3 which will cover general limitations of this thesis and Wikipedia data.

This chapter has compared before and after levels of activity in different time frames around meetups. It is important to highlight that it is not possible to draw causal claims with the observational digital trace data which is being used in this study. As users are not and cannot be randomised into attending meetings, there might be other unobserved factors which drive the relationship. Further, other approaches could be feasible and might lead to more fine-grained results concerning the short and long term effects of meetups. For example, the collection of daily activity rates could be used in an interrupted time series approach (Bernal et al. 2017). This would allow assessing whether a meetup works as a sort of shock. The timing of meetups itself could also be considered to allow for more advanced panel data analysis with the meetup as an event to assess dynamic treatment effects (see also Goodman-Bacon 2021). Also, I have only focused on the change in the number of edits—further studies could look at the quality of edits. This would allow to find out whether the quality of edits increases after a collaborative editing event such as an editathon.

Further, newcomers—defined as users not having made an edit before taking part in a meetup—have been excluded in this study. The analysis could be extended to specifically focus on newcomers (like the study of Farzan et al. 2016), comparing the Wikipedia trajectories of those starting with an offline encounter with a comparable control group of users who have registered at the same point in time but not taken part in a meetup. This is especially interesting for the Wikimedia Foundation in terms of evaluating the impact of organised editathons and other events.

In my data, I observe activity data of all users ever active on Wikipedia in its twenty years of existence. Across the years observed, user data is retained, and accounts are generally not deleted. From a technical perspective, there is thus no dropout from this longitudinal dataset. However, across time, many users stop being active: they stop contributing towards the online encyclopaedia, or they might also stop attending offline meetups. In my analyses, I have considered long-term changes in behaviour and who started to contribute after meetings, however, I have not specifically addressed a withdrawal from online and/or offline components of the project. In this regard, future research can focus on leavers of the website and contrast them with those that remain active.

Defining what counts as collaboration comes with a number of arbitrary decisions (see for a critical discussion of this also section 7.3); in an ideal case, robustness checks could be conducted comparing different operationalisations, however these come with extreme computational costs. The fact that anonymous edits were skipped when parsing the data from the XML data dump causes the level of collaboration to be overestimated: some registered users might not be editing after one another, but instead after an unregistered user. However, as this edit was not parsed, this was not captured.

The distinction between social and work meetings also carries a subjective component and is not clear-cut. Reliability could be assessed with a second coder. Also, the definition of “having been an administrator” is simple; this could have been modelled more complexly. It could have taken into account how much time passes until the person becomes an administrator. It might well be that a former administrator has a different Wikipedia activity level and outlook than users who will become administrators in the near future. These complexities have been ignored in this chapter but might help to better contextualise the findings of Stegbauer (2009).

When matching attendees to comparable non-attendees, the matched users were always users that never partook in meetings. Another approach would be to match users who have had an identical treatment history, i.e. attended the same number of previous meetings (at the same time) (see for such discussions in the recent experimental methodological literature e.g. Imai et al. 2021). However, when following this approach, the pool of potential matchable users would have shrunk enormously, as those going to more than one meetup could only be compared with the pool of other meetup goers. Such a matching procedure allows to better assess the effects of additional meetups on a user, but this is not the focus of this thesis. This could be followed up upon in future research, i.e. when asking the question of whether there is a diminishing return in meetups.

Even though the network of collaborations was framed as one, no explicit network model was employed due to constraints of computational power, time, and scope. This study aimed at analysing a long time frame (2001-2020) with a large number of events (over 4000 meetups). Understanding this from a network perspective becomes a very complex undertaking, with new nodes of users entering the meetup scene and making new ties. Taking on another perspective and focusing on specific points in time reduces the data load and might make more complex models more feasible. Making use of network models would allow the explicit modelling of tie interdependencies where the rest of the network structure and attributes of actors are taken into account (Cranmer and Desmarais 2011). Future research could, for example, make use of (temporal) exponential random graph models or stochastic actor-oriented models to uncover the generative processes of collaboration network formation as they allow simultaneously incorporating interdependence and covariate effects (Block et al. 2018, 2016; Goodreau et al. 2009; Hanneke and Xing 2006). Further, the meeting and collaboration ties between Wikipedians could be modelled as part of a multiplex network, making use of very current state-of-the-art methodological advancements (see e.g. Bródka et al. 2018; Giordano et al. 2019; Snijders et al. 2013; Solá et al. 2013; Vörös and Snijders 2017).

Notwithstanding these limitations, this study was the first large-scale analysis of the effect of informal meetups in the German Wikipedia. It has shown that meetups have on average positive effects on the individual contribution behaviour. While studies of other online communities have shown that offline gatherings between community members can have detrimental effects on the community as a whole, this does not seem to be the case for Wikipedia. Instead, the community around the most successful online public good is supported by the offline social capital which has developed through such meetings.

5 Norms and Norm Enforcement on Wikipedia: Testing Coleman's Mechanism

This chapter focuses on norms and their enforcement on Wikipedia. Wikipedia lacks strong controlling instances and authorities; instead, each and every contributor is responsible for following the norms and rules of the platform. In the following, I will outline to what extent offline network structures are relevant determinants in explaining norm-related behaviour.

5.1 Introduction: Norms on Wikipedia

Social norms are a fundamental concept in the social sciences. They are key in explaining social order and over-coming collective action problems (Olson 1974; Parsons 1937). Social norms can be understood as a group's expectations that prescribe or proscribe certain behaviours and they are supported by informal positive or negative sanctions (Hechter and Opp 2001). Some norms are enforced by those personally affected by the norm observance or violation, while other social norms call for third (unaffected) parties to act. Norm enforcement is costly. Actors are more likely to enforce norms that benefit them directly than social norms that benefit others; given these costs, it is not obvious why and under what conditions unaffected actors sanction others. The social network people are embedded in has been suggested to be key in explaining norm enforcement. Dense network structures are argued to provide an opportunity structure in which those who punish norm violators can be rewarded by third parties (Coleman 1988, 1990). This then leads to more frequent punishments and in turn fewer norm violations in such networks.

The internet as a social space is not norm-free. Studies have focused on the norms governing spaces like Reddit[146] (Chandrasekharan et al. 2018) or Facebook (McLaughlin and Vitak 2011; Vorvoreanu 2009), and others have investigated what norms govern the usage of social media platforms, i.e. by asking what is deemed an appropriate use case of these platforms (e.g. Waterloo et al. 2017). For example, a few studies have explored how journalistic norms are treated on Twitter (Bentivegna and Marchetti 2017; Lasorsa 2012; Parmelee 2013).
In the case of Wikipedia, norms are central to the functioning of the project: Wikipedia lacks supervisors and external control mechanisms; instead, every editor is expected to follow the rules of the platform. Only with working self-regulation is it possible to create and sustain the encyclopaedia. The main principles of Wikipedia are summarised in five pillars which generally apply to all language editions[147]:

1. Wikipedia is an online encyclopaedia.
2. Wikipedia is written from a neutral point of view.
3. Wikipedia offers free content that anyone can edit, use, modify, and distribute.
4. Editors on Wikipedia should interact with each other in a respectful and civil manner.
5. Wikipedia does not have firm rules[148].

These pillars express the values of neutrality, openness, sharing, trust, and dialogue (Jørgensen 2012). Building upon these pillars follows a more complex system of norms, rules, and guidelines. The creation and refinement of policies are the results of complex social negotiations (Forte and Bruckman 2008). They become explicitly written down on their own dedicated site and branch out into many detailed explanations and essays, but remain, overall, fluid[149]. Analysing the content of these norms, Reagle (2010) characterises Wikipedia as an encouraging environment aimed at problem orientation,

[146] See https://www.reddit.com.
[147] See in English https://en.wikipedia.org/wiki/Wikipedia:Five_pillars or German https://de.wikipedia.org/wiki/Wikipedia:Grundprinzipien.
[148] Notably, the German Wikipedia does not list this principle.
[149] See in the English Wikipedia for example https://en.wikipedia.org/wiki/Wikipedia:List_of_policies and https://en.wikipedia.org/wiki/Wikipedia:Expectations_and_norms_of_the_Wikipedia_community, and in the German Wikipedia for example https://de.wikipedia.org/wiki/Wikipedia:Richtlinien.

spontaneity, empathy, equality, and provisionalism. These guidelines and rules vary across language versions (see for a cross-cultural comparison of Wikipedia norms Hara et al. 2010). Also, how exactly such rules are followed and played out can vary across versions. For example, the German language Wikipedia is described as more offensive and expressing a harsh tone in discussions, as well as putting the most emphasis on article quality. It is also described as being generally more regulated than the English version (Jørgensen 2012).

Morgan and Filippova (2018: 5) describe Wikipedia as being "governed by a complex and sophisticated set of community-created policies and practices that are developed (Forte and Bruckman 2008), interpreted (Joyce et al. 2012) and enforced (Beschastnikh et al. 2021) in a highly contextual, contingent, and decentralized fashion." This set of written and unwritten rules is complex, and this creates a challenge for editors, specifically new ones.

Not all contributions adhere to the guidelines the community has defined. There is vandalism[150]—the practice of making edits deliberately intended to obstruct or defeat the project's purpose. Users make honest errors, do not know better, or work sloppily or inconsistently. To uphold the quality of the encyclopaedia, it is necessary to correct such edits. Wikipedia has mechanisms in place to undo previous changes, allowing the sanctioning of users who make unsuitable edits. Such undoings can have strong effects on Wikipedians: Halfaker et al. (2011) have shown how experiencing such reverts can be very daunting for newcomers, and Jankowski-Lorek et al. (2013) and Turek et al. (2011) have shown that a shared history of undoing one another leads to opposing votes in elections on Wikipedia. Reverts are demotivating but have a positive net influence, leading to more quality work done in Wikipedia (Halfaker et al. 2011).

This chapter will conceptually replicate and extend the study of Piskorski and Gorbatâi (2017) who tested whether embeddedness in dense online networks leads to increased norm punishments, increased rewards, and fewer norm violations: the mechanism proposed by Coleman (1988, 1990). Piskorski and Gorbatâi (2017) find support for this using monthly data from 2006 from the English Wikipedia. This chapter will replicate their analysis, but it will additionally broaden the view of the network to include the offline ties between Wikipedians. The main question this chapter aims to answer is thus to what extent embeddedness in dense offline networks influences an editor's norm-relevant behaviour on Wikipedia.

[150] See https://en.wikipedia.org/wiki/Wikipedia:Vandalism.

The rest of the chapter is structured as follows: the next section will firstly present the current state of research on norms on Wikipedia. It will then present the theoretical considerations on norms in general and introduce the mechanism proposed by Coleman (1988, 1990) as well as testable hypotheses. In section 5.3, I will describe the methods and data used and critique the approach employed by Piskorski and Gorbatâi (2017). Data on norms will be described in detail to better understand reverting behaviour on Wikipedia and to understand the typical violators and enforcers. The results of the analysis regarding the hypotheses are presented and discussed in section 5.4. Lastly, I will draw conclusions, and discuss the results of this study in the light of both the study conducted by Piskorski and Gorbatâi (2017) and the general theoretical arguments.

5.2 State of Research and Theoretical Considerations

Social norms are a fundamental concept in the social sciences. They can be understood as a group's expectations which are either prescriptive, encouraging certain actions, or proscriptive, discouraging other actions. Norms are supported by informal positive or negative sanctions (Blake and Davis 1964; Hechter and Opp 2001; Homans 1950; Popitz 1980).

Social norms are an important factor in shaping everyday life, they are key in explaining social order and over-coming collective action problems and have been studied extensively across the disciplines (Arrow 1970; Durkheim 1893; Holländer 1990; Olson 1974; Ostrom 1990, 2000; Parsons 1937, 1953; Weber 1920 [1904]): anthropologists have described how social norms differ across cultures (Geertz 2008 [1973]), economists are interested in their effect on market behaviour (Akerlof 1976), they are discussed in combination with law (Posner 2002), and from a sociological perspective, their emergence, their functions, and their enforcement are key topics of past and present research (Coleman 1990; Durkheim 1893, 2013 [1958]; Hechter and Opp 2001; Parsons 1937; Voss 2001). Norms have also been studied within the context of Wikipedia. The current state of research on norms on Wikipedia will be summarised in the next section. Section 5.2.2 will then discuss norms more theoretically and derive the hypotheses tested in this chapter.

5.2.1 State of Research

Norms play an important role on Wikipedia. Previous research has stated and described how the exact norms in place on Wikipedia are language-specific and how they are shaped by the culture they come from. Hara et al. (2010) conducted a cross-cultural comparison of Wikipedia norms, examining the Wikipedia language versions in English, Hebrew, Japanese, and Malay. Similarities and differences are found and discussed using Hofstede's dimensions of cultural diversity and against the background of the size of the respective language communities. In his study of the German Wikipedia, Jørgensen (2012) highlights it as being generally more regulated than the English version, exhibiting a rather harsh tone, and as putting article quality at the forefront.

Analysing the content of norms, Reagle (2010) characterises Wikipedia as an encouraging environment aimed at problem orientation, spontaneity, empathy, equality, and provisionalism. Bear and Collier (2016) and Menking and Rosenberg (2020) state that Wikipedia also includes competitive and aggressive behaviour and generally exhibits masculine norms, which they consider important to explain the lower female participation. Heaberlin and DeDeo (2016) study the evolution of norms on the English Wikipedia across a 15-year period. They find, for example, that the earliest norms dominate the network (defined as the interconnected Wikipedia pages on norms and rules) and also persist over time. These are the core norms covering Wikipedia's main principles of neutrality, verifiability, civility, and striving to find consensus.

Goldspink (2010) analyses discussion pages from specific articles to examine the effect of norms and rules on editor communicative behaviour; he thus focuses on conversations about editing instead of the actual editing. He finds that the detailed and specific behavioural etiquette published in Wikipedia has only little influence on the character and style of interactions on discussion pages. The rules and guidelines are also rarely invoked, and Goldspink (2010) further did not find evidence of active negotiation of expectations and standards and convergence of behaviour towards these norms.

Morgan and Filippova (2018) have studied the influence of norms on behaviour, focusing on the *Teahouse* on Wikipedia. The Teahouse is an institution in the English Wikipedia, founded in 2012, which specifically allows newcomers to ask questions and request guidance. In the Teahouse, users are expected to welcome newcomers in a friendly fashion and answer their questions without citing extensive Wikipedia policies. These expectations are explicitly shown to users signing up as "hosts" to the Teahouse; however, experienced Wikipedians can also answer questions without previous sign-up. Morgan and Filippova (2018) make use of this setup and its resulting information asymmetry to contrast the effects of descriptive—informing one about how others act in similar situations—and injunctive—prescribing the valued social behaviour—norms (see on descriptive vs. injunctive norms also Cialdini et al. 1991). They find that exposure to congruent injunctive and descriptive norms increases the probability to perform a behaviour the most while conflicting social norms can negatively impact pro-normative behaviour. Generally, injunctive norms are shown to have a stronger effect than descriptive ones.

The work of Morgan and Filippova (2018) or also Beschastnikh et al. (2021)—the latter focusing on policy citing on article discussion pages—study the enforcement of specific norms and explicit policy use. Panciera et al. (2009) adopt a broader view and consider the reverting of previous content as a way to enforce norms. Panciera et al. (2009) find that highly active Wikipedia users more often invoke norms than the rest of the userbase. Over the life span of an editor, this value also increases. Goldspink (2010) find no statistically significant difference in the probability for either registered or non-registered editors to invoke norms or rules when focusing on article discussion pages. However, it is important to note that only a few unregistered users make use of these more advanced features on Wikipedia, and they do form a special subgroup. On the aspect of governance more generally, a number of studies have focused on self-governance on Wikipedia (see e.g. Forte and Bruckman 2008; Viégas et al. 2007a) and on the bureaucratisation of Wikipedia (see e.g. Rijshouwer et al. 2021); these will not be discussed further.

The study of Piskorski and Gorbatâi (2017) used data from Wikipedia to test the mechanism regarding norm violations put forward by Coleman (1988, 1990). As their study will be replicated and extended in this chapter, their theoretical underpinning will be discussed in detail in the next section.

5.2.2 Explaining Norm Compliance and Norm Enforcement: Coleman's Mechanism

Norms encourage or discourage actions but understanding why actors comply is not always straight-forward as compliance can be costly to the individual. If an actor expects a benefit from a norm violation without fearing punishment, they are unlikely to comply. If all actors are acting in such a way and violate the norms, they will all be worse off than if everyone observed the norm. This creates the first-order free rider problem (Coleman 1990). Through rewards of norm conformity and punishments for violations, norms can be upheld (Bendor and Swistak 2001).

Some norms are enforced by those personally affected by the norm observance or violation (second party), while other social norms call for someone unaffected (third party) to act (Coleman 1990). Sanctions are used to enforce compliance with social norms (Posner and Rasmusen 1999). Negative sanctions (punishments) are used to discourage non-conformity while positive sanctions (rewards) encourage conforming behaviour. The sanctioning of those violating norms can be understood as a volunteer's dilemma: it is a situation in which each actor can either go forward with the sanctions (which come with a small cost but are beneficial to everyone as they keep up the norms) or wait for others to do so (Przepiorka and Diekmann 2013). Actors are more likely to enforce norms that benefit them directly than social norms that benefit others; given the costs of norm enforcements, it is not obvious why and under what conditions unaffected actors sanction others (this forms the second-order collective good problem, see e.g. Voss 2001). Experiments in the laboratory (Diekmann and Przepiorka 2015; Fehr and Fischbacher 2004) and in the field (Balafoutas et al. 2014; Diekmann et al. 2013; Przepiorka and Berger 2016) show that individuals expect punishment and enforce norms with costly sanctions, both as second or third parties. What conditions impact the enforcement of norms?

Norms are more likely to be enforced if those applying sanctions are compensated for their costs. Experimental evidence has shown that actors are most likely to observe norms when those who sanction norm violators are rewarded (Horne 2001). The social network an actor is embedded in and in particular its density has been stressed as an important factor for the creation and particularly the enforcement of norms (Burt 1982; Coleman 1988, 1990; Durkheim 1897; Lin 2001; Simmel 1902; Tajfel 1970, 1981). Actors can punish or reward strangers, but it can be expected that actors are more likely to sanction and reward others they know as they are more likely to observe each other's behaviour, to care about the behaviour, and to offer valuable rewards or effective punishments (Piskorski and Gorbatâi 2017).

Coleman (1988, 1990) proposed that dense networks provide an opportunity structure for rewarding those that enforce norms which leads to fewer norm violations. Social relationships facilitate punishments against norm viola-

tions as well as rewards for such punishments. For better understanding, an example of this setup has been given in Piskorski and Gorbatâi (2017: 1188-1191) and will be briefly summarised in the following. Consider a group in which actor i violates a norm which benefits themselves but negatively affects all actors in this group. When making the decision about violating the norm, i estimates the likelihood that someone in the group, e.g. actor j, will impose a costly punishment. This likelihood is higher if there is another actor k who can reward the punisher j more easily. Coleman (1990) argued that such a reward to actor j for punishing the offending i is most likely in a group with high density (where everyone is connected to everyone else).
Assuming a scenario in which j and k are connected to i but not to each other, k might not notice j's punishment; and even if k notices it, they might find it difficult to reward j. This lower probability of obtaining a reward will reduce the likelihood of punishment by actor j. This, in turn, will make it more likely that actor i will violate the norm.
In this process, there are thus three key actions:

1. Violation of norm
2. Punishment of norm violator (enforcing norm)
3. Reward of norm enforcer

At its core, it is argued that the opportunity structure in high-density networks enables the compensation of norm enforcers which in turn reduces the incidence of norm violation.
Piskorski and Gorbatâi (2017) deduce the following two sets of hypotheses from this reasoning which will also be tested in this chapter[151]. The first set of hypotheses refers to how frequently actors in dense networks experience these actions.

Hypothesis 1a: Actors embedded in dense networks experience fewer norm violations against them.

Hypothesis 2a: Actors embedded in dense networks more frequently experience that others punish norm violators on their behalf.

[151] These hypotheses are *not* taken from the study Piskorski and Gorbatâi (2017) verbatim because they set up hypotheses concerned with the likelihood of occurrence of specific behaviours. However, in the main models, both Piskorski and Gorbatâi (2017) and I focus on the extent of specific behaviours.

Hypothesis 3a: Actors embedded in dense networks more frequently experience that others reward them when they punish norm violators on behalf of others.

The second set of hypotheses is concerned with how frequently actors in dense networks engage in these actions.

Hypothesis 1b: Actors embedded in dense networks violate fewer norms against others.

Hypothesis 2b: Actors embedded in dense networks more frequently punish those who violate norms against others.

Hypothesis 3b: Actors embedded in dense networks more frequently reward those who punish those violating norms against others[152].

Piskorski and Gorbatâi (2017) extend their argument beyond the focal group of actors i, j, and k to include the structure of relationships among alters of these actors. Consider a scenario in which most alters of actors j and k, who are not connected to actor i, are connected to each other. These alters form a dense network and can provide actors j and k with additional rewards for punishing actor i when that actor violates a norm (leading, in turn, to a lower rate of norm violations). Then compare it to a scenario in which most alters of actors j and k, who are not connected to actor i, are not connected to each other. The lack of density between the alters makes it unlikely that they will provide additional rewards for punishing actor i when that actor violates a norm.
Building upon the mechanisms outlined by Coleman (1990), the effects outlined in hypotheses 1a and 1b are expected to be stronger when a contributor's alters form a dense social network outside the social milieu of the focal contributor. This leads to the following two hypotheses stated by Piskorski and Gorbatâi (2017: 1191):

[152] Originally, the hypothesis reads "Actors embedded in dense networks are more likely to reward those who violate norms against others." (Piskorski and Gorbatâi 2017: 1190) which embodies, as I assume, a further error in wording.

Hypothesis 1c: Actors embedded in dense networks experience even fewer norm violations against them when these actors' alters are also surrounded by dense networks.

Hypothesis 1d: Actors embedded in dense networks violate even fewer norms against others when these actors' alters are also surrounded by dense networks.

The next section will outline the methods and data used to test these hypotheses.

5.3 Methods and Data

The following section will describe the data, methods, and statistical approaches used to analyse norm-relevant behaviour on Wikipedia. It will discuss how norm violations, punishments, and rewards can be conceptualised and understood on Wikipedia. Continuing the remarks given in the introductory section 5.1, it will be outlined what kind of norms govern Wikipedia and what role they generally play. Following this, I will describe how I measure norms in the following analyses and I will describe the data. The approaches taken by Piskorski and Gorbatâi (2017) will be critically discussed. I will refer to chapter 3 when making use of the general data which is used in all three topical chapters.

5.3.1 Understanding Norms on Wikipedia

Norms are central to the functioning of Wikipedia and have evolved from within the community of editors. The main principles of Wikipedia are summarised in five pillars which apply to all language editions and cover the basic values and the basic goal of Wikipedia: Wikipedia is an encyclopaedia and content should be neutral, open, and shareable, and those contributing should interact with each other in a civilised manner. Building upon these basic pillars, a more complex system of norms, rules, and guidelines follows which has developed over the years. Many of the guidelines and expectations on Wikipedia are made explicit and written down[153].

[153] See in English https://en.wikipedia.org/wiki/Wikipedia:Five_pillars or German https://de.wikipedia.org/wiki/Wikipedia:Grundprinzipien and all the pages these sites link to.

In this context, there is also the often-quoted guideline on what Wikipedia is not[154]. According to it, Wikipedia is not a dictionary, not a place to invent any new theories or models, not a place for gossip or advertisements, not a place for essays or praise, not a chat, not a webspace provider for self-display, not a database for large amounts of structured data like phone books or directories of addresses or URLs, not a collection of sources, not a general directory of persons or organisations, not an agenda of events or a news ticker, and Wikipedia is also not a collection of tutorials or travel guides. Some of Wikipedia's sister projects fulfil these tasks—Wikivoyage is a place for travel recommendations, Wikibooks deals with textbooks, and Wikinews is designed to follow very recent developments and the news. Wikipedia, in contrast, is clearly defined as an encyclopaedia stating relevant knowledge. What is considered notable varies between language versions of Wikipedia[155], is open for dispute and can change over time; votes have been held for adjustments on these criteria[156].

Next to its requirement that all articles need to be suitable for an encyclopaedia which guides the scope of the project, the second of the five basic principles of Wikipedia requires one to take a neutral point of view (NPOV). It states that articles need to be free of bias and should be written from a neutral perspective[157]. All statements on Wikipedia need to be backed up by sources, different points of view need to be presented in a balanced way, and articles need to be written in a factual matter. The third basic principle of Wikipedia is that all content must be free. Fourthly, Wikipedia does not allow any personal attacks against users. The Wikiquette[158] further specifies how users should or should not behave. Lastly, the fifth pillar states that Wikipedia has no firm rules. While Wikipedia has policies, their contents and interpretations can evolve and users are encouraged to be bold without agonising over mistakes[159].

[154] See in English https://en.wikipedia.org/wiki/Wikipedia:What_Wikipedia_is_not or in German https://de.wikipedia.org/wiki/Wikipedia:Was_Wikipedia_nicht_ist.

[155] What is considered notable in the German language version is defined here https://de.wikipedia.org/wiki/Wikipedia:Relevanzkriterien.

[156] See for a vote about notability criteria for corporations for example here https://de.wikipedia.org/wiki/Wikipedia:Meinungsbilder/Relevanzkriterien_f%C3%BCr_Unternehmen_und_Marken.

[157] See https://de.wikipedia.org/wiki/Wikipedia:Neutraler_Standpunkt.

[158] See https://de.wikipedia.org/wiki/Wikipedia:Wikiquette.

[159] This fifth pillar is not listed on the German Wikipedia page containing the project's basic principles. Still, its spirit is present as the German Wikipedia also encourages its users to ignore all rules (see https://de.wikipedia.org/wiki/Wikipedia:Ignoriere_alle_Regeln) and be bold (see https://de.wikipedia.org/wiki/Wikipedia:Sei_mutig).

Edits on Wikipedia are expected to follow these principles and guidelines. Each edit that has been saved becomes published and can be reverted if it does not meet the standards set out in the policies. The article is then restored to its previous version[160]. It is down to each user to check new content and correct mischief and errors[161]. In more extreme cases, users can become blocked from Wikipedia, either temporarily or permanently[162]. Users can be blocked if they maliciously destroy Wikipedia pages, take part in edit-wars, violate the basic principles, threaten others with legal steps, or have other issues on the user-level (such as an unsuitable username, abuse multiple user accounts, or do not respect the terms of use). In cases of disputes and conflicts between users, the arbitration committee can help to solve conflicts in a more formal dispute-resolution process[163].

In the following analysis, I will concentrate on violations of norms on the level of edits which are corrected through subsequent reverts. How exactly norm violations and their enforcement can be measured will be discussed in the following.

5.3.2 Considerations on Measuring Norm Violations, Punishments and Rewards

How can norm violations on Wikipedia be measured? Piskorski and Gorbatâi (2017) have defined norm violations as follows: if user A makes an edit which is not clearly vandalism[164], and user B undoes this edit without adding an explanation, user B is violating a norm and user A is the victim. If user C steps in and undoes the previous undo of user B to restore the article version back to include the contribution made by user A (the authors call this *reverting*), user C is punishing user B. They consider it a reward for user C when they become a victim and another user steps in (i.e. in this case, A is being rewarded).

Piskorski and Gorbatâi (2017) back up and justify their setup after having conducted interviews with a random sample of Wikipedians to elicit their

[160] In exceptional cases, edits can also be deleted making them irretrievable to the general public. This is, however, a rare exception. It can, for example, occur when private information is shared.

[161] See https://de.wikipedia.org/wiki/Wikipedia:Grundprinzipien#Wer_sorgt_f%C3%BCr_die_Einhaltung_dieser_Richtlinien?.

[162] See https://de.wikipedia.org/wiki/Wikipedia:Benutzersperrung.

[163] See https://de.wikipedia.org/wiki/Wikipedia:Schiedsgericht.

[164] They identify edits which are vandalism based on article length. Simply put, a large difference in article length is seen as an act of vandalism.

experience of undoings[165]. Piskorski and Gorbatâi (2017: 1192–1197) argue that many interviewees considered the usage of the undo link a serious norm violation, and when asking users who have left Wikipedia, having their edits undone was mentioned as a key reason for leaving. The statements provided in these interviews are in line with previous research; Halfaker et al. (2011) have also found that the undoing of edits is demotivating and encourages the withdrawal from Wikipedia. Still, I argue that it does not imply that the undoing itself was unjustified. This is also highlighted in some of the interview material Piskorski and Gorbatâi (2017) present: many users think that the use of the undo button can be legitimate. However, the interviewees mention that appropriate undos should include an edit summary. They argue that failure to explain an undo constitutes a normative violation on Wikipedia. This is then, essentially, the norm Piskorski and Gorbatâi (2017) focus on: the norm not to undo other contributors' work without a proper explanation (Piskorski and Gorbatâi 2017: 1186). They exclude the undo of vandalism from this as, as they argue, the uncommented undo of clear vandalism is justified.

The norm violation of the uncommented undo can either be ignored or not; not ignoring meant to punish the violator by undoing the undo and thus restoring the previous version. This sends a clear message to the norm violator, making it very public that a norm was violated. Piskorski and Gorbatâi (2017) discuss that many interviewees made a distinction between reverting undos of their own content and having a third-party contributor revert the undo of their content on their behalf. It was seen as a benefit and motivator if someone else reverted the undo; it is also not seen as an act of revenge but as a more legitimate action. Such third-party undos can also be rewarded. One user interviewed by Piskorski and Gorbatâi (2017) was quoted to say that some users are known as being very active and reverting undos, and that one starts to pay attention to their edits and revert undos of their edits as a way to thank them. Piskorski and Gorbatâi (2017) argue that this comment and others along similar lines point to a dual nature of the revert: from the point of a contributor who violated the norm by undoing an edit, a revert of an undo is seen as a punishment; from the perspective of the contributor whose edits were undone, the same revert of an undo by a third party is a sign of appreciation and a reward.

[165] They do not give any detail on how large the sample was.

These definitions of norm violation, norm enforcement, and rewards laid out by Piskorski and Gorbatâi (2017) come with several problems. I will not replicate their study using the same definitions. First of all, the implementation is somewhat dependent on the state of the software. In their paper, the algorithm Piskorski and Gorbatâi (2017) developed and used to identify norm-relevant behaviour only works with (English) Wikipedia data from before 2006. As of today (July 2022), the German Wikipedia is set up in a way so that generally all undoing actions have a comment accompanying them[166]. One could differentiate between standard comments and more personalised ones; however, this is not necessarily straight-forward to implement because standard comments, as of today, depend on the device—for example if the mobile view was used—used to edit Wikipedia.

Second and much more importantly, I do not consider the basic definition of norm violation proposed by Piskorski and Gorbatâi (2017) to be appropriate. They define the undoer to be the norm violator, expecting them to be undoing "good edits" (e.g. Piskorski and Gorbatâi 2017: 1217). With this definition, every undoing without an explanation is a norm violation except in the case of clear vandalism. However, in many cases, seemingly "good edits" are not so good after all: edits are being reverted if well-intended changes do not follow the guidelines of Wikipedia. Such edits might, for example, be written in a wrong fashion and include a personal point of view[167], introduce information which was previously discussed not to be included[168], are not well sourced[169], or are deviant in some other way[170]. Also, vandalism is not that easy to detect. While deleting a whole article is clearly vandalism, other edits can be factually wrong and introduced to harm the project in subtle ways which are difficult to detect[171]. Another common practice of vandalism

[166] See https://de.wikipedia.org/wiki/Hilfe:Wiederherstellen.

[167] See for example https://de.wikipedia.org/w/index.php?title=Jens_Spahn&diff=206563228&oldid=206563216.

[168] Such discussions generally take place on the discussion site of an article and are referred to. See for example undos relating to the deletion of disambiguation links here https://de.wikipedia.org/w/index.php?title=Donald_Trump&diff=216339396&oldid=216331998.

[169] See for example the questioning of a friendship between celebrities, https://de.wikipedia.org/w/index.php?title=John_Stamos&diff=200891938&oldid=200795190.

[170] See for example the listing of an album of a band which is not norm compliant before the album was official released, https://de.wikipedia.org/w/index.php?title=Senzezium&diff=218123049&oldid=218040567; or the inclusion of web links in the main text, https://de.wikipedia.org/w/index.php?title=Universit%C3%A4tsbibliothek_der_Helmut-Schmidt-Universit%C3%A4t&diff=177074435&oldid=177074400.

[171] See for example edits made on the page of the political party *Volt Deutschland*, https://de.wikipedia.org/w/index.php?title=Volt_Deutschland&diff=215299208&o

is the replacement of single words with profane ones to change the meaning of sentences. Such forms of vandalism are not captured by the algorithm employed by Piskorski and Gorbatâi (2017).

While it is possible to undo other users' edits out of spite, I argue that generally, edits which do not improve Wikipedia articles in a way consistent with the guidelines are undone. I consider it problematic to refer to the user being undone as the victim by default. Piskorski and Gorbatâi (2017) only consider undoings without edit summaries as norm violations. While this makes some sense, it can better be considered *another* form of norm violation; it does not make the previous user necessarily a victim, but rather makes both the previous user and the undoer to norm violators (of different norms). Most importantly, it is far-fetched to assume that someone would revert an undo just because the editor undoing did not leave an edit summary. If the undo was reasonable, there is no point in reverting it even if it is considered better-practise to leave a comment.

Thus, instead of following the approach laid out by Piskorski and Gorbatâi (2017), I adopt the perspective that the user being undone is by default considered the one violating a norm and the one undoing the edit is sanctioning (see for an illustration of my setup also table 5.1). My operationalisation is more in line with what Panciera et al. (2009) consider norm enforcement. They also consider the user reverting edits as the one enforcing the norm, but they do only consider a subset of reverts as norm-relevant: only those that make some reference to those Wikipedia pages that discuss norms explicitly by mentioning "Wikipedia:" or "WP:" in the comment field are considered norm-relevant reverts. As a robustness check, I ran models with their restricted definition (see section A.3.8). Additionally, I ran models where I excluded instances in which reverts got themselves reverted as it could be argued that it is unclear who is "right" in these situations (see section A.3.7).

I want to highlight that it might especially be the German Wikipedia which exhibits this logic, and which forms the basis of my argument. I do not want to cast doubts on the findings of Piskorski and Gorbatâi (2017) who analyse the English Wikipedia. The content and importance of norms and how they are practised varies between language versions of Wikipedia (see for a cross-cultural study Hara et al. 2010). Jørgensen (2012) has specifically analysed the German Wikipedia. Her study highlights the strong focus on the quality of the end-product, the encyclopaedic articles, in the German community.

`ldid=215298781`. New content was introduced as part of a satirical late-night show and remained on the page for a week before it was undone.

Table 5.1: Illustration of an article's edit history.

Time stamp	**User**	**Comment**	**Considered as...**
		...	
2015-06-26, 1:14	8755	added information	
2015-06-26, 2:36	9630	added information	victim
2015-06-27, 11:09	65915	added funny information	norm violation (punished by 8755)
2015-06-27, 18:15	8755	revert	norm enforcement (enforcing on behalf of 9630)
		...	
2015-11-15, 18:21	9630	added information	victim
2015-11-15, 19:59	74024	added fake information	norm violation (punished by 9630)
2015-11-15, 20:13	9630	WP:rv	norm enforcement (enforcing on behalf of themselves); victim
2015-11-15, 22:47	8755	added information	norm violation (punished by 65915)
2015-11-15, 22:47	65915	rv	norm enforcement (enforcing on behalf of 9630)
		...	

The article quality is seen as more important than the wiki-process as such. I consider this to also mean that correcting wrong edits is more important than writing edit summaries, so that it can be argued that any edits which damage the end-product—the article quality—are norm violating.

The undoing of an undoing (what Piskorski and Gorbatâi (2017) called a revert[172]) can either be done by the initial user doing the edit, i.e. user A, or an unaffected third party like user C. This setup is in line with Piskorski and Gorbatâi (2017), however, my argument is different. In cases where an edit written by user A is reverted by user B, I consider the edits made by user A as norm violating. Rewarding user B is possible in one of two ways[173]:

1. Other users can *thank* user B. This is a feature which got activated in the German Wikipedia in 2013[174]. While it is possible to see who thanked whom in the logbook[175], it cannot be retrieved which edits users were thanked for.

2. Other users can post on user B's talk page to express their gratitude. This can come in the form of text messages but can also include the giving out of awards to honour their actions.

[172] I do not adopt this terminology as it is *not* the one employed in the (German) Wikipedia. I use the terms *undo* and *revert* interchangeably.

[173] See for more details on expressing thanks on Wikipedia also https://en.wikipedia.org/wiki/Wikipedia:Expressing_thanks.

[174] See https://de.wikipedia.org/wiki/Hilfe:Echo/Danke.

[175] See https://de.wikipedia.org/wiki/Spezial:Logbuch/thanks.

The second option requires checking the actual content of the contribution to users' talk pages. Given computational constraints, this is not feasible for this study (downloading information about actual article text content requires multiple terabytes). Receiving recognition in these ways has been shown to positively influence contributor retention (Gallus 2017; Matias et al. 2020; Restivo and van de Rijt 2012, 2014; van de Rijt et al. 2014).
Given these considerations, the next section will outline in more detail how I measure norm violations, norm enforcements and rewards in this chapter.

5.3.3 Measurement of Norm-Relevant Behaviours on Wikipedia

The previous section summarised the measurements of norm violations, punishments, and rewards in the study of Piskorski and Gorbatâi (2017) and sketched out alternatives. What does this mean for the present analysis?
To capture the extent to which a given contributor experienced norm violations on Wikipedia, I construct a variable *number of times contributor i's edit was edited by another contributor who was subsequently undone*. This measures the number of instances in which contributor i's edits were violated by other contributors during the time t (not including instances of self-violation). This measure can be used to test hypotheses 1a and 1c.
To capture the extent to which a given contributor violated norms on Wikipedia, I construct a variable *number of times contributor i was undone*. This measures the number of instances when contributor i's edits were undone by other contributors during the time t (not including instances of self-violation). This measure can be used to test hypotheses 1b and 1d. Please note Piskorski and Gorbatâi (2017) use this as a measure of *experiencing norm violations* while I consider this the actual *violation of a norm*.
Hypothesis 2a, which is concerned with experiencing that others punish norm violators, is tested using a measure counting the *number of times that user j's edits following user i's edits are undone by someone other than i* (for example by k); this is identical to and can also be thought of as the number of times i's edits are being restored by someone else than themselves (not including instances of self-violation). These instances are thus a subset of the norm violations experienced; they only include those instances in which the one being violated was not the one enforcing the norm. This means that in the situation illustrated in table 5.1, the instance where user 9630 enforces a norm on behalf of themselves is not counted. In line with this,

Table 5.2: Overview of hypotheses and measurement regarding norm-relevant behaviour.

Hyp.	**Actor i embedded in dense networks...**	**Measurement**
1a	exp. fewer norm violations	times i's edit was edited by other contributor who was subsequently undone
2a	exp. more that others punish	times j's edits following i's edits are undone by k
3a	exp. more rewards when they punish	times user has been thanked by others (+ interaction)
1b	violates fewer norms	times contributor i was undone
2b	punishes more violators	times that i undid edits by j following edits of user k
3b	rewards more punisher	times user thanked others (who punished)
1c	exp. fewer violations when alters dense	times i's edit was edited by other contributor who was subsequently undone (+ interaction)
1d	violates fewer norms when alters dense	times contributor i was undone (+ interaction)

"exp." is short for "experiences".

hypothesis 2b (expecting more punishment from users embedded in denser networks) is then tested by counting the *number of times that k undid edits by j following edits of user i* (not including instances of self-violation). To test hypotheses 3a and 3b which are concerned with rewards, I count the *number of times user i thanked others* (hypotheses 3b) and *number of times user j was thanked by others* (hypotheses 3a). Testing hypotheses 3a and 3b require the inclusion of an interaction effect between receiving/giving rewards and having undone others. Including such an interaction is not possible in the model on giving rewards, as the giving is tie-dependent. I thus follow a second modelling strategy in which I only count thanks given to those that have punished norm violators in the previous time period. A simplified overview of hypotheses and measurements is given in table 5.2 (for the exact wording of the hypotheses, please refer back to section 5.2.2).
With this operationalisation, hypothesis 1a will be supported if I observe that contributors embedded in dense networks have fewer of their edits undone. Hypothesis 1b will be supported if I observe that contributors embedded in dense networks undo fewer edits. Support for hypotheses 1c and 1d is given when these effects are stronger when the contributors' alters are also embedded in dense networks. Hypothesis 2a will be supported if contributors embedded in dense networks experience more undos of edits by third

parties following their own edit. Similarly, hypothesis 2b will be supported if contributors in dense networks undo more edits made by others who have edited after third-party contributors. Finally, the last two hypotheses will be supported if contributors in dense networks who have undone others receive more thanks (hypothesis 3a) and thank others who have undone others more frequently (hypothesis 3b).

To construct the dependent variables, I aggregated the occurrences of norm violations, punishments, and rewards over the time period t. I focus on the year 2015 as it has observed the highest punishment activity in any year after 2013 (the thanking feature has been introduced at the end of 2013). I observe and aggregate norm-relevant behaviour and network structure for each of the twelve months. This approach is in line with Piskorski and Gorbatâi (2017). The data on norm-relevant behaviour is based on the activity logged in the meta dump (see for details section 3.1). It is not that straight-forward to identify edits as reverts. The meta data used also includes the edit summaries of edits. Any summaries including the whole or abbreviated versions of the word "revert" and the German pendants "zurückgesetzt" or "rückgängig" were considered reverts (see also illustration in table 5.1). Both languages and the corresponding expressions are commonly used in the edit summaries of the German Wikipedia. The automatically created edit summary when reverting edits in the German Wikipedia currently reads: "Änderungen von [user] auf die letzte Version von [user] zurückgesetzt" (Translation: "Changes of [user] reverted to the last version by [user]."). There is also a tag which marks edits as being reverts; however, unfortunately, these tags are not included in the meta data[176]. These tags do not become part of the comments. This approach which relies on user-written labels has been used by previous studies such as Kiesel et al. (2017) and Suh et al. (2007).

To measure rewards, all instances where one user has thanked another have been collected with a web scraper using *RSelenium* from the logbook[177].

The next section will describe the data collected across the years to better understand the dynamics regarding norm violations and punishments. The data of 2020 is excluded to allow yearly aggregations as data was only collected up to the end of March[178].

[176] To see what is available, check https://meta.wikimedia.org/wiki/Page_metadata or an example edit which should have such a tag according to the visual editor but lacks information in its meta data https://de.wikipedia.org/w/api.php?action=query&prop=revisions&revids=220218910.

[177] See https://de.wikipedia.org/wiki/Spezial:Logbuch/thanks.

[178] Dynamics on Wikipedia have also significantly changed in the course of the Covid-19 pandemic as a recent studies suggest (see e.g. Ruprechter et al. 2021). With many

5.3.3.1 Who Is Punishing Whom?

In 2001, the first year of the German Wikipedia, four edits were reverted. Most edits were reverted in the year 2010 (a total of 717'094 reverts). The absolute number of reverts across the years is displayed in the stacked bar plot in figure 5.1. The figure further differentiates who reverted whom. The number of reverts has increased in the early years of Wikipedia up until around 2007 when it stabilised until it started to decrease starting in 2011. Since around 2014, it has been on a stable level with around 400'000 reverts each year.

Most years, the majority of reverts are done by registered users who revert unregistered ones (so-called IPs). Similar to the development of the total number of reverts, the number of such $User > IP$-reverts increased in the early years but has been on a decreasing trend in the recent past. Instances in which a user reverts another user also occur relatively often. These cases had been increasing in the early years and remain on a relatively stable level since 2007 with around 200'000 reverts per year. Instances in which IPs revert other IPs or users are comparatively rare, particularly the former. Bots tend to make routine changes and fixes in Wikipedia and are also seldom involved in reverts.

It is important to understand these numbers relative to the total amount of edits created. These are displayed in figure 5.2. Data from the total volume stems from the official Wikimedia stats[179]. In 2001, there were a total of 2037 edits, the majority, 1702, stemming from registered users, and 335 coming from IPs. In the year with the most contributions, 2007, 14'001'049 edits were made, 1'245'673 by bots, 3'318'693 by anonymous users, and 9'436'683 by registered users. Up to 2007, the contributions of all user groups had increased. The number of contributions by registered users has since decreased slightly over time, and there is a notable decrease in the number of contributions by IPs. Contributions by bots had increased up to around 2012 and since also decreased.

What does this mean for understanding the reverts? Calculating a proportion of edits reverted per year, I find that, across all years, on average 3.4 per

newcomers to Wikipedia and increased edits, the Covid-19 pandemic has also led to a change in how Wikipedia was used and can be considered an external shock.

[179] See https://stats.wikimedia.org/#/de.wikipedia.org/contributing/edits. Wikimedia stats allows one to download detailed data on statistics of all Wikimedia projects. The definitions of bot in this and the previous figure are not necessarily identical as different data sources are used. The reverts are counted using the meta data dump and the bots are identified from the lists of bots; the figure referring to the total edits is based on global statistical data provided by Wikimedia.

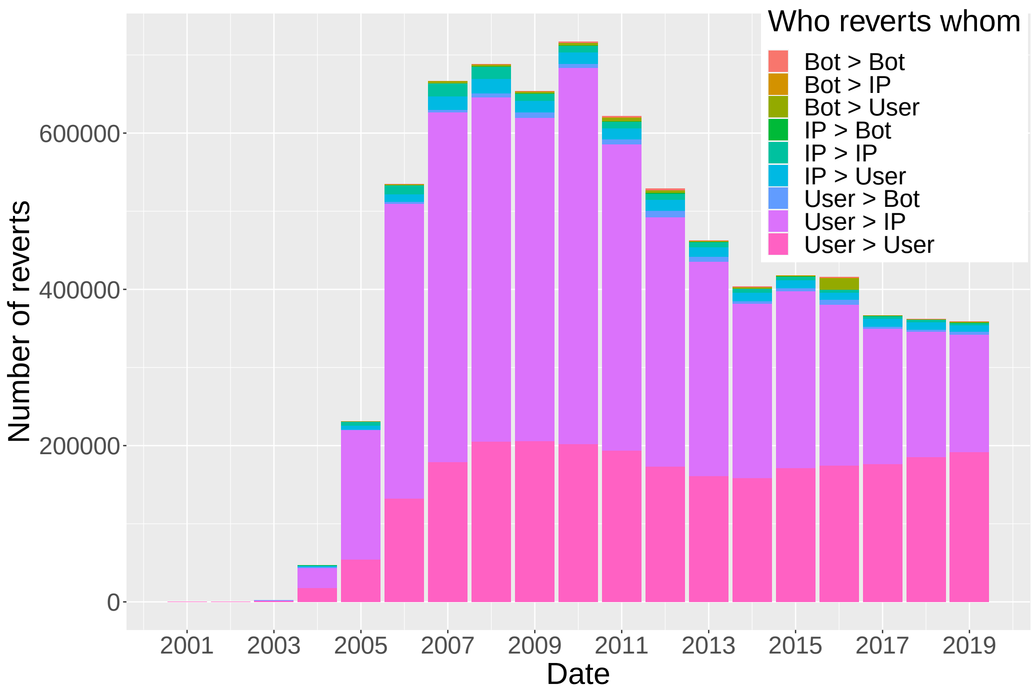


Figure 5.1: Absolute number of reverts across time, differentiating who reverted whom.

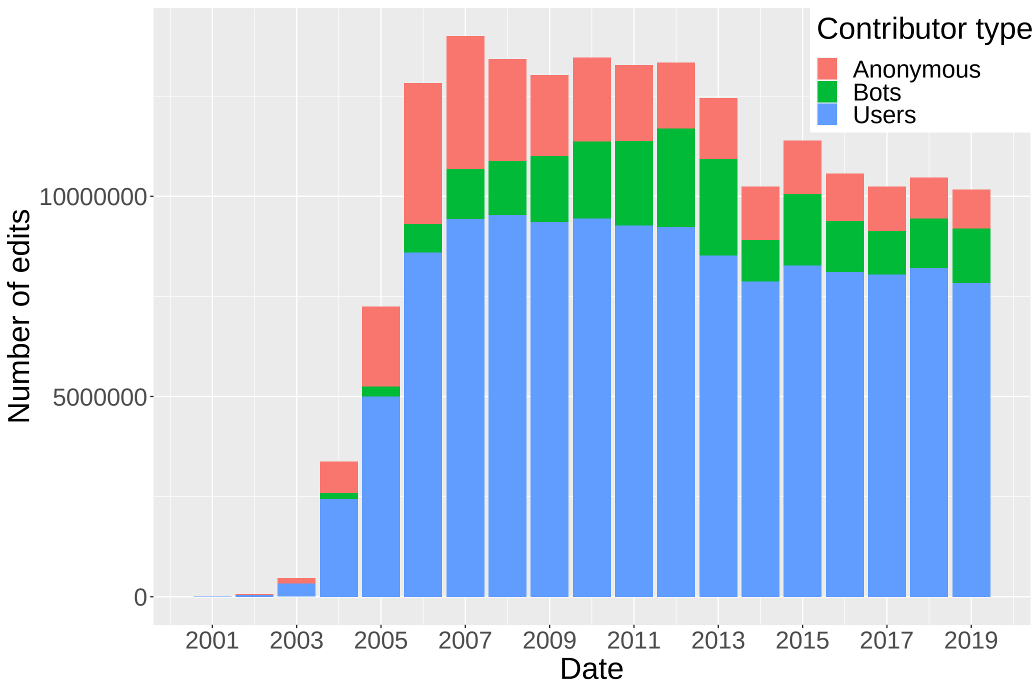


Figure 5.2: Number of edits across time, differentiating different types of contributors.

cent of edits are subsequently being reverted (standard deviation 1.63). The smallest percentage of edits were reverted in the first year with only around 0.20 per cent of edits being undone. The percentage increased up to a maximum of 5.3 per cent in the year 2010. Piskorski and Gorbatâi (2017: 1197) classify 2 per cent of all edits as norm-relevant reverts where no note was left (excluding acts of vandalism). Ignoring whether or not a note was left, they obtain a 7 per cent rate of edits which can be classified as an undo or revert of an undo; this rate is in line with other research they quote (Anthony et al. 2009; Buriol et al. 2006; Kittur et al. 2007b). My number is notably lower; however, all these previous studies work with the English Wikipedia.

Figure 5.3 displays the proportion of reverts experienced per contributor type. There is an astounding difference by contributor type. In 2010, almost one in four edits made by unregistered users on Wikipedia were subsequently reverted as they allegedly violated some guidelines of the platform. On average, 13.7 per cent of all edits made by IPs are reverted each year. This share has varied to a greater extent (standard deviation 7.51) than the share of edits reverted by registered users of which, on average, a share of 1.8 per cent (standard deviation 0.81) are reverted per year. Only a small percentage of edits made by bots are being reverted, on average 0.36 per cent (standard deviation 0.20).

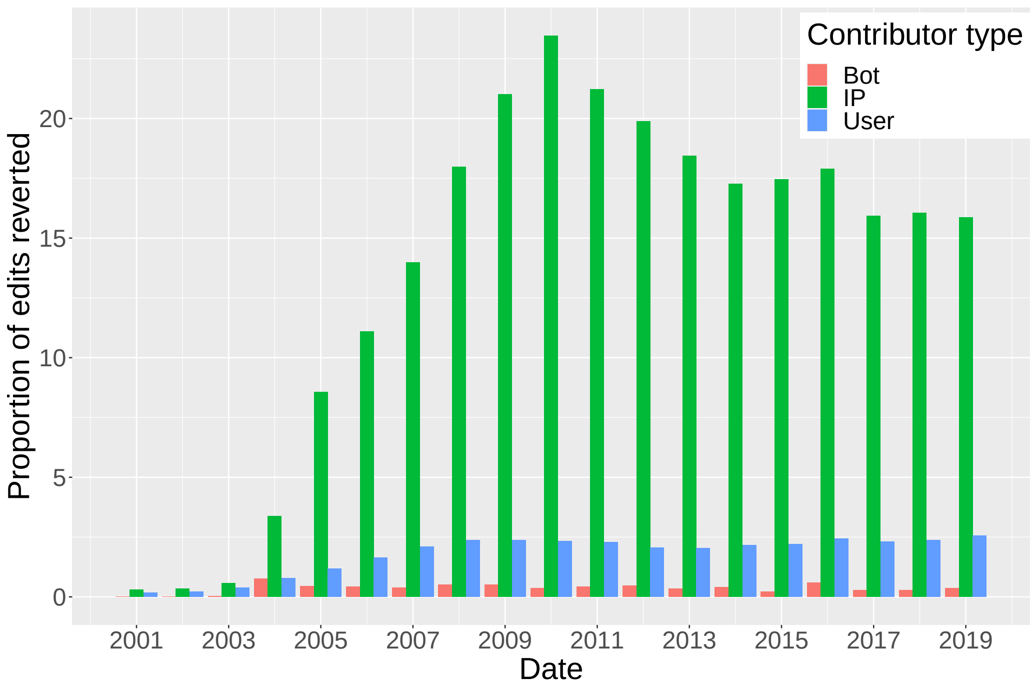


Figure 5.3: Proportion of edits reverted across time, differentiating different types of contributors.

Across all years, 95'157 unique users have reverted (excluding those accounts that have since been deleted or were not logged in); triple that amount, namely 348'699 unique users have been reverted. While some users have only reverted others once, one user reverted others 141'353 different times. On average, users who have used the revert feature at least once reverted others 73.4 times. However, with a median of 2, this distribution is highly skewed (standard deviation 1147.86). 37.3 per cent of reverts by registered users are done by those that were, are, or will be administrators.

Users who have been reverted at least once, have on average been reverted 7.9 times. With a median of 1 and a maximum of 192'240, the distribution is again very skewed (standard deviation 333.77). 12.0 per cent of edits made by registered users who are subsequently reverted were contributed by users who were, are, or will be administrators.

The tenure of both reverters and revertees of edits is relatively similar. On average, revertees' first edit on Wikipedia was 4.27 years ago (median 2.78, standard deviation 4.40, minimum 0, maximum 18.52) while reverters made their first edit 4.59 years ago (median 3.66, standard deviation 3.63, minimum 0, maximum 18.52). Frequently, the same pair of users have reverted one another (this can also be caused through so-called edit-wars). While, on average, one user reverted another one 2.08 times (median 1), the maximum is a high of 12'334 times (standard deviation 23.77). Users can also revert their own edits; across all years, this was the case for 6.5 per cent of edits (489'863 observations).

5.3.3.2 Who Is Violating Whom?

Following the previously outlined definition, user i is considered a victim of a norm violation if they have made an edit which was followed by an edit of user j which was subsequently undone. With my setup, only norm violations which are undone are identified, so that consequently, the number of victims of norm violations is almost identical to the number of norm enforcers discussed in the previous subsection 5.3.3.1 (discrepancies are caused by rare instances of edits being deleted). The violator is the one being reverted as outlined in the previous subsection—however, who are the victims of those norm violators and who is violating whom?

The absolute number of violations across the years is displayed in figure 5.4, again differentiating who is violating whom. Across the early years of Wikipedia, IPs were violating users the most, while in the most recent years, the number of users violating other users has increased.

Again, this must be understood in relation to the total volume of edits. This pattern is partly caused by the fact that the number of edits made by IPs has decreased. Generally, it is important to read these numbers in

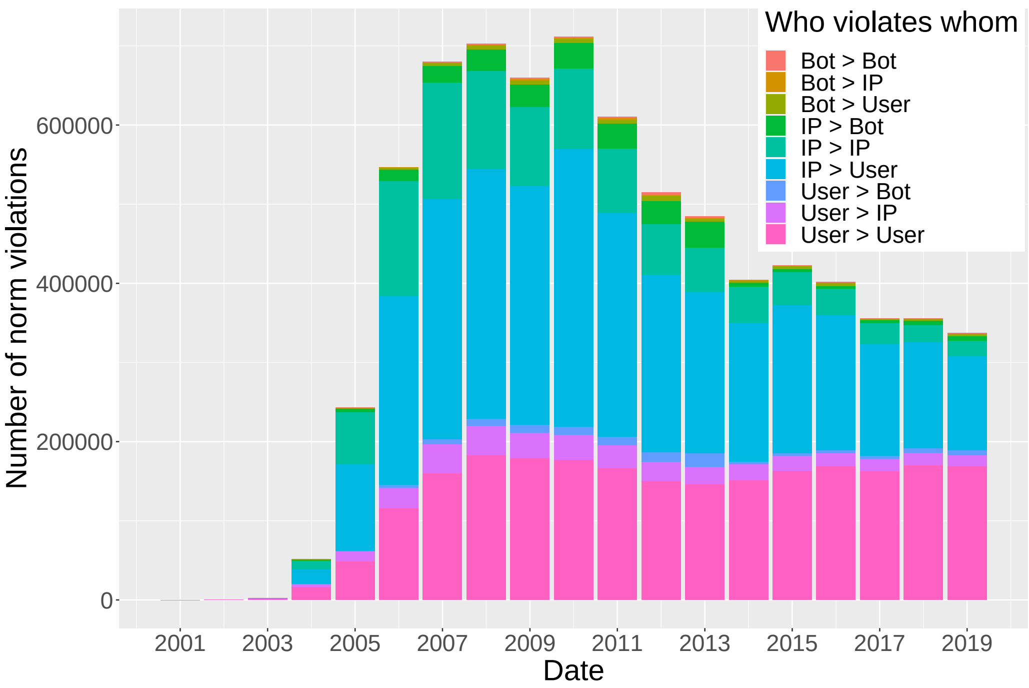


Figure 5.4: Absolute number of norm violations across time, differentiating who violated whom.

conjunction with those outlined in section 5.4; violation must be understood in conjunction with punishment. I calculate the proportion of edits violated per year per contributor type; see figure 5.5. In stark contrast to the revert of edits, there is not such a notable difference in the proportion of violated edits across the different contributor types (with the exception of bots, which are violated much less): on average, 4.1 per cent (standard deviation 2.10) of all edits made by IPs, 3.6 per cent (standard deviation 1.66) of all edits made by registered human users, and 1.4 per cent (standard deviation 0.94) of all edits made by bots are violated each year.

Across all years, 232'432 unique, registered users have been victims of norm violations (excluding those accounts that have since been deleted or were not logged in). On average, users who have been violated at least once, have been violated 8.12 times (median 1, standard deviation 405.24, minimum 1, maximum 192'240). In 24.0 per cent of norm violations, the victim was an administrator on Wikipedia at some point in time. On average, an editor being violated made their first edit on Wikipedia 4.40 years ago (median 3.33, standard deviation 3.78, minimum 0, maximum 18.55). On average, one user violated another user 1.74 times (median 1, standard deviation 22.63, minimum 1, maximum 22'020). Like self-reverts, self-violations can

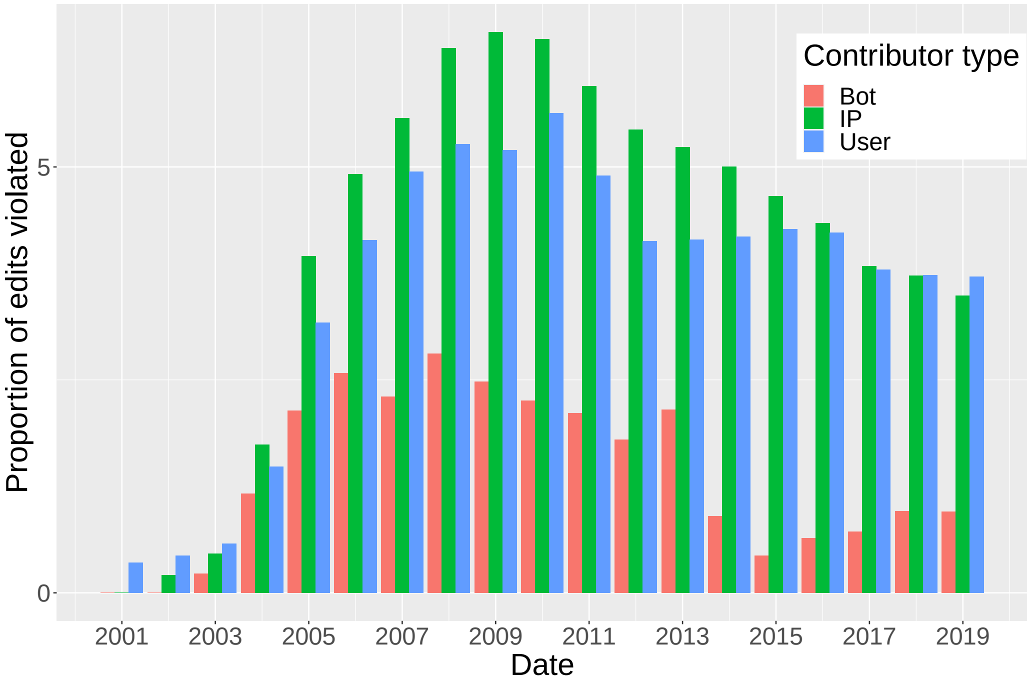


Figure 5.5: Proportion of edits reverted across time, differentiating different types of contributors.

occur. Across all years, 7.4 per cent of cases are such self-violations (553'359 observations).

5.3.3.3 Who Is Rewarding Whom?

Rewards form the last piece of norm-relevant behaviour. I measure rewards with the thanking feature. Only registered users can give thanks to each other. The feature has been introduced in 2013, and up to 2020, 754'526 instances of one user thanking another have been recorded in the logbook. In 748'518 of these cases, usernames and IDs could successfully be matched (see also section 3.2). The absolute number of thanks given across the years is displayed in figure 5.6. After being introduced at the end of 2013, the feature has been increasingly used across the years with well over 100'000 thanks given per year.

Across all years, 29'164 unique users have thanked others and 40'035 users have received thanks. It is thus not a feature which is used by the majority of Wikipedians. One user has thanked others 17'785 times, while others have only used the feature once. On average, a user who has used this feature at least once thanked others 25.67 times (median 2, standard deviation 194.86). 17.7 per cent of thanks were given by those that were, are, or will be admin-

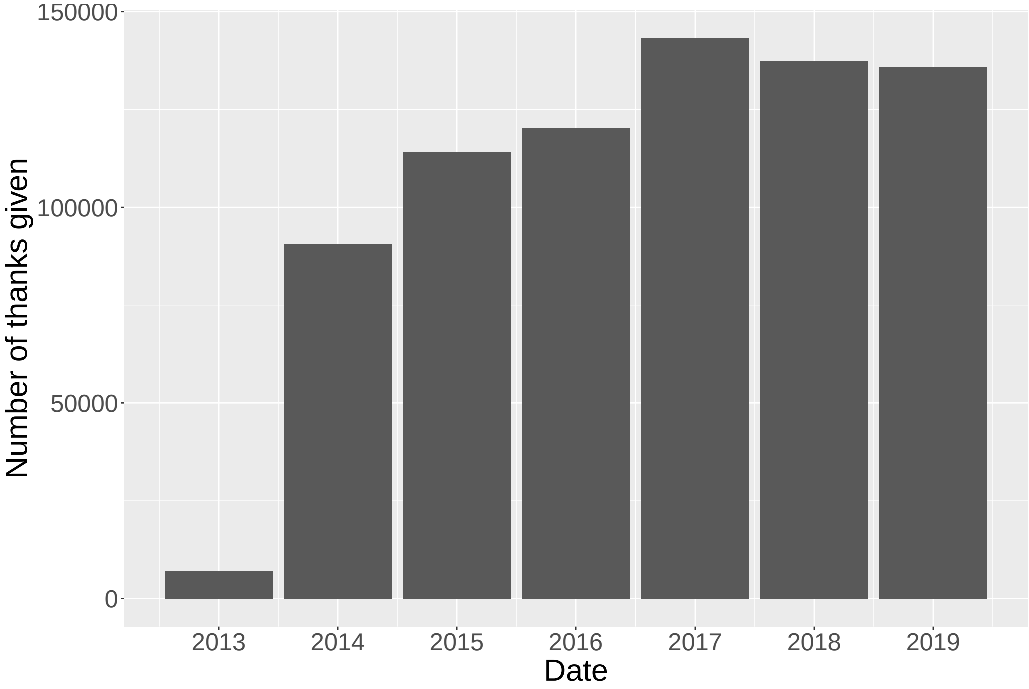


Figure 5.6: Absolute number of thanks given across time.

istrators, and on average, users that use the feature have been active for 7.39 years (median 7.90, standard deviation 4.48, minimum 0, maximum 18.39). Regarding receiving thanks, users who have received at least one thank you, have on average received 18.70 thanks (median 1, standard deviation 170.24, minimum 1, maximum 24'103). 12.0 per cent of thanks were given to those who were, are, or will be administrators, and, on average, users that received thanks have made their first edit 8.10 years ago (median 8.77, standard deviation 4.29, minimum 0.00007, maximum 18.50). In some instances, the same pair of users have thanked each other multiple times. While, on average, one user thanked another one 2.00 times (median 1), the maximum is a high of 663 times (standard deviation 5.42).

5.3.4 Risk Set and Data Reduction

The previous section described norm-relevant behaviour on Wikipedia in general to allow for a richer understanding of the dynamics of reverting. To test the hypotheses in section 5.4, the data will be reduced to a subsample of users who are expected to be immersed in the culture of norms and rules on Wikipedia. In line with the study of Piskorski and Gorbatâi (2017), I have decided to exclude all users with less than 25 edits. Additionally, bots are

excluded. This should guarantee that only users who are actual humans and who have an understanding of norms on Wikipedia are in the dataset.
In line with Piskorski and Gorbatâi (2017), I focus on activity in a single year. I focus on the year 2015. I thus construct a dataset which contains up to 12 observations of all users who have made at least 25 edits up to that month for the year 2015, excluding bots. I merge these users with their monthly norm-relevant behaviour and their network densities. I then have a total of 1'193'966 observations. I exclude all users who have been inactive in a specific month with inactivity being defined as not having made at least one edit (an inactive user can neither contribute to Wikipedia nor observe norm violations). As many users tend to become inactive across time, many observations are excluded with this step, and I end up with a total of 140'151 observations. To account for outliers, I further exclude the top 0.5 per cent of observations with the highest amount of norm enforcements, leading to a total of 140'016 observations of Wikipedians across the year 2015[180]. The distribution of these norm enforcements (referring to hypothesis 2b) is very skewed, and a very high number of restoring edits on behalf of others can likely mean that users routinely check any new changes conducted on Wikipedia and restore anything that seems suspicious; these users are thus inherently different and will not be analysed here.

5.3.5 Independent Variables

This section will present the independent variables included in the models. First, I will focus on the network measures included to test the hypotheses; then, I will discuss the control variables. A descriptive overview of all variables is given in table 5.3.

5.3.5.1 Online Network Measures: Collaboration Ties

Collaboration on Wikipedia is measured as outlined in subsection 3.1.2.1. It deviates from the definition employed by Piskorski and Gorbatâi (2017). Instead of taking a specific time frame into account, I define two users as collaborating when they have edited an article after one another, i.e. have interacted with each other's version of an article. This leads to a symmetric contributor-to-contributor matrix R_t whose elements, γ_{ijt}, consist of the number of instances during period t in which contributors i and j both con-

[180] A model including outliers is run as robustness check, see section A.3.6.

tributed after one another to the same article. In line with Piskorski and Gorbatâi (2017), I construct $\bar{\gamma}_{ijt}$ equal to one if $\gamma_{ijt} > 0$ and zero otherwise. The density around contributor i is calculated as the number of relationships between contributors with whom contributor i has co-edited, represented by $\bar{\gamma}_{ijt}$, and divided by the number of possible relationships between contributors with whom i has co-edited (see Piskorski and Gorbatâi 2017: 1200-1201). I calculate this using the *make_ ego_ graph()* functions of the R package *igraph*. In my setup, the collaboration network is a directed network, but I treat it as undirected in this case; the way the density is calculated in the software package, the density of the directed network treated as undirected can reach a maximum of two (this is a monotone transformation and does not affect the results). To test hypotheses 1c and 1d, I also calculate the network density around the alters. A user's egocentric and their alters' online network densities are positively correlated with Pearson's ρ equal to 0.41 (and $p < 0.001$).

Like Piskorski and Gorbatâi (2017), I focus on one year of Wikipedia activity and divide it into months. For each observed monthly value in time t, I take into account the online network values at $t-1$, i.e. the month before.

5.3.5.2 Offline Network Measure: Meetup Ties

The following analysis will enrich previous work, particularly by considering offline ties created between Wikipedians at informal meetups. For each month, the meetups taking place in the year before will be considered. This means, the number of reverts is counted and regressed on the offline density which has developed in the previous twelve months. I employ the same definition of density as in the online network. However, I assume that the offline network has a longer life span than the online one. Many informal meetups of Wikipedians only take place once a month, other larger meetups are annual events. Due to this slower pace of offline interaction, I take all offline meetups in the past 12 months into account to calculate the density measures.

To test hypotheses 1c and 1d, I also calculate the network density around the alters. A user's egocentric and their alters' offline network densities are very strongly positively correlated with Pearson's ρ equal to 0.83 (and $p < 0.001$). Both the offline and online egocentric densities of a contributor as well as the correlation of their alters densities do not show a strong correlation (correlation of egocentric online and offline densities: $\rho = -0.025, p < 0.001$, correlation of alters' online and offline densities: $\rho = -0.044, p < 0.001$;

while very small in size, the coefficients are still significant due to the large sample size).
Those not taking part in meetings do not have a meetup network. I assign those observations an offline network density of zero and include a dummy variable indicating whether users have taken part in a meetup or not (this approach is known as the missing-indicator method, see e.g. Groenwold et al. 2012).

5.3.5.3 Control Variables

A number of control variables are included in the analysis, based on previous research on Wikipedia and norms outlined in section 5.2.1, as well as the study of Piskorski and Gorbatâi (2017).
As the length of membership in a community can be expected to matter, years of tenure is controlled for. Tenure is measured as time since the first edit. Negative numbers are replaced with zero when users have made their first edit in the year under surveillance; they are replaced with missing in other cases as they must be caused through name changes or other account issues which are not possible to account for.
I also include previous activity measured as the log of the cumulative number of edits by contributor i prior to t, as well as i's most recent activity in the last month as control variables. This is obtained from the meta dump (see for details section 3.1). The latter also captures opportunity: the more edits users have made in the past month, the more edits could have been undone. In contrast to Piskorski and Gorbatâi (2017), I cannot control for the number of norm violations witnessed, as each edit made can be a potential norm violation. As a further control, I include a dummy variable indicating whether users have been an administrator at the current point in time. Networkwise, I control for the degree of contributors (network size)[181]. This matters as density measures can be sensitive to the number of alters.
To control for potential time trends and temporal heterogeneity, I include time period dummies[182]. An overview of all descriptives is given in table 5.3.

[181] In contrast to Piskorski and Gorbatâi (2017), I do not include network squared as it tends to lead towards model convergence problems; when included, it is not significant.

[182] In an alternative model, time was modelled as a fixed effect of months. As both approaches lead to identical results but the one with three period dummies comes with less computational costs, it is used across models.

Table 5.3: Descriptive information on all variables included in the models.

Variable	**Mean (SD) or %**	**Min/Max**
Number of experienced norm violations (1a, 1c)	0.20 (0.88)	0 / 96
Number of conducted norm violations (1b, 1d)	0.27 (1.55)	0 / 168
Number of own edits restored by others (2a)	0.15 (0.61)	0 / 45
Number of edits restored on behalf of others (2b)	1.22 (7.45)	0 / 240
Number of thanks given (3a)	0.73 (3.53)	0 / 200
Number of thanks received (3b)	0.71 (4.33)	0 / 294
Number of thanks given to norm enforcers (3a)	0.035 (0.40)	0 / 27
Number of thanks received from norm enforcers (3b)	0.033 (0.32)	0 / 25
Offline network egocentric density	0.039 (0.18)	0 / 1
Offline network alter density	0.0092 (0.052)	0 / 1
Offline network size	1.54 (9.35)	0 / 225
Attended meetup (in meetup network)	5.08%	
Online network egocentric density	0.51 (0.41)	0 / 2
Online network alter density	0.063 (0.14)	0 / 2
Online network size	30.09 (101.80)	0 / 8640
Total edit, this month (log)	1.88 (1.81)	0 / 11.14
Total edit (log)	6.32 (2.05)	3.22 / 13.83
Years since first edit	6.34 (3.24)	0.00005 / 14.46
Was admin	1.36%	
Month of year (Jan-April)	26.53%	
Month of year (May-August)	25.59%	
Month of year (September-December)	47.88%	
Observations	140016	
Number of groups	33204	

Given are mean (standard deviation), median, minimum / maximum.

5.3.6 Statistical Approach

To test the hypotheses outlined, I use negative binomial models following Piskorski and Gorbatâi (2017). Negative binomial regressions are used to model count data, requiring the dependent variables to take only non-negative integer values (Fox 2008 chapter 15; Long 1997 chapter 8). The negative binomial regression is a generalisation of the Poisson regression, loosening the restrictive assumption that the variance is equal to the mean and thus accounting for overdispersion. It models a non-linear relationship and can be estimated using a maximum likelihood estimation. The traditional negative binomial model is based on the Poisson-gamma-mixture distribution which allows to model Poisson heterogeneity using a gamma distribution.
It can be formulated as follows:

$$Pr(Y = y_i|\mu_i, \alpha) = \frac{\Gamma(y_i + \alpha^{-1})}{\Gamma(y_i + 1)\Gamma(\alpha^{-1})} \left(\frac{\alpha^{-1}}{\alpha^{-1} + \mu_i}\right)^{\alpha^{-1}} \left(\frac{\mu_i}{\alpha^{-1} + \mu_i}\right)^{y_i}.$$

Negative binomial models can be extended to account for zero inflation, meaning count variables with excessive zeros. Such a model assumes that excess zeros are generated by a separate process from the count values. Piskorski and Gorbatâi (2017) do not use zero-inflated models. I check for zero inflation but as no excess of zeros is found, I employ the standard negative binomial regression model as well. As I observe the same users across multiple points in time, my models exhibit a multilevel structure (Raudenbush and Bryk 2001). A random effect negative binomial model is modelled including user IDs as random effects.
In total, I have eight (two different measurements of rewards) dependent variables. First, I check bivariate relationships. Then, I run three models for each of these variables. The models include all control variables aforementioned, but the first model only includes the offline density, the second model includes only the online density, and the third model includes both network measures simultaneously to check whether one type of network effect overrides the other.

Robustness Checks I conduct several robustness checks with regression results shown in the appendix (see section A.3) and discuss them in section 5.5. I run logit models instead of negative binomial models to model the likelihood of conducting specific behaviours instead of the extent for both the full as well as the bivariate models. For the multivariate models, I also repeat the analysis with a dataset including only those users who previously attended a meetup. Those not attending offline meetups do not have an offline meetup network which might influence the effect of density. Further, the results may depend on the fact that the users taking part in meetups are a specific, self-selected group with potentially diverging dynamics from the others. It could also be the case that the online contacts of those that have offline contacts play a different, potentially more negligible role.

Next, I run models which include users previously excluded as outliers. To consider the ambiguity of situations in which reverts are reverted again, I also present one model excluding such instances. Further, I employ another definition of norm enforcement which is more restrictive and only considers reverts which include a reference to "WP:" as (norm-)relevant. This follows the approach of Panciera et al. (2009). Next, I use a second measure of online connections, the talk relation (see subsection 3.1.2.2). To check for unobserved individual heterogeneity, I also run two-way fixed effects (FE) models. These models have become a default method to estimate causal effects from panel data as they adjust for unobserved unit-specific and time-specific confounders.

Lastly, to account for sensitivities of the measure of density—it depends on the number of alters, its distribution can be skewed, and it can be sensitive to the exact operationalisation specification[183]—models were run which use a categorical measure of network density. Three categories of density are differentiated: low, where there are no ties between alters, high, where at least 90 per cent of alters are also linked to each other, and a medium level density. Users taking part in meetups generally never have the lowest level of density regarding offline meetups: at least part of their alters are always connected except if they only went to meetings where they were the only attendant or only met one other user.

Statistical Software Negative binomial models are estimated using *glmmTMB* (Brooks et al. 2017). Performance checks are conducted using *performance* (Lüdecke et al. 2021) as well as *DHARMa* (Hartig 2021).

[183] Such issues particularly occur when asking respondents directly about friendship ties (see e.g. Kerckhoff 2019 chapter 6).

5.4 Results: Testing Coleman's Norm Enforcement Mechanism

This section will conceptually replicate and extend the analysis of Piskorski and Gorbatâi (2017) and test the hypotheses set out in section 5.2. First, bivariate associations will be presented and then multivariate models follow.

Bivariate Models In a first step, I model bivariate relationships between the number of norm violations, norm punishments, and rewards experienced and conducted, on one hand, and the offline and online network densities, on the other hand. First, comparing users who took part in meetings and those who did not, I find that the meetup group is a subgroup with different dynamics in some (but not all) regards. Two-sample t-tests reveal that users attending meetups tend to be the victim of norm violations slightly but insignificantly more often (mean: 0.20 vs. 0.21, $t = -0.63, p > 0.10$), violate norms more often (mean: 0.26 vs. 0.45, $t = -8.24, p < 0.001$), are punished for norm violations equally often (mean: 0.15 vs. 0.15, $t = 0.56, p > 0.10$), punish norm violations significantly more often (mean: 0.96 vs. 6.00, $t = -25.74, p < 0.001$), receive more thanks (mean: 0.56 vs. 4.26, $t = -37.00, p < 0.001$) and thank more often (mean: 0.52 vs. 4.33, $t = -28.11, p < 0.001$).

Next, I run negative binomial models with network densities and the meetup indicator (in the offline models) as only predictors. While accounting for the multilevel structure with random effects of users, I find that those embedded in denser offline networks violate significantly fewer norms, while those in denser online networks tend to violate significantly more norms and experience more norm violations. This does not hold for alters; if the alters of an actor are embedded in denser online networks, they both violate significantly fewer norms and experience fewer norm violations. The effect of alters' offline network density on the number of norm violations conducted is not significant, but they tend to experience more norm violations (on the 10 per cent significance level). Those embedded in denser offline or online networks are further significantly less likely to punish norm violators, as well as thank others or receive thanks. I find those in dense online networks experience norm punishments more often (there is no significant effect of the offline network density). All results are based on the regression tables in section A.3.1.

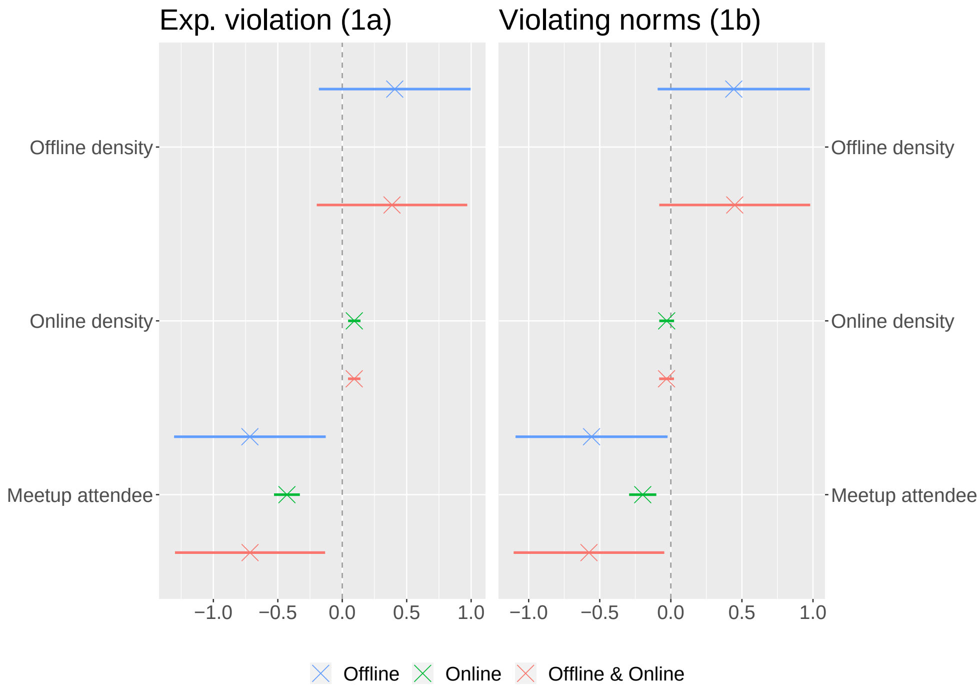
The bivariate results provide support for hypothesis 1b for the offline component and for 2a for the online component. Hypotheses 1a, 2b, 3a or 3b are not supported at all. Hypotheses 1c and 1d require the inclusion of interaction effects in the next step, but the initial bivariate relations suggest some support for the online density regarding hypothesis 1d: if ego's alters are embedded in dense online networks, he is less likely to experience or conduct norm violations.

Multivariate Models In a second step, I will now present the multivariate negative binomial models, including all control variables. Estimation results of variables relevant for hypotheses testing are reported using coefficient plots. The corresponding tables including the effects of all control variables can be found in the appendix, see section A.3.3.

Figures 5.7 and 5.8 report estimations relating to contributors experiencing norm violations (left) and violating norms themselves (right). Experiencing a norm violation is captured by the number of times contributor i was edited by another contributor who was subsequently undone in time t; norm violation during time t is modelled by the number of times contributor i was undone. Coefficient plots are based on table A49 in section A.3.3.

As shown in figure 5.7, I find that the egocentric offline network density of a contributor does not significantly influence the number of times they are the victim of norm violations (left, hypothesis 1a) or violate norms themselves (right, hypothesis 1b), judging by the conventional 5 per cent significance level. However, a contributor surrounded by a dense egocentric online network tends to experience significantly more norm violations. There is no significant effect of egocentric online network density on the number of conducted norms violations. These effects remain stable when including both the offline and online measures in the same model. Generally and in contrast to the bivariate findings based on t-test, users attending offline meetups are shown to be significantly less likely to experience or conduct norm violations. I do not find any effects of the offline network density and only limited effects of the online one. The positive and significant effect of online network density on the number of norm violations experienced is inconsistent with hypothesis 1a and the findings of Piskorski and Gorbatâi (2017).

The models shown in figure 5.8 include the network densities of ego's alters (based on table A50 in section A.3.3). The model regarding a contributor's own norm violations (1d, right) does not show any effects of the network structure significant on a 5 per cent level.



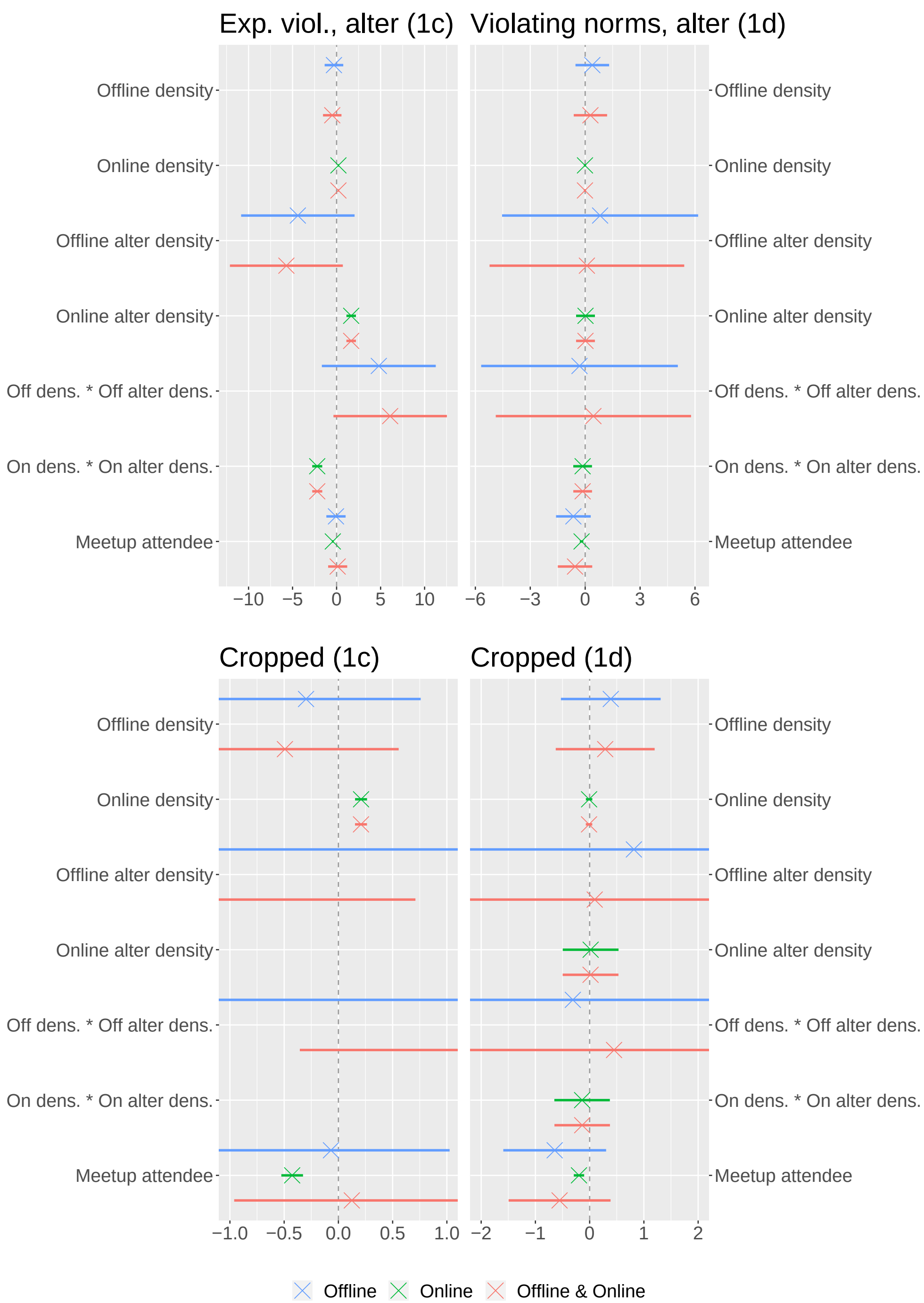
Note: Horizontal line reflects 95 per cent confidence interval.

Figure 5.7: Negative binomial estimates that 1a) contributor experiences norm violations, and 1b) contributor violates norms.

The models on the left regarding the experience of norm violations (hypothesis 1c) tell a rather complex story. All main and interaction effects regarding both the egocentric and the alters' offline network density are insignificant in these models (on a 5 per cent level). The main effect of both the egocentric and the alters' online network density are positive and significant, but I observe a negative interaction. To better understand this dynamic, see the marginal effects plots in figure 5.9 based on the model including offline and online measures simultaneously[184]. These patterns do not unambiguously support hypothesis 1c. The plot shows that those whose alters are embedded in dense online networks experience more norm punishments when they are themselves embedded in low-density online networks, but the pattern changes when they are embedded in dense online network (density higher than 0.75).

Figure 5.10 reports estimations relating to contributors experiencing that others punish norm violators on their behalf (left) and on punishing norm violators themselves on behalf of others (right). Experiencing norm punishments is captured by the number of times contributor i was edited by another

[184] Wide confidence intervals are caused as the average online alter density is rather low and there are few observations with high values. Also, please note online density can reach a maximum value of 2. Plotted are predicted values up to a density of 1 for better legibility and clarification as the lines stay relatively flat after that.



Note: Horizontal line reflects 95 per cent confidence interval. Bottom plots are cropped for better visibility of small effects.

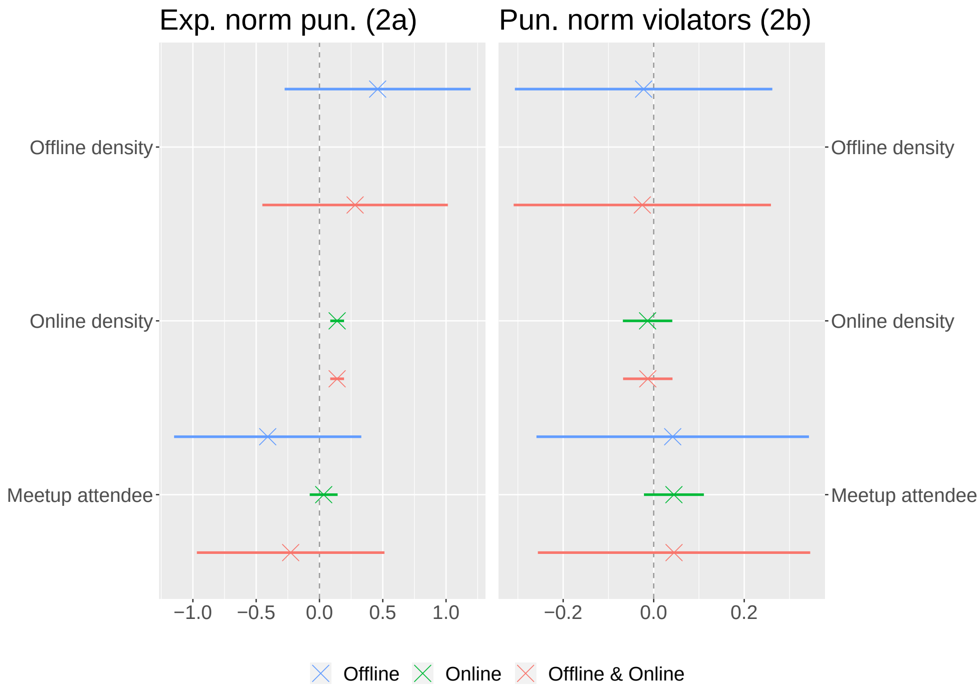
Figure 5.8: Negative binomial estimates that 1c) contributor experiences norm violations, and 1d) contributor violates norms, including network measures of alters.

contributor who was subsequently undone by another contributor in time t; punishing norm violations during time period t is modelled by the number of times contributor i undid edits which followed on another contributor's edit. The figure is based on table A51 in section A.3.3.

Figure 5.9: Marginal effects of online network densities on experiencing norm violations, including network measures of alters (1c).

As shown in figure 5.10, I find no effects of the egocentric offline network density of a contributor; the offline network density does not influence how often a contributor experiences norm punishments (hypothesis 2a) or punishes others (hypothesis 2b). Generally, users attending offline meetups behave similarly to those not attending any meetings in these regards. While online network density does not exhibit a significant effect on the number of norm punishments conducted, there is a significant positive effect regarding the experience of norm punishments: contributors embedded in high-density online networks experience more norm punishments. This is consistent with hypothesis 2a. The effects do not change when including offline and online measures simultaneously.

Lastly, figures 5.11 and 5.12 report estimations relating to contributors receiving (left) and giving (right) rewards (based on tables A52 for figure 5.11 and A53 for figure 5.12 in section A.3.3). Receiving rewards is captured by the number of times contributor i received a thank you during time t; accordingly, giving rewards during time period t is measured as the number of thanks given by contributor i. This is testing whether contributors are more likely to receive or give rewards when they are embedded in dense offline networks, as asserted in hypotheses 3a and 3b. The interaction effect included in the top left figure specifically tests whether those more likely to



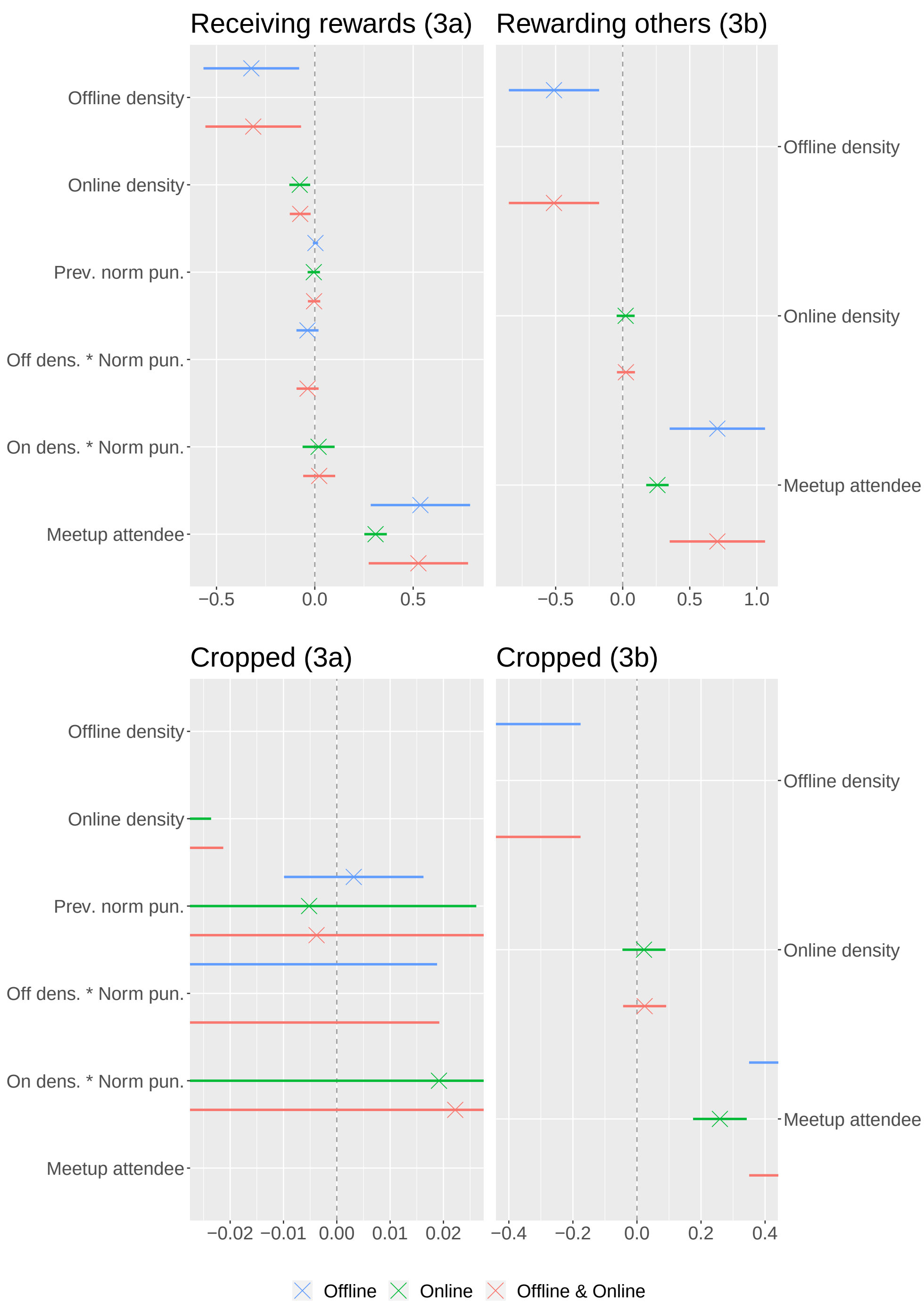
Note: Horizontal line reflects 95 per cent confidence interval.

Figure 5.10: Negative binomial estimates that 2a) contributor experiences norm punishments, and 2b) contributor punishes norm violations.

receive rewards are those who punished norm violators more often; such an interaction is not possible to include in the model regarding giving rewards as this giving is tie-dependent[185]. I thus run a second set of models displayed in figure 5.12 which only counts thanks given to those that have punished norm violators in $t-1$.

I do not find any evidence for hypotheses 3a or 3b. While the direction of the interaction effect between online network density and previously conducted norm punishments is positive, it is not significant on a 5 per cent level. The main effects suggest that those embedded in denser online or offline networks receive fewer rewards (if they have not conducted any norm punishments, i.e. the interaction effect equals zero; left plots in figure 5.11). Those in dense offline networks also reward others less (right plots), and those in dense online networks reward others who have previously conducted norm punishments less (right plot in figure 5.12). Generally, those attending meetups receive and give more rewards (see figure 5.11).

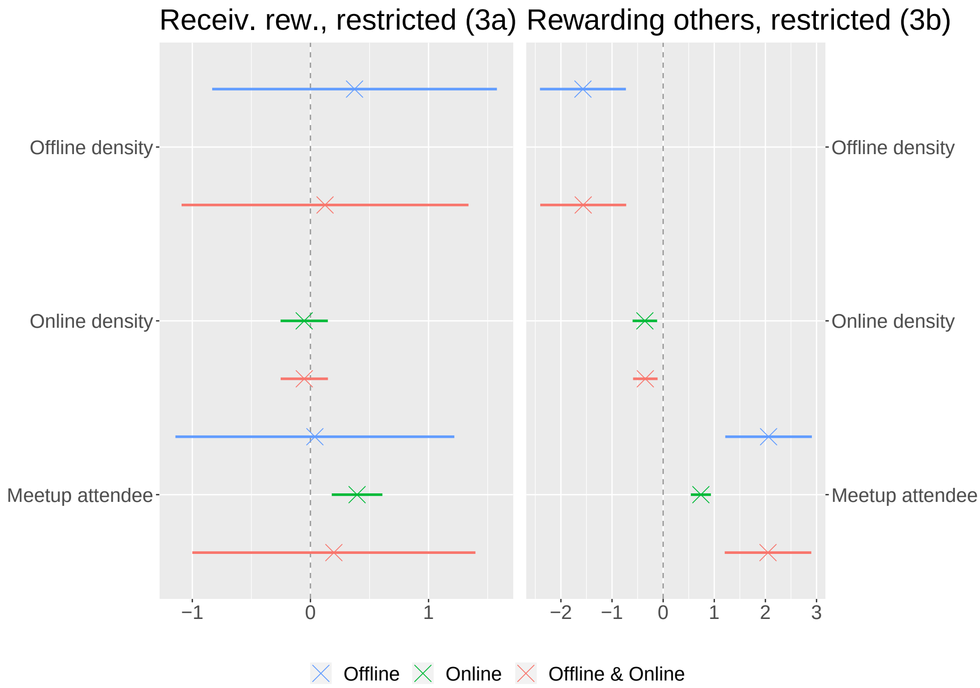
[185] What I mean by this is that a reward given by user X to user Y depends not only on user X' characteristics but also on User Y's previous norm-related behaviour. A model would thus need to account for all ties.



Note: Horizontal line reflects 95 per cent confidence interval. Bottom plots are cropped for better visibility of small effects.

Figure 5.11: Negative binomial estimates that 3a) contributor receive rewards, and 3b) gives rewards.

Taken together, these results only provide very limited support for the hypotheses laid out. This contrasts with the conclusions of Piskorski and Gorbatâi (2017). The results suggest that contributors in dense online networks 1) experience more norm violations, 2) more frequently punish others who violate, and 3) generally less frequently receive rewards and reward less those having



Note: Horizontal line reflects 95 per cent confidence interval.

Figure 5.12: Negative binomial estimates that 3a) contributor receive rewards, and 3b) gives rewards. Only thanks received by users who have punished norm violators are taken into account.

previously punished norm violators. Those attending meetups tend to both experience and conduct fewer norm violations, and they give and receive generally more rewards. However, the density of the offline network does not play a noteworthy role in explaining online norm violation and norm enforcement, except that those in high-density offline networks generally give fewer rewards. Other determinants included as controls in the models tend to have a large and significant effect. Further, it is notable that there is very little subject-variation regarding experienced norm punishments[186].

5.5 Robustness Checks

In the previous section, I presented and discussed the main negative binomial models. Several robustness checks (see section 5.3.6) shall be reviewed here. This will allow assessing how sensitive the results are to model specifications and whether alternative setups might lend more support to Coleman's mechanism tested. I will particularly discuss instances in which the results

[186] The variation is not 0 as could be assumed from the number reported in the regression tables in the appendix (see section A.3), but very small.

obtained from the alternative models are notably different to the main models.

In a first step, I modelled the bivariate relations as binary decisions (see tables in section A.3.2). Contrary to the continuous models (but in line with the bivariate negative binomial models), I find that actors embedded in denser online networks are significantly more likely to violate norms themselves (contrary to hypothesis 1b for the online component; see table A44). I find a significant and positive effect of the egocentric offline network density on the probability for a user to experience norm punishments (supporting hypothesis 2a), but a negative effect on a user's probability to punish norm violators (contrary to hypothesis 2b; see table A46). Reiterating the finding of the restricted main model (and of the bivariate negative binomial models), those embedded in dense online networks also seem to be less likely to reward others (contrary to hypothesis 3b; see tables A47 and A48).

The multilevel logistic models presented in section A.3.4 are consistent with the main negative binomial models presented. In another alternative model, I focus on the subset of users who have taken part in meetings (see section A.3.5) to check whether this leads to diverging results, particularly regarding the offline network. This approach can account for the fact that most Wikipedians have not attended any offline meetups. Contrary to the main models, I do not find a significant positive online density effect on the experienced norm violations (hypothesis 1a; see table A59). Regarding hypothesis 2b, I find an unexpected negative effect of online density (see table A61).

When including all outliers in the analysis (see section A.3.6), effects remain stable compared to the main models. The same holds true when excluding situations in which reverts got themselves reverted (see section A.3.7). However, some results change notably when using a different measure of norms where only a subset of reverts is considered norm-relevant (see section A.3.8; norm-relevant behaviour defined in line with Panciera et al. (2009)). In this case, I observe significant negative effects of the online network density on the number of norm violations conducted and experienced (supporting hypotheses 1a and 1b for the online component; see table A74), while the offline network density remains irrelevant. Regarding hypothesis 1d (again, online component only), the negative main effect of ego's online density remains; however, I find a significant negative main effect of the alters' online network density which seems to be compensated with a positive interaction effect between ego's and alters' online densities (see table A75). Contrary to hypotheses 2a and 2b, I further find negative online density effects in these models (see table A76). Modelled as an interaction effect, I find some evidence for hypothesis 3a: those embedded in denser online networks are more likely to receive rewards if they have punished norm violators more often (see table A77). All these differences between these models run as a robustness check and the main models presented point towards the need to better understand the difference between reverts and explicitly norm-evoking reverts.

Next, I used another measure of online collaboration based on interactions on talk user sites. Models are shown in section A.3.9. Results shift when analysing these talk interactions: there is a positive effect of talk ties on violating norms or being the victim of norm violations contrary to both hypotheses 1a and 1b (see table A79), and, supporting hypotheses 2a and 2b, there is a positive effect of network density on the frequency of experiencing that others punish norm violators on their behalf and the frequency of punishing those who violate norms against others (see table A81). Also, users with a denser talk network receive and give more rewards on average (see tables A82).

In section A.3.10, I present FE models to better model potential causal effects. Such models focus on within-variations of users across time and do not compare different users with each other; given the very low within-subject variation regarding experienced norm punishments, there are model fit issues and the models will not be discussed (models 1-3 in table A86). Compared to the main models presented, I do not find significant effects of the egocentric online network density regarding the experience of norm violations (see table A84). Regarding the interaction with alters, effects tend to decrease in size and significance but are, direction-wise, generally in line with the main results presented (see table A85). Regarding the punishing of norm violations (hypothesis 2b), I find unexpected, significant negative effects of the online density (see table A86).

Lastly, I use categorical measures of density (see section A.3.11). With this, I find that those being embedded in offline networks with medium or high density experience significantly fewer norm violations (supporting hypothesis 1a), and that those in medium-density offline networks also violate fewer norms (there is no significant difference between those in offline networks with low density vs. high density, this is thus only partly supporting hypothesis 1b). While those with a medium level of online network density violate more norms and experience more norm violations compared to those in low-density networks, those in high-density networks experience significantly fewer norm violations (see table A89). Model estimations regarding hypotheses 1c and 1d (see table A90) cannot be interpreted meaningfully as the models did not converge with their more complex data structure with multiple interaction effects between the categories. Similarly to the model on norm violations, I find that users embedded in online networks with a medium density experience more punishments and punish others more (partly supporting hypotheses 2a and 2b). Regarding rewards (see table A92), I find positive main effects of being in networks with higher offline or online density, but no significant interaction which would support hypothesises 3a or 3b (see also table A93)[187]. Generally, the patterns of the models in section A.3.11 are counter-intuitive and difficult-to-explain.

In summary, it cannot be argued that the results obtained in section 5.4 are stable across many different model specifications. They are somewhat sensitive to the modelling strategy employed. Overall, the results are rather mixed.

5.6 Conclusions

This chapter has focused on norms and norm enforcing behaviour on Wikipedia. Coleman (1990) formalised the intuition of the importance of dense networks and argued that high-density networks enable (third) parties to compensate norm enforcers for their expenses. Such rewards can encourage actors to punish those who violate norms, and in turn, reduce the prevalence of violations in the first place. In their study, Piskorski and Gorbatâi (2017) tested this mechanism using data from the English Wikipedia and find consistent support using the online network between contributors. In this chapter, I conceptually replicated and extended their study to test the same set of hypotheses by additionally taking the offline network between Wikipedians into account.

My results do not lend much support to the argument put forward by Coleman (1990). An overview of the direction of effects expected and found is given in table 5.4. I neither find that actors embedded in dense online or offline networks violate fewer norms against others nor are they less frequently the victim of norm violations; there is thus no support for hypotheses 1a and 1b (on the contrary, those in dense online networks experience more norm violations). I also do not find that actors embedded in dense networks experience even fewer norm violations against them or violate even fewer norms

[187] These models also exhibit some fit issues, please note the extremely large standard errors of the interaction effects and of the intercepts.

Table 5.4: Overview of expected and observed effects regarding norm-relevant behaviour.

Hyp.	Actor i embedded in dense networks:	Exp. density effect	Offline	Online
1a	exp. fewer norm violations	-	+ (n.s.)	+
2a	exp. more that others punish	+	+ (n.s.)	+
3a	exp. more rewards when they punish	int. +	- (n.s)	+ (n.s.)
3a restr.		+	+ (n.s.)	- (n.s.)
1b	violates fewer norms	-	+ (n.s)	- (n.s.)
2b	punishes more violators	+	- (n.s.)	- (n.s.)
3b	rewards more punisher	+	-	+ (n.s.)
3b restr.		+	-	-

"exp." is short for "experiences" in the second column, while "Exp." stands for "Expected" in the first row. "int." stands for "interaction effect" and "n.s." for "not significant". Effect of densities refer to the multivariate models including offline and online measures simultaneously.

when their alters are also surrounded by dense networks as the revealed pattern is quite complex (no support for hypotheses 1c and 1d; not shown in table 5.4 for better readability). Supporting hypothesis 2a, I find positive statistical effects of an actor's offline (not significant) and online network density on their extent of experiencing punishments. Contrary to what is expected following hypothesis 2b, I do not find those embedded in dense networks to punish more violators. Regarding rewards, there is also no evidence for the mechanism proposed by Coleman (1990). When focusing on all users, I do not find that users who have previously conducted norm punishments receive more rewards, thus not supporting hypothesis 3a. There is no evidence of a positive effect of network density on giving rewards; much on the contrary, I observe negative effects of both offline and online densities on the number of rewards given in the restricted dataset (no support for hypothesis 3b). Overall, there is some sensitivity towards model specifications, and no clear conclusions emerge from my analyses.

My multivariate models suggest that users who have attended offline meetups tend to experience both fewer norm violations and violate fewer norms, and they give and receive more rewards. However, overall, the density of the offline network does not play a noteworthy role in explaining online norm-relevant behaviour. There is thus no support for Coleman's mechanism based on the offline network, but the results do suggest that those taking part in meetups behave differently online than those not attending offline gatherings in some regards. This difference might be caused by the actual offline meetups, but it might also well be that there is a difference in the personality of those who attend offline meetups which causes differences in the online behaviour as well. This selection effect makes it difficult to test causal relationships.

How can these results be explained and why are they not in line with previous findings by Piskorski and Gorbatâi (2017)? My results suggest that those embedded in dense online collaboration networks experience significantly more norm violations and reward others significantly less, and they do not receive more rewards, punish more violators, or violate fewer norms themselves; these findings seem counter-intuitive.

To explain why those in dense networks reward less and are not observed to punish more, it could be argued that this is a case of diffusion of responsibility: those with denser networks might assume that many others also observe the norm violation or the enforcement and that another user will take action. Like in a volunteer's dilemma, users have an incentive not to act and this is particularly the case in larger groups (Diekmann 1985). It further might well be that those embedded in dense online networks make use of other conflict-solving mechanisms and use other features and ways to punish and reward more often. Contributors with dense online networks might want to solve issues preferably through discussions instead of reverts and use the discussion pages of articles and users to flag problems and express gratitude. Some anecdotal evidence for this can be found: checking users with high offline and online densities does show active user (talk) pages where thanks were given and awards received[188]. This means, there are other forms of positive and negative sanctions, but they come in a form which I do not observe in my study setup. These forms are systematically missing, i.e. the proportion of instances I missed is correlated with network density (Piskorski and Gorbatâi (2017: 1213-1214) do not expect to face this issue). I further find that users in dense online networks experience more norm violations; to explain this observation, one might argue that these users are exposed to more edits and thus experiencing more norm violations (and more norm punishments), even though I aimed to account for this by controlling for total and recent activity.

In all of this, it is important to keep the context and the nature of Wikipedia in mind. Wikipedia is a collective good where all users contribute voluntarily. These users are a self-selected group of people. Correcting mistakes and enforcing norms is in itself an appreciated and reputable task, but it is also

[188] See for example the user K https://de.wikipedia.org/wiki/Benutzerin:Kritzolina who is an active contributor, administrator, and meetup organiser and has a history of awards or user A https://de.wikipedia.org/wiki/Benutzer_Diskussion:Aka with archives full of thank you messages, see for example https://de.wikipedia.org/wiki/Benutzer_Diskussion:Aka/Archiv/2010/09#Danke or https://de.wikipedia.org/wiki/Benutzer_Diskussion:Aka/Archiv/2006/05#Danke_auch_von_mir.

normal for norm violations to occur. Generally, it could thus be assumed that the willingness to punish is greater than in other contexts and there might be other dynamics at play. Still, punishing norm violations can come with some costs to the individual. Being reverted is demotivating to others, does have negative effects (Halfaker et al. 2011) and also harms the relationship between the one being reverted and those reverting (see on voting e.g. Jankowski-Lorek et al. 2013; Turek et al. 2011).

Wikipedia further also observes some divisions of labour: users tend to find their niche to work in, and some do focus on checking recent changes, fixing errors, and reverting clear policy violations. Against this background, it could also be assumed that those deciding to be a "punisher" face smaller costs of punishing. This can also explain why there are "outliers" in the data, understood as users who have punished many others. Such individual differences are shown to be important determinants of coordinated actions and can facilitate effective punishment (see e.g. Przepiorka and Diekmann 2013). In the setting of the German Wikipedia, the well-known user *Eingangskontrolle* (English: entry control) made it their task to check new articles' fit on Wikipedia and whether they are notable; if this was not the case, they flagged the article. A user who focuses on such tasks does not build a (dense) network[189].

When comparing the results from my study with those from Piskorski and Gorbatâi (2017), it is important to keep in mind that my study setup diverges in a number of ways. Most notably, my definition of norm violation is very different. Piskorski and Gorbatâi (2017) conceptualise an undoing as norm violation. This definition is not in line with other research like Halfaker et al. (2011) and Panciera et al. (2009) who consider the undoing an enforcement mechanism. On the other hand, with my definition of norm enforcement it can be questioned to what extent the victim of a norm violation was actually a victim. If user j destroys an article after user i, user i can be considered a victim if they claim some ownership about the current state of the article—otherwise, it is mostly the collective good Wikipedia which is hurt[190]. I further always assume that the user reverting is "right". Also, with

[189] It is also interesting to note that in the case of Eingangskontrolle, a check user inquiry has been raised (see here https://de.wikipedia.org/wiki/Wikipedia:Checkuser/Anfragen/Eingangskontrolle,_Bahnmoeller). This means that it was formally checked whether Eingangskontrolle is a legitimate user or should be blocked. The final decision was to block Eingangskontrolle as they were found to be the second account of another person and that the two accounts were used in an inappropriate way in some contexts.

[190] Depending on the understanding of victim, it might also be argued that self-violations should be included in the analysis.

my operationalisation, only norm violations which are subsequently punished can be identified. This means, I do not observe any norm violations which are not punished. Violations that are never corrected are not taken into account in this analysis. This falls short of the reality of Wikipedia and affects how well Coleman's argument can be tested as it is based on comparing levels of norm enforcement. While I distinguish between norm violations which are punished by third parties and those punished by the victim of the norm violation, in both cases norms are being enforced. An ideal dataset would include hand-labelled instances of norm violations, allowing one to further understand which norm violating edits were subsequently reverted and which were not. Also, it is possible to only partially violate some norms which would lead to edits not being reverted but partially undone. However, such labelling, especially at a large scale, is time-consuming and difficult. In the future, capable machine learning algorithms might be able to detect norm violations. Automatic detection of vandalism is in the interest of many Wikipedians, and such algorithms have been developed (see e.g. Flöck et al. 2012; Martinez-Rico et al. 2019; Potthast et al. 2008; Smets et al. 2008). However, norm violations are much more subtle, and their automatic detection is thus a more complex undertaking (see for a similar undertaking regarding Reddit Chandrasekharan et al. 2018). Also, in my study, I consider all of Wikipedia: I do not focus only on the article mainspace, but take edits across all namespaces into account, assuming that the same rules and mechanism are valid in the talk or user namespace. The analysis could be refined by future research, making distinctions between different namespaces. With another algorithm parsing the meta data and identifying reverts without a personalised edit summary, future research could aim at replicating the study by Piskorski and Gorbatâi (2017) more closely using data from the German Wikipedia. Such a study could speak closer to the reliability of the findings of Piskorski and Gorbatâi (2017), but it still requires a critical discussion regarding the understanding of norm violations, punishments, and rewards. Further, more insights could be gained when testing Coleman's argument more narrowly, namely restricted to behaviour *within* a network. With the current setup, norm violations, punishments, and rewards against anyone on Wikipedia are considered. In an alternative setup, only those norm violations, punishments, and rewards happening within networks could be included. Such details regarding the setup do not tend to be an issue in the more usual laboratory studies because, in lab experiments, participants tend to be able to interact only with those they are connected to. Different network structures and network positions and their effect on behaviour are then assessed (see e.g. Fatas et al. 2019). On Wikipedia, users have public information about all actions and can punish and reward, even when not being tied to one another. Additionally, to further account for exposure to (potential) norm violations, a setup could be followed which concentrates on relative rates of violation and punishment. Considering rewards, it is an important limitation that I do not know what contributors are being *thanked for*. I do not know why they receive the reward and cannot identify whether a norm enforcer is being thanked by a second or by a third party or is being thanked for another activity altogether. This data is unfortunately not available.

Besides advances in the technical labelling and identification of norm violations, future research might want to understand the substantial meaning and understanding of norms in more detail. Piskorski and Gorbatâi (2017) have conducted some interviews with a small sample of Wikipedians, and as it has been shown that norms on Wikipedia are a matter with cross-cultural differences (Hara et al. 2010), in-depth interviews with (German) Wikipedians could help to better understand their understandings of norm violations and punishments and which role reverts on Wikipedia play. Such interviews could also help at revealing the importance of network ties and their longevity to Wikipedians. Only answers from Wikipedians can help researchers to find out whether a meeting or a collaboration which was five days, five months, or five years ago is still meaningful to the actors involved.

Continuing the cross-cultural work of Hara et al. (2010), it would be interesting to follow up upon differences in reverting patterns. Simply comparing the number of reverts I obtained from the German Wikipedia with those reported from the English Wikipedia in other studies (Anthony et al. 2009; Buriol et al. 2006; Kittur et al. 2007b; Piskorski and Gorbatâi 2017) reveals different and lower numbers. The different language versions of Wikipedia allow for relatively straight-forward cross-cultural comparisons.

This chapter also broadly sketched what type of user reverted whom. The descriptives revealed that a large portion of edits made by unregistered users, so-called IPs, were subsequently reverted. Such descriptions could be extended to better understand revert dynamics. Generally, registering an account gives a user a fixed Wikipedia identity which others will start to recognise. Logging in under a username allows the build-up of trust and respect through a history of good edits[191]. Future research should try to understand why such

[191] Which is explicitly stated in the English Wikipedia, see https://en.wikipedia.org/wiki/Wikipedia:Why_create_an_account.

edits are being reverted. It might well be that unregistered users do not know the rules of Wikipedia or do not even share the goal of Wikipedia and conduct vandalism instead of productive edits (see also Javanmardi et al. 2009). However, experiencing such reverts might also be demotivating to (yet) unregistered users, stopping them from getting registered in the first place—the same way reverts have been observed to be demotivating to newcomers to Wikipedia in the study of Halfaker et al. (2011). The setup of Wikipedia also allows for the assessment of whether the quality and the extent of norm punishments of specific articles depend on the proportion of registered and unregistered users working on it; with this, lab studies which are focused on the effect of newcomers on cooperation could be tested in the field (e.g. Otten et al. 2021).
More generally, edits which are reverted could be investigated in more detail, and the properties of the editor undoing and the one being undone could be compared for example regarding their edit count, and their online and offline networks (see for such analyses also Panciera et al. 2009). Such an analysis comes with its computational costs, as each revert is executed at a specific moment in time and needs to be merged with those time-varying indicators.

Notwithstanding the limitations discussed, this study was the first to replicate, extend and critically discuss the findings of Piskorski and Gorbatâi (2017). It is an important task of research to remain critical of published knowledge and to test previous findings in different contexts. This study was also the first to combine data of offline networks on online norm behaviour and which focused on the role offline ties play regarding norm enforcement. While there is evidence that users who partake in meetings differ in regard to their norm-relevant behaviour from those that do not, I found very little evidence for the relevancy of offline network density on online norm-relevant behaviour. Regarding online networks, I could only very limitedly replicate the findings of Piskorski and Gorbatâi (2017). Future research in other online and offline environments needs to critically reflect on the data availability and operationalisation of norm enforcements, punishments, and rewards, and test the mechanism put forward by Coleman (1988, 1990) in further contexts. In the context of Wikipedia, this study provides important descriptions and ideas which form a starting point for future research.

6 If I Know You Offline, I Will Vote for You Online? Elections on Wikipedia

The following chapter will focus on voting processes on Wikipedia. It will investigate who is being nominated and elected to become administrator, as well as who is voting in these elections. The chapter aims at answering the questions of how both running to become an administrator and voting in elections can be explained. As with all other chapters in this thesis, the focus lies in understanding what role offline meetups play in this context.

6.1 Introduction: Voting on Wikipedia

Wikipedia is based on beliefs about decentralisation and anti-authoritativeness; each contributor is responsible for following the guiding principles as there are no correcting editors or other comparable controlling instances (see previous chapter 5). Still, there are selected users with special rights, permissions, and duties: administrators and bureaucrats. Administrators and bureaucrats are users trusted with access to certain tools and they are expected to observe a high standard of conduct and to use the tools fairly and never to gain an advantage in a dispute. Administrators on Wikipedia have access to additional technical features which support maintenance such as controlling page protection, blocking users from editing, or deleting pages. Bureaucrats have even more technical privileges as they are responsible for granting and removing administrator rights. They are not necessarily powerful supervisors, but important maintainers[192].

[192] There is a third group of special users: stewards. Stewards have the most technical duties and rights and can modify all local and global user rights. They are a multilingual group of individuals, serving all Wikimedia projects. Stewards are elected and reconfirmed annually by the global Wikimedia community. To be electable as a steward, candidates must meet certain account and activity requirements; amongst others, they must have been holding administrator rights on one Wikimedia project for at least three months.

As of July 2022, there are over 1000 administrators and 19 bureaucrats in the English Wikipedia; the German Wikipedia is notably smaller with about 200 administrators and five bureaucrats[193]. Given the small number of bureaucrats, the following analyses on elections will focus on administrators. Typically, administrator privileges are only granted to users who have contributed to Wikipedia for an extended period of time and are actively engaged in the community. Any user who is eligible to vote may nominate themselves or other eligible candidates, as well as participate in the election. Being granted these additional rights is considered a sign of trust (Kordzadeh and Kreider 2016). While the extra rights are primarily technical in nature, in practice, it has been shown that technical and social power cannot be entirely uncoupled (Forte and Bruckman 2008).

To become an administrator, users have to undergo an election process in which the community assesses their trustworthiness. Votes are cast on the promotion of single candidates that have been nominated (by others or themselves at any point in time). Relevant criteria include a strong edit history, varied experience in different namespaces, and having helped with chores such as dealing with vandalism. The official requirements to become an administrator on the German Wikipedia are straight-forward: a user must have been registered and contributing for at least two months and must have reached a minimum number of total (200) as well as recent edits (50 edits in the last two months); the same requirements are also restricting who is eligible to vote. Eligibility criteria vary between different language versions of Wikipedia and have changed over time. Becoming an administrator is one of the strongest forms of getting intertwined with the project and the community.

Elections on Wikipedia are comparable to other elections in the offline world but exhibit some remarkable features: elections are public and all information on the candidate and the voters are displayed and retained. Much previous research in political science is concerned with elections and voting processes: from understanding and explaining voting behaviour in the past (e.g. Bühlmann and Freitag 2006; Campbell et al. 1960; Downs 1957; Lazarsfeld et al. 1944; Topf 1998) to forecasting future election results as precisely and early on as possible (e.g. Leiter et al. 2018; Lewis-Beck and Rice 1984; Murr and Lewis-Beck 2022; Murr et al. 2019), electoral research is a popular field of research.

[193] See for an overview of current numbers https://meta.wikimedia.org/wiki/Administrators_of_Wikimedia_projects/Wikipedias.

Several studies have previously researched voting behaviour on Wikipedia, most of them following a machine learning paradigm. They aimed less at explaining the data generating process but instead on modelling and validating prediction models, framing voting as a prediction or classification problem (see e.g. Asim et al. 2018; Burke and Kraut 2008; Leskovec et al. 2010a; Nuñez-Gonzalez and Graña 2014, 2017). Numerous studies have also taken the social network in voting processes into account. This chapter will build upon these previous lines of research and adopt a sociological perspective. I will try to understand how behaviour at elections on Wikipedia can be explained and specifically, how the participation in offline meetups might influence an editor's voting behaviour as well as their decision to run for administrator.
This chapter will explore four different explananda:

1. Who runs for administrator?
2. Who becomes administrator?
3. Who votes in elections?
4. Who votes supportively/opposingly in elections?

Given all four questions, the focus will lie on the relevance of offline meetups. This chapter is structured as follows: in the next section, I will discuss voting theory and the previous state of research on elections on Wikipedia. The section will start with the classical studies of voting, highlight the importance of social ties in the voting process, and discuss public voting assemblies which share notable similarities with elections on Wikipedia. Testable hypotheses will be derived. After the theoretical part, the data and methods used for this chapter will be discussed before the results are presented in section 6.4. I then draw conclusions in section 6.5.

6.2 Voting Theory

There is a long history of research on voting behaviour. Starting with classical prominent studies by Campbell et al. (1960), Downs (1957) and Lazarsfeld et al. (1944), researchers have since tried to explain and predict voting behaviour.
There are several theories which emphasise different factors which may shape citizens' voting behaviour. Many influential theories ignore the influence of

an individual's social network in forming vote choices—and instead focus on effects of a person's political attitudes such as party identification, or on rational calculations including the parties' ideological positions (e.g. Campbell et al. 1960; Downs 1957; Lee et al. 2017). However, other theories offer models of electoral behaviour in which individuals are analysed within their social networks and environments. These streams take the social network and/or the contextual dimensions of a voter into account. The importance of social contacts in voting was firstly stressed by Berelson et al. (1954), Katz and Lazarsfeld (1955) and Lazarsfeld et al. (1944). They discussed how the social group a voter belongs to plays a notable role in voting behaviour and that social characteristics determine political preference. Lazarsfeld et al. (1944: xiii) conducted surveys on individual voting in presidential elections and identified the information flow through networks of interpersonal communication as a decisive factor: "[...] face-to-face contacts turned out to be the most important influences stimulating opinion change". In the evolving line of research, face-to-face contacts were made out to be of central importance in processes of opinion formation. In contrast to what was expected at the time, the data clearly showed that voting is not an individualistic act, not only determined by a voter's personal predisposition and exposure to the media. Personal influence was discovered to be an important variable in explaining voting behaviour (Eulau 1980) and voting was found to be a group experience (Lazarsfeld et al. 1944). Further, political homogeneity of social groups was found, noting that people who work, live, or play together are likely to vote for the same candidate.

Most existing research has since confirmed that social influences play a decisive role in voting: observational and experimental studies have shown how the decisions of if and how to vote can be affected by people in one's social network such as family and household members, friends, and co-workers (see e.g. Bond et al. 2012; Huckfeldt 2003; Huckfeldt and Sprague 1991; Kenny 1992; McClurg 2004; Nickerson 2008; Pattie and Johnston 2000; Santoro and Beck 2016). Many previous studies have shown that formal—such as memberships in association or religious communities—as well as informal networks—such as with family, friends, and neighbours—play a significant role in explaining and understanding political participation (Fieldhouse and Cutts 2012; Giles and Dantico 1982; Huckfeldt 1979; Lim 2008; McClurg 2003; Putnam 2000; Verba et al. 1995; see for an overview also Campbell 2013). Presently, voting tends to be considered a social act partly driven by the social context of the voter (Bhatti and Hansen 2012).

People discuss their political attitudes within their networks which can shape their individual choices (Pattie and Johnston 2001). Discussions with friends who are interested in politics can help people to learn about reasons for participation and about the mechanics of politics. These ties can help diffuse information on how to get involved and about the current state of the political sphere (Knoke 2004; McClurg 2003). Huckfeldt and Sprague (1991) see individuals as parts of loosely knit networks in which information is transmitted through discussions. Individuals then adjust their opinions on the basis of the perceived quality of the information from individual discussants (the effects of personal conversations have also been discussed for example in Italian campaigning, see Campus et al. 2008). Sinclair (2012) point out how social relationships are more than mere sources of information and how they can actively influence political decisions. Basic political acts are shown to be subject to social pressures: others in a social network notice and might conform to expressions of political opinion, in particular if conformity is likely to be highly visible. The social network can matter as the group can instil shared attitudes that drive the given behaviour, or by a desire to conform to dominant group behaviour (Bhatti and Hansen 2012). The interplay of personal and individual attitudes and network effects or influences is complex. Lazer (2001) stresses the co-evolution of these processes as individuals simultaneously shape and are shaped by the networks they are embedded in. Verba et al. (1995) have developed a model of civic voluntarism. In their study of non-voters, they classify them into three groups: those that cannot vote due to a lack of resources like time, money, and civic skills; those that do not want to vote due to a lack of motivation and interest, as well as a lack of considering their vote meaningful; and those that were not asked to vote due to a lack of being recruited through their social network.

Recently, the role of the internet has also been increasingly discussed in research on elections (see for an overview e.g. Zhuravskaya et al. 2020). For example, it has been found that the spread of the internet and social media has contributed to the electoral success of populist parties in Europe (see e.g. Schaub and Morisi 2020). In line with this, much research in the past few years has investigated mis- and disinformation—often termed "fake news"—on the internet and in particular on social media. Also, bots—software applications that run automated tasks (scripts) over the internet—have reportedly been used to interfere in political discussion online and manipulated elections (Ferrara 2020). More generally, it has also been shown that social media can be used to mobilise voters. In their paper which gained a lot of media attraction, Bond et al. (2012) describe a field experiment on Facebook which involved 61 million participants. During the 2010 US congressional election, they showed Facebook users in their treatment group either messages with information about elections, or another version of the message that showed which Facebook friends indicated that they voted. They found that the social message that mentions Facebook friends increased self-reported voting participation. Compared to validated turnout, the effect decreased substantially though. The message only containing information about the election did not have an effect on voting (see also the replication study for the 2012 US presidential election Jones et al. 2017). Bond et al. (2012) and Jones et al. (2017) argue that their results provide evidence that online social networks can spur social influence by activating offline social relationships.

Rainie (2012), studying the US presidential election 2012, has highlighted that social media has become a significant place of political discussion. He found that 22 per cent of registered voters have let others know how they voted on a social media network site, that 30 per cent have been encouraged to vote by family and friends via posts on social media, and 20 per cent have encouraged others to vote themselves (with percentages varying greatly across different age groups). Comparing online and offline networks in the 2011 parliamentary elections in Egypt, Rizk (2014) found that physical, offline networks were significantly more influential than digital networks in shaping people's voting decisions (but low literacy levels and limited access to the internet need to be kept in mind).

de Zúñiga and Valenzuela (2010) have combined online and offline social networks in the studying of civic engagement. Focusing on the strength of ties and the size of networks, they find that online networks entail greater exposure to weak ties, but generally, that the effects of both online and offline networks on civic engagement are similar. Their results are based on egocentric network data from a national survey. This study was sparked by research suggesting that media consumption—particularly television and internet use—was a strong but negative predictor of civic engagement (Kraut et al. 1998; Putnam 2000). However, these propositions were challenged, and it was highlighted that it matters how time with media is spent exactly; media can both encourage or discourage civic behaviour (Shah et al. 2001; de Zúñiga et al. 2010).

Going under the term of online voting, a large body of research has investigated E-Voting systems, most studies focusing on the Estonian case. Unt et al. (2017), for example, analysed whether the online voting system takes away the social nature of voting and reduces the sense of civic duty. Using individual level log data on internet voting in Estonian elections between 2013–2015, they find that online voting still takes place in groups and is a collective experience.

Most of the previous studies in political science are concerned with secret ballot voting—today's most popular form of voting. However, the Wikipedian context is quite different: voters take part in a dynamic voting process where the votes of others are observable. There is no norm for voting secrecy. The voting process on Wikipedia is thus more comparable to a public assembly vote. Furthermore, the voting pages on Wikipedia also work as channels of communication, allowing the candidates to introduce themselves and answer questions, allowing for negotiation and discussion.

6.2.1 Public Assembly Voting

The body of research on elections has been primarily developed on the basis of large European and American elections where voters are making decisions between parties and candidates and vote anonymously and secretly. Elections on Wikipedia, in contrast, are peculiar cases: over the course of usually two weeks, registered users decide whether nominated others should be granted special rights and gain the status of administrator or bureaucrat. In this voting process, they can ask questions and comment on a public site, thus expressing their vote in a public space. This also means voters can observe each other. Votes cast on Wikipedia become public information.

In the "real world" today, such public voting processes exist only in a few selected places such as many Swiss communes, a few Swiss cantons and generally smaller town meetings. In contrast to secret ballot voting, they have received much less attention from the scientific community. See for research on public assembly votes for example from Switzerland Gerber et al. (2019), Schaub (2012), Stadelmann-Steffen and Dermont (2016) and Stadelmann-Steffen and Gerber (2020) and from New England Bryan (2004), Mansbridge (1983) and Zimmerman (1999). Besides these studies, public assembly votes have been largely ignored (Stadelmann-Steffen and Dermont 2016). Most of the previous research efforts focused on discussing how democratic such public votes are as well as on explaining general election participation; it has been found that voter turnout is generally much lower in assembly meetings than by ballot (Bryan 2004; Ladner 1991, 2002; Zimmerman 1999). However, this reduced turnout is explained by the extra effort necessary to vote during an assembly meeting and is not applicable to online votes on Wikipedia.

Also, in contrast to assembly votes, Wikipedians do not vote at the same time but vote after one another; while this somewhat resembles a roll-call system which is in place in legislative votes (Peoples 2008), the strategic elements of these roll-calls are not in place on Wikipedia as there is no defined set and order of voters and people are also free to change their vote during the course of the election.

Manin (2015) has explicitly pointed out the disadvantages of non-secret voting, identifying three dimensions: 1) social control, 2) private rewards, and 3) dominance by the powerful. Open voting allows for pressure and influence, particularly from one's immediate social environment such as friends, family, neighbours, or colleagues. Voting can also become a transaction open for rewards as the action can be monitored. Thirdly, the rich and powerful have resources necessary for social control or for bargains which gives them an advantage. Due to the observable nature of the decisions of all others involved, social pressure can influence an individual's decision. There are many experiments on the effect of group conformity and social pressure. Most prominently, Asch (1955) conducted laboratory experiments in which he tested the urge to social conformity. His results were impressive: respondents in his experiments gave wrong answers to rather simple and obvious questions to conform with a majority giving a wrong answer. This study has been replicated across multiple countries and different behavioural domains (see for a meta-analysis Bond and Smith 1996).

Regarding voting, much attention has been paid to the importance of conformity on turnout (Coleman 2004), including the effects of social pressure on the electoral behaviour of people. Social pressures can emphasise the social norm of voting, its value within a community, and the public nature of voting records, reminding one that voter turnout is monitored. Sending mailers with these reminders has been shown to increase voter turnout (Gerber et al. 2008, 2010; Panagopoulos 2010) and interpersonal voter contact has also shown to produce an increase in participation (Gerber and Green 2000; Nickerson 2006; Rosenstone and Hansen 1993; Townsley 2018). These personal strategies of campaigning have been shown to be effective. Also, the mention of elections on social media profiles has been found to increase voter turnout (Bond et al. 2012; Haenschen 2016). These studies have not focused on public assemblies but on secret ballot voting. However, when such effects exist in secrecy, it can be assumed that they are even stronger in public. In the case of public votes, the behaviour of a person's network is visible; when behaviour is visible, it becomes especially influential (Sinclair

2012). As the social network has shown to matter when deciding to vote, the network can also induce compliance with desired social norms (Mallinson and Hatemi 2018).

6.2.2 Elections on Wikipedia: State of Research and Hypotheses

The previous sections demonstrated that social networks and their dynamics can significantly impact the real-world decision to vote. This section will now outline how features of social networks can influence elections in the virtual space and use the offline theories to derive hypotheses testable in the online space. This study is not the first to investigate determinants of voting and election success on Wikipedia. The majority of the previous research stems from machine learning oriented fields in which they aim less at explaining the data generating process but instead frame it as a prediction problem (election participation prediction problem and vote sign prediction problem).
This study is concerned with hypotheses regarding four different explananda: **r**unning as administrator (hypotheses R), **w**inning elections (hypotheses W), **v**oting in elections (hypotheses V), and voting supportively, i.e. voting **p**ro, in elections (hypotheses P). The hypotheses will be derived in the following and previous research will be discussed. While the first two subsections will focus on the successful promotion of candidates and the characteristics of the newly elected administrators, I will then go beyond the individual perspective to focus on ties. Subsection 6.2.2.3 will focus on the relationship between voter and candidate, and subsection 6.2.2.4 will discuss to what extent the relationships between voter and other voters matter. Much previous research, even rather recent studies, used the Wikipedia dump of 2008 and the dataset prepared by Leskovec et al. (2010a,b) or focused on the Polish Wikipedia (like e.g. Turek et al. 2011). To my knowledge, there is no research on elections in the German Wikipedia or more generally, in other online communities with comparable election processes.

6.2.2.1 Running to Become an Administrator

Before an election can take place, users need to be nominated, either by themselves or by others. Which people are trying to become leaders—which users are running as administrators? These questions have gained only little attention so far. Beyond open-source online projects, positions of leadership generally come with additional rights and privileges, such as better pay or more autonomy, for example in occupational management positions. However, reiterating the points made in section 4.2 when discussing productive behaviour on Wikipedia, contributing towards Wikipedia comes with little utility in return. Just as active article writers, administrators do not receive any sort of financial payment.

Making again use of the framework outlined by Crowston and Fagnot (2018) (see section 4.2), it can be argued that face-to-face meetings offer an additional venue for interaction and strengthen a user's commitment to the online community. Understanding Wikipedia as a social movement, administrators can be compared to leaders of such. Ganz (2010) discusses the challenges regarding leadership in social movements and highlights the important role of relationships. Given the general importance of networks in social movements (see e.g. Diani and McAdam 2003), it can be expected that a user who is involved in the offline component of Wikipedia might also be more inclined to get even more involved online. Another line of argumentation is also imaginable: instead of arguing that users who are active meetup goers also want to take on a more involved role in the online community, it might also be the case that users want to become administrators first and decide to take part in meetings to signal more commitment (or even campaign at meetings) and increase their chances. Stegbauer (2009 chapter 15), who has also explored face-to-face meetings of Wikipedians, mentioned that meetings are integral in deciding on new administrators and that attendees talk about who should be nominated next.

All lines of argumentation lead me to expect a positive effect of the attendance of meetups, and thus the following hypotheses:

Hypothesis R1: The more meetups a user has attended, the more probable they are to run as administrator.

Hypothesis R2: The more other users a user has met, the more probable they are to run as administrator.

The network position of users might further affect their probability to run as administrator. Centrality is a node attribute which captures how central or important a node is in a network. I assume that users which are central in the offline network might also strive for a position of importance in the online space.

Hypothesis R3: The probability to run as administrator increases the more central the position of a user in the offline network is.

6.2.2.2 Promotion Success: Candidate's Characteristics

In elections, the candidate(s) with more (or enough) voter support wins. In line with ideas based on the concept of social capital (see section 2.1.1), being connected to others positively influences the probability to be elected: relationships have value and having positive and supportive ties should increase support at elections. Furthermore, potentially strong ties in the offline world should be helpful as these offer additional channels a candidate can activate for support. Research on face-to-face meetings further suggests that meetings work as informal spaces where attendees select or at least discuss new administrators (Stegbauer 2009 chapter 15) so that meetings can also expose users to information about elections; they might be even encouraged to run as administrator. Attending meetings might further signal stronger commitment to Wikipedia. It might thus function as an indicator of a candidate's quality. Given the public nature of meetings, information about meetup attendance is generally available to the voters even if they have not attended meetings with the candidate; in this sense, it can work as a cue about candidates (similarly, in "real-world" elections, prior political experience can work as such a cue, see on this e.g. Portmann 2022). In this line, I assume that the sheer attendance of meetings also influences the probability of winning. This reasoning can also be applied to the network position: more central nodes are expected to be more likely to become administrator as this also signals commitment and power.
In summary, this leads me to the following three hypotheses regarding the probability of winning elections:

Hypothesis W1: The probability to win an election increases with the number of meetings a candidate has attended.

Hypothesis W2: The probability to win an election increases with the number of voters a candidate has met.

Hypothesis W3: The probability to win an election increases the more central the position of a candidate in the offline network.

To date, a large body of research focused on what characteristics make a candidate most successful on Wikipedia. While there are some basic requirements in place which must be fulfilled so that a user is eligible to run as administrator (minimum tenure and activity), just fulfilling the minimal requirements is not enough. Burke and Kraut (2008) and Kordzadeh and Kreider (2016) highlighted which individual factors are relevant for the success and promotion of users: they find that having an extensive and diverse experience on Wikipedia, a high level of total contributions, and a longer tenure exhibit positive effects on the probability of being promoted. Also, users who undertake article-level coordination and who make their contributions transparent by making use of technical features like edit summaries are more likely to be elected. On the other hand, the number of attempts at becoming an administrator negatively impacts the probability to be elected. Burke and Kraut (2008) also include social activity by including editing on user talk pages. In particular, they measure whether candidates interacted with other administrators and bureaucrats. While they do not discuss their effects in detail, their overall model fares well at predicting successful election outcomes.

This is in line with the findings of Picot-Clémente et al. (2015) who also take the ties of a candidate into account and find that interaction with other users and other administrators, measured as exchanging messages on talk pages, is relevant in explaining promotion success. Oppong-Tawiah et al. (2016) use semantic analysis and make use of the comments posted on election pages. They find that the most influential determinant in explaining promotion success is structural capital in the community's core activity (measured as eigenvector centrality) while being socially connected to other community members, in general, is important. They distinguish two measures of social connectedness in their analysis: sentiment score (reflecting the aggregate public opinion measure of a candidate's level of social connectedness at the overall community level) and sentiment similarity index (reflecting social connectedness at the individual dyadic level). While both measures show positive and significant effects, the effect of sentiment similarity is remarkably larger. Interaction effects further show that low centrality can be mitigated by cultivating high social connectedness.

Overall, research suggests that being connected to others online positively influences the probability to be elected; my study will test to what extent this translates to offline connections.

6.2.2.3 Voter-Candidate-Relationship

While the previous subsection focused on individual characteristics of successful candidates, the following one will focus on the *voter* and their relationship to the candidate, i.e. on the ties. Hypotheses regarding the probability to vote at all and the probability to vote positively in elections will be derived in this and the following subsection.

A direct relationship between a potential voter and the candidate can make the potential voter more likely to actually vote. On one hand, this might follow from perceived obligations to support friends (social capital encompasses obligations to others, as argued e.g. by Coleman 1990). As the voting process on Wikipedia is public, candidates know who voted and who supported them so that it is visible to them whether their friends and acquaintances have fulfilled their expectations; there thus can be a certain pressure to vote. On the other hand, beyond Wikipedia in the context of secret ballot voting, there is a well-documented friends-and-neighbours-effect which shows that local ties of a candidate are crucial and that candidates in various electoral settings receive more electoral support in and around their hometown area (Arzheimer and Evans 2012; Campbell et al. 2019; Herron and Lynch 2019; Jankowski 2016; Johnston et al. 2015; Key and Heard 1949; Put 2021; Put and Maddens 2014; Tavits 2009). The mechanisms underlying this effect remain largely untested apart from the study by Campbell et al. (2019). Using survey experiments, they find that local roots allow voters to make inferences about politicians' actions. This argumentation can also hold in the context of Wikipedia: voting for a user one knows reduces uncertainty as one better knows what to expect. Generally, if two users have met, they have more information about one another and can thus also be more likely to cast an informed vote (without needing to occur extra costs by collecting information via other avenues).

In this study, it will be tested whether meetup ties lead to an increase in the probability to vote at all, and whether meetup ties influence the probability to vote supportively (assuming positive interactions at offline meetings):

Hypothesis V1: The probability to vote increases if the user knows the candidate, i.e. they have attended a meeting together.

Hypothesis P1: The probability to vote positively increases if the user knows the candidate, i.e. they have attended a meeting together.

In a previous study using data from the Polish Wikipedia, Jankowski-Lorek et al. (2013) and Turek et al. (2011) model the election process using a multidimensional social network, distinguishing different forms of ties (like co-editing, reverting, or discussion on talk pages). They find positive effects of co-editing while having a shared revert history leads to opposing votes. There is only weak evidence that the discussion interaction matters.

When voting, users assess whether a candidate is a good fit for the position. This assessment can, on one hand, be a simple assessment of whether the candidate fulfils certain criteria. On the other hand, it can also be a relative assessment in which the attributes of a candidate are compared to the voter themselves. Whether a positive vote will be cast is then not a function of just the candidate alone, but a function of both the candidate and the voter and their relation to each other (Leskovec et al. 2010a). I assume that candidates which fare better on this relative assessment are more likely to be supported as voters search for the most qualified users to become administrators. As outlined in the previous subsection, I assume, and it has been shown (by Oppong-Tawiah et al. 2016; Picot-Clémente et al. 2015), that being strongly embedded within other users makes a candidate more probable to be successful in their candidacy. Taken together, I expect that the centrality of users is also assessed in relative terms:

Hypothesis P2: The probability to vote supportively increases the more central the position of a candidate in the offline network in comparison to the position of the user.

Using the English Wikipedia, Leskovec et al. (2010a) analysed the assessment strategies of voters (years 2004 to 2008). Certain forms of relative assessments have shown to matter in their analysis. Positive votes were observed to be more probable when a nominee has a greater number of edits and/or greater number of barnstars—awards given by other Wikipedians—than the voter.

6.2.2.4 Voter-Voter-Relationship

While the previous subsection has focused on the relationship between an election's candidate and the voters, I will now address the relation between different voters.
Voting in the "real world" is described to be a social experience with people sharing political decisions, discussing them, and often voting together (Unt et al. 2017). The voting process on Wikipedia can be observed by everyone, and it can be argued that observing friends who are voting can highlight one's duty to also vote (Verba et al. 1995); social interactions can have a mobilising effect (Rosenstone and Hansen 1993). Additionally, it can reduce the cost of information: a potential voter might be able to get information about the election directly from their voting contact or trust their decision altogether without needing additional information (Sinclair 2012). Furthermore, there might also be the expectation of one's friend to share the same opinion. In Wikipedia's setting, conformity is highly visible so that voting might be influenced by social pressure (Sinclair 2012).
In summary, in line with these arguments brought forward regarding public voting, it can be expected that users might vote like their offline friends. This leads to the following hypotheses:

Hypothesis V2: The probability to vote increases, the more other voters a user knows.

Hypothesis P3: The probability to vote supportively increases, the more other voters who vote supportively a user knows.

Hypothesis P4: The probability to vote supportively decreases, the more other voters who vote opposingly a user knows.

Only little research has been conducted on this so far. Cabunducan et al. (2011) and Lee et al. (2012) found that voters tend to participate in elections that their contacts have participated in, and they find evidence that an individual's decision-making is influenced by their contacts' actions. Several network characteristics are also influencing the voting decisions, such as degree, betweenness or closeness. In their setup, ties are based on communication on users' talk pages.

6.3 Methods and Data

This section will describe the data, methods, and statistical approaches used to analyse elections and voting behaviour on Wikipedia. It will also give a descriptive overview of the data used and describe the election process in more detail. I will refer to chapter 3 when making use of the general data which is used in multiple of the three topical chapters.

6.3.1 Election Data

The following will discuss the election data used. In a first step, I will outline how elections on Wikipedia work and what they entail. Following this, I will discuss the data collection, and lastly, describe the data collected.

6.3.1.1 Understanding the Election Process

The process of becoming an administrator on Wikipedia has not been stable throughout the past twenty years but has evolved with Wikipedia. The process was less regulated in the early days of Wikipedia when it was also generally easier to become administrator. Potential candidates were found through the mailing list of Wikipedia by asking users about their interest in the position and the task. In January 2003, there were seven administrators. As of May 2003, suggestions for administrators were starting to be centrally collected on a site on Wikipedia, and since 2006, each candidacy is being discussed on its designated subpage. In the beginning, there was no well-defined procedure for elections; candidates needed to be endorsed by other users and bureaucrats had substantial leeway in promoting other users.
As of March 2004, following a suggestion[194], new guidelines for the promotion process were drafted[195]. Generally, to become an administrator on Wikipedia, an eligible user (formal eligibility criteria will be discussed in more detail below) must be nominated or self-nominate. This is possible at any point in time; there are no calls for application and there is also no fixed number of

[194] See https://de.wikipedia.org/w/index.php?diff=871105.
[195] See https://de.wikipedia.org/w/index.php?diff=977809.

administrators. During the election, the voting community looks for a variety of factors beyond the eligibility criteria which allow them to determine the trustworthiness of nominees; successful candidates generally must have shown significant positive contributions to Wikipedia. Relevant criteria include a strong edit history, user interaction, varied experience (from article contribution to discussions on Wikipedia policies), and helping with chores such as dealing with vandalism[196].

Nominations will generally remain active for two weeks during which Wikipedians are welcome to make comments and ask questions. While all, even unregistered, users can comment on the election and ask questions, only users that are logged in can numerically cast votes in the *support*, *oppose*, and *neutral* sections. For a candidate to be appointed administrator, at least 50 users should have voted supportively within two weeks (this number increased over the years), with at least two thirds of the total votes cast being in favour of the candidate. At the end of the voting period, bureaucrats will review the discussion and have some room for interpretation in determining whether the requirements for the candidate and those voting have been met. In other language versions, bureaucrats tend to have even more room in deciding whether to promote a user to administrator and the election is seen not as a strict vote, but as a consensus-building process. This is less the case in German Wikipedia where the results of the elections are decisive.

Votes on Wikipedia can be and often are accompanied by a statement. In many cases, users give a short reasoning on why they have made their choice. These reasonings can be extensive, particularly when users oppose a candidate. In any case and even if not eligible, users are invited to join the discussion about a candidate on the corresponding talk page of an election. On these discussion pages, additional questions are raised for the candidates to answer. These often refer to past performance of the potential candidate, asking about why they have made certain decisions (e.g. reverted certain edits) and about their general attitudes towards maintenance topics such as their stance on sock puppets or the notability criteria. Discussion pages can also be used to discuss the introductory text of the administrators or discuss the statements other users made when casting their votes. These discussion pages can be friendly spaces in which a few users ask for clarifications on certain statements or behaviours. However, they can also be conflict-laden such as the discussion page of one female candidate: in the course of this dis-

[196] See for information about relevant criteria https://en.wikipedia.org/wiki/Wikipedia:Guide_to_requests_for_adminship and https://de.wikipedia.org/wiki/Wikipedia:Administratoren.

cussion, the user was not only harshly criticised multiple times for her past behaviour, but there was also a discussion on the general tone of the election. Users were discussing to what extent the election showed misogynistic tendencies. As the election also ended as a rather close call with numerous users opposing her, some asked for a second ballot. In the end, she became an administrator after a recount of the results.

Administrators can be re-approved or rejected via the process of re-elections. A motion for re-election can be supported at any time by signing the re-election page created for each admin in the Wikipedia namespace. Re-election occurs if at least 25 users support the motion within one month or 50 users support the motion within six months. Any administrator is free to stand for re-election even if the number of supporters of the re-election motion is not reached. However, if it is reached, re-election is mandatory unless the administrator voluntarily steps down[197].

All previous elections are archived[198]. Overall, considering all previous requests for adminships, the majority of candidates were successful (60 per cent success rate to become a new administrator). Some candidacies were ended early for manifold reasons. Firstly, some users who ran for administrator were not eligible and their candidacy thus not valid. Second, some users, while technically eligible, were not well-known enough in the Wikipedia community and faced some critical questions after the start of their election. In these cases, they often retracted their request for adminship themselves.

Eligibility to Vote To find effects of features of candidates and voters, the pool of possible candidates and voters must be known to make adequate comparisons. The pool of possible candidates and voters is assumed to consist of everyone eligible. Active and passive eligibility criteria are identical on the German Wikipedia; everyone eligible to vote is also eligible to run as administrator. Eligibility criteria are stated publicly on a designated Wikipedia page[199].

These criteria comprise the following features (as of April 2020):

- The user has a registered account.

[197] See https://de.wikipedia.org/wiki/Wikipedia:Administratoren#Wiederwahl.
[198] See https://de.wikipedia.org/wiki/Wikipedia:Adminkandidaturen/Archiv.
[199] See https://de.wikipedia.org/wiki/Wikipedia:Stimmberechtigung#Allgemeine_Stimmberechtigung.

- The user has been actively working on Wikipedia for at least two months (i.e. the first edit of a user cannot be younger than two months before the election date).
- The user has made at least 200 edits in the article namespace (i.e. not counting edits on talk or discussion pages), with at least 50 in the last 12 months.

Blocked users, sock puppets[200], bots, and other additional accounts of the same person are excluded from the election processes.
In the early days of Wikipedia, there were no well-defined eligibility criteria. A first rule book was set in March 2004[201]. The criteria then included that users must have a registered account, must have been active on Wikipedia for at least two months, and must have made at least 50 edits. These criteria were extended in April 2005 after a vote[202], and again in January 2010[203]. In 2005, the expected total number of edits was increased, and in 2010, the requirement of having shown some recent activity was added.

6.3.1.2 Collecting Election Data

Data on the voting processes is not available in a structured meta data format because it is not process-generated. However, the elections generally followed a pre-defined structure which allowed for an easier, more automated collection process than for the meetups. For each election, there is generally one separate Wikipedia page[204]. This page presents an introduction of the candidate, the beginning and end date of the election, and designated *support*,

[200] Sockpuppetry is an online phenomenon referring to the creation of fake accounts made for purposes of deception. On Wikipedia, sockpuppetry refers to the misuse of multiple Wikipedia accounts. While there are valid reasons for the creation and maintenance of multiple accounts—such as maintaining a bot account which fulfils small, automatable tasks, or for other legitimate reasons such as for reasons of privacy, security, or humour (see for an overview of legitimate uses https://en.wikipedia.org/wiki/Wikipedia:Sockpuppetry#Legitimate_uses)—it is not permitted to use sock puppets to deceive or mislead other contributors, disrupt discussions, distort consensus, avoid sanctions like blocks, or otherwise violate community policies. Users are generally expected to use only one account to maintain accountability and increase community trust. See for more information on sock puppets https://en.wikipedia.org/wiki/Wikipedia:Sockpuppetry and, in German, https://de.wikipedia.org/wiki/Wikipedia:Sockenpuppe.
[201] See https://de.wikipedia.org/w/index.php?diff=977809.
[202] After a a so-called *Meinungsbild*, see https://de.wikipedia.org/wiki/Wikipedia:Meinungsbilder/Stimmberechtigung.
[203] See https://de.wikipedia.org/wiki/Wikipedia:Meinungsbilder/Erg%C3%A4nzung_der_Wikipedia-Stimmberechtigung.
[204] Archiving standards slightly changed across the years.

oppose, and *neutral* sections for the voters. Voters make an edit in the section corresponding their opinion and sign with their name.

A script was written in *R* which functioned as a web scraper using the packages *rvest* (Wickham 2016b) and *httr* (Wickham 2020), visiting all years of elections and extracting the election information. All elections are archived[205] with separate archives for the years. The voting process has changed slightly throughout the years which required a slightly different web scraper for the different years. In the early days of Wikipedia in 2003, potential administrators were mostly suggested by one user and then accepted the nomination, while in 2020, 300 people cast their votes in favour or against candidates.

The web scraper visited each election page and tried to collect the candidate's name, the date the election closed, and all voters taking part in the election as well as the direction of their vote. Aborted elections were also collected. To collect the voters and their opinion, the web page was split into separate parts by the section headings. The web scraper then collected which user signed under which text part, therefore identifying which user voted how. In case a username appeared in multiple parts of the text, it was classified as a problematic vote and checked manually. This happened in cases where users changed their opinion and crossed out one of their votes or if they put their vote in one part but commented on a vote cast by someone else in another part. The latter happened for example if they started a discussion with a voter in another part or if they indicated that a user was not eligible to vote. This is one potential source of error in the data: if a user only commented in one part of the voting process without commenting somewhere else and without voting, the user was registered as having voted. If a user voted in one part and then retracted their opinion without changing it to another part of the text, this was also not registered by the web scraper. If a user voted multiple times in an election in the same way (e.g. supporting a candidate twice), only one vote was collected. If a user voted multiple times in an election but in different ways (both supporting and opposing a candidate in the same election), both votes were counted. This only happened very rarely; most of the time, users changed their minds explicitly and crossed out their previous vote.

Eligible Voters Using the data dump (see section 3.1), a list of all eligible users was created for each election date based on tenure and activity. Users that were not eligible to vote but still voted are excluded from the analysis.

[205] See `https://de.wikipedia.org/wiki/Wikipedia:Adminkandidaturen/Archiv`.

As bots are not eligible to vote, they were excluded[206] Users that were blocked at the time of the election for at least two weeks were also excluded[207]. Sock puppets are not as easily and clearly identifiable as bots as there is no flag as sock puppet. It is thus not possible to identify them from the list of eligible users. It can only be assumed that they were blocked or not active enough to gain eligibility in the first place.

Eligible Candidates A list of eligible voters can be collected for the point in time of the elections. However, any day could be the start of a new election when focusing on potential candidates. Considering the dynamic nature of the present eligibility criteria, the pool of potential candidates can change from day to day; however, new users can only join the sample after having been registered for at least two months, and it is also the activity from the past two months that is taken to assess the recent activity.

As a daily collection of all eligible candidates is computationally expensive and not feasible, monthly collections were executed[208]. Eligibility data was collected for each first of the month (data on total edits and most recent edits) and merged with any other network and activity data up to that point. These monthly data were then collapsed into yearly data for easier analysis. The independent variable, in this case, was whether a user was running as an administrator in the course of the year.

Users are able to run for administrators multiple times a year. Users that are currently administrators are also able to stand for re-election. However, this analysis is only concerned with the first transition towards adminship. Thus, users that are currently administrators are considered not to be eligible for election.

[206] Bots are listed and generally flagged on Wikipedia and were collected from the following sites: https://de.wikipedia.org/w/index.php?title=Spezial:Benutzer&offset=&limit=500&group=bot, https://de.wikipedia.org/wiki/Kategorie:Benutzer:MediaWiki-Systembot, https://de.wikipedia.org/wiki/Kategorie:Benutzer:Bot_ohne_Flag, https://de.wikipedia.org/wiki/Kategorie:Benutzer:Inaktiver_Bot_ohne_Flag, and https://de.wikipedia.org/wiki/Kategorie:Benutzer:Inaktiver_Bot_mit_Flag.

[207] The list of blocked users was obtained from https://de.wikipedia.org/wiki/Spezial:Logbuch/block and older entries from https://de.wikipedia.org/wiki/Wikipedia:L%C3%B6schkandidaten/Archiv:Benutzerblockaden-Logbuch. Details on information given in the logbooks can be obtained here https://de.wikipedia.org/wiki/Hilfe:Benutzer_sperren.

[208] A monthly collection can also be broadly justified with the Nyquist–Shannon sampling theorem from the field of signal processing. The theorem states that a sufficient sample-rate is anything larger than double the bandwidth samples per second (Shannon 1949). Applied to this context, a monthly sampling should be sufficient as new users can only join the sample after having been registered for at least two months.

When merging the voting data with the eligibility data, there were 22 cases in which an election featured an administrator candidate who was not actually eligible to run. This was especially prevalent with elections happening around the date of criteria changes. It might well be the case that these criteria changes were effective a few days later than recorded or that the users were negligent in enforcing the stricter rules right away. Those elections that did seemingly not have an eligible candidate are excluded from later analysis in section 6.4.

6.3.1.3 Description of Election Data

Overall, 1213 elections took place on the German Wikipedia in the time frame observed (including re-elections). The first election recorded took place on April 9, 2003 and did not have any recorded voters, and the last one ended on March 16, 2020 after 257 users voted. Both elections led to a new administrator. In total, 60.1 per cent of elections were successful and the candidate became a new or re-elected administrator.

The distribution of elections over time is pictured in figure 6.1. Please note that elections happening in 2020 are not plotted to allow for better comparability across years as data collection took place in April 2020. Up to April, a total of five elections took place in 2020 with three being successful (60.0 per cent). As seen from the figure, the number of elections peaked in the early years of the German Wikipedia and decreased across the years. The proportion of elections with a successful outcome remains relatively similar across the years. A decrease in the number of elections can be explained by a decreasing need for new administrators once a stable stock had been established.

The number of voters per election varies from 0 (in the early days of Wikipedia) to 533 with a mean of 168.35 (median 165, standard deviation 110.91). The number of votes has increased steadily in the first years of the German Wikipedia and has remained stable, attracting around 200-300 voters per election (see the boxplots in figure 6.2). In 2003, when there was no real election procedure in place, no votes were being cast and counted.

Across all elections, the number of supporting votes is, with a mean of 113.16 (median 99, standard deviation 88.92, minimum 0, maximum 400), much higher than those of the opposing votes with a mean of 40.54 (median 24, standard deviation 43.35, minimum 0, maximum 257). As seen in figure 6.3, there is no notable relationship between the number of supporting and opposing votes cast in an election.

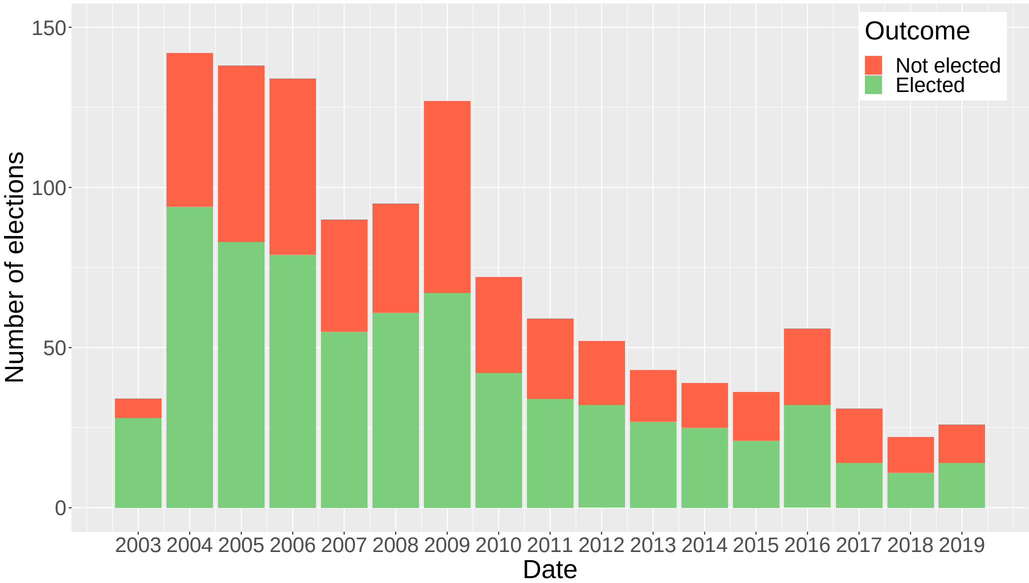


Figure 6.1: Temporal distribution of elections.

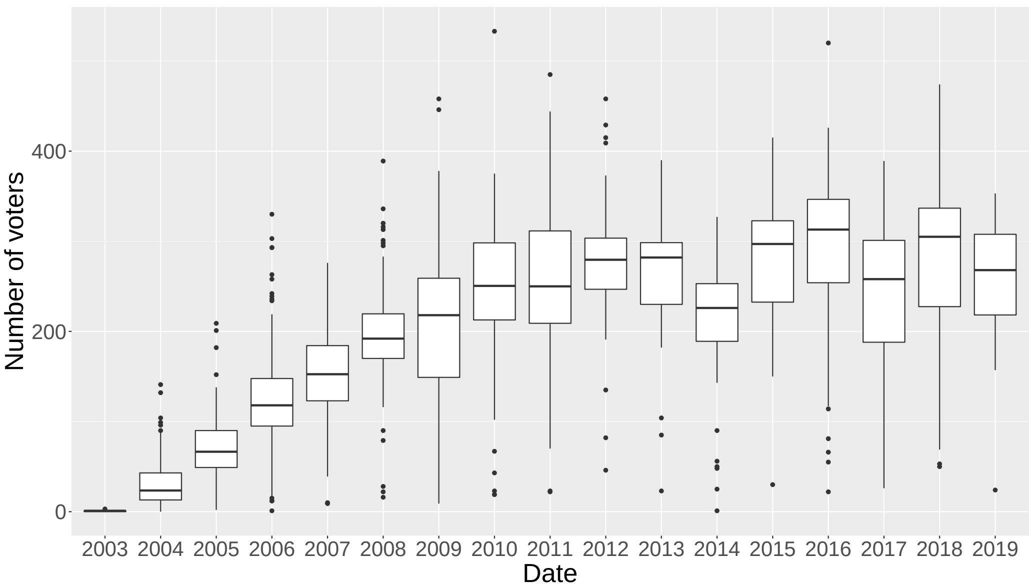


Figure 6.2: Number of votes per election across the years.

6.3.2 Data Setups

The different explananda and hypotheses laid out in section 6.2 require four different setups of the data.

1. Who runs as a candidate in elections? The data includes all eligible users, observed in each year in which they were eligible for at least one month. The idea is to compare those running to become administrator with those not running (as well as to analyse within-user changes over time).

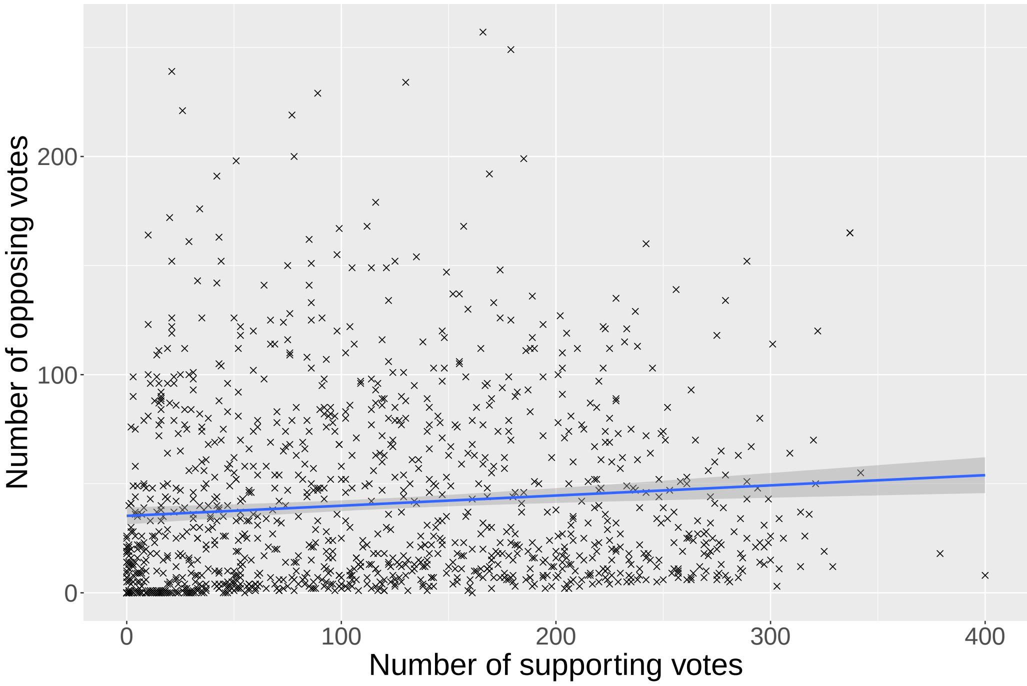


Figure 6.3: Supporting and opposing votes per election.

2. Who is successful in, i.e. wins, elections? The data includes the candidates of all elections. The idea is to compare successful candidacies with unsuccessful ones.

3. Who votes in elections? The data includes all eligible users observed at all elections they were eligible at. The idea is to compare those voting at the election with those not voting (as well as to analyse within-user changes over time).

4. Who votes supportively/opposingly in elections? The data includes all users who have voted in elections. The idea is to compare those voting supportively with those voting opposingly (as well as to analyse within-user changes over time).

Regarding the decision to run as candidate, I observe users and their behaviour from 2002 to 2020, a total of 19 years. Across these years, I have 123'012 observations of users who were eligible in the corresponding year for at least one month and thus had the opportunity to run as an administrator and did or did not do so. Candidates running twice in the same year were considered to have run (no distinction was made between the number of times ran) and re-elections were discarded. I observe a total of 837 years in which a user ran for administrator (this means they ran at least once in the year). This data refers to setup 1.

Regarding actual elections realised, I observe 1191 elections (1213 elections in total minus 22 missing a valid candidate) where a total of 756 different users (re-)ran for administrator. Most users only ran once, others up to 9 times (mean 1.58, median 1, standard deviation 0.96). 718 of these elections were successful. This data is used in setup 2.
For setup 3, I have 6'791'107 observations belonging to 30'004 different users who were eligible to vote in at least one of the 1191 elections. While some users were only eligible to vote in one of these elections, others were eligible for all 1191 elections taking place (mean 226.30, median 131, standard deviation 232.90). I observe 200'852 instances in which users used their right to vote.
Lastly, for setup 4, I focus on those 200'852 instances in which users voted. Like most previous research, I exclude users who have given a neutral vote, so that I observe a total of 183'263 instances in which users voted (and with n=135'230, most of those instances are supporting votes). The dataset includes 5022 different users who voted; some of them only once, others up to 807 times (mean 36.49, median 7, standard deviation 74.53).
Apart from the second setup, the data at hand is rather large. Particularly setup 3 features an extremely large number of observations. This amount of data becomes computationally expensive and thus difficult to work with. To deal with this, only a subset of the data is analysed (see more on this in the next section). Given that this chapter is concerned with the effect of offline meetings on online voting behaviour, the subset of data will include those users who have attended meetups in the past and match them with similar others who have not attended meetups; the procedure is discussed in the next section. This will lead to a sample of observations where meetup attendees are over-represented, but this will still allow the identification of the effects of offline network features.
In all of these setups, I generally use the same variables for analysis. However, their distribution can vary greatly depending on the setup (i.e., the number of edits of the average voter can be very different compared to the average candidate). The variables used and their measurement are presented in section 6.3.4.

6.3.3 Subsampling Data

The datasets analysed in this chapter tend to be too large to handle, so the data will be subsampled. For each meetup attendee in the dataset, a comparable non-attendee will be identified following the procedure described in section 3.3.3. It is important to note that the matched non-attendees do not form a “control group” in this chapter as they did in chapter 4. This chapter does not identify a treatment effect. However, data needs to be subsampled, and sampling those who have attended meetings and a comparable group most similar to them seems like the most reasonable approach so as to not decrease the sample size of users who have attended meetups (to get better precision) and find a fair group of comparison.

For setups 1 and 3, all users in a given year, who have attended a meetup in the previous year, are being sampled, and a matching non-attendee needs to be searched. To find a comparable user, for each year, each eligible user having attended a meetup was matched with one not having attended a meetup (in setup 3, the focus was on each election instead of each year). For setup 4, the data identified for setup 3 was subset to only include users that have voted. Users were matched on the basis of similar covariates. The matched non-attendee was found by comparing users based on the following equally weighted features:

1. Days since registration
2. Sum of activity (number of edits, logged) on Wikipedia since registration up until the election
3. Recent activity (number of edits in the last two months, logged) in the article mainspace of Wikipedia before the election
4. Revert activity (setup 1 only):
   a) Number of times reverted others (logged)
   b) Number of times got reverted by others (logged)
5. Collaboration activity:
   a) Number of users previously collaborated with (in case of setup 3: proportion of voters at an election)
   b) Eigenvector centrality in collaboration network
6. Talk activity:
   a) Number of users previously talked to (in case of setup 3: proportion of voters at an election)
   b) Eigenvector centrality in talk network

The most similar other user was identified and selected as a matched non-attendee. Users were compared using a distance measure based on ordinary least squares between Wikipedian X who was eligible at an election and has attended meetups in the recent past and all those eligible to vote but without having attended a meetup in the past year and not already matched to another user for that specific election. With this approach, the data was subsampled without losing information on those having attended meetups.

6.3.4 Variables and Data Description

The variables used and their measurement are discussed in the following. All descriptives are given in table 6.1 for the four different setups using the full data, and in table 6.2 using the subsampled data the models are based on.

6.3.4.1 Network Measures

To test the hypotheses laid out in section 6.2 and to understand the role meetups play, several network measures regarding the offline network of Wikipedians are calculated. The measure of *centrality* describes how central nodes are in a network. A large number of different centrality measures exist, and new measures are developed and suggested regularly (see for new measures in recent years e.g. Colladon and Naldi 2020; Gaye et al. 2015; Rhouma and Romdhane 2018; see for a review e.g. Landherr et al. 2010). The different centrality measures conceptualise centrality and importance of nodes in different ways.

A user's *degree* can be considered one measure of centrality. Degree centrality is the historically first and conceptually simplest measure of centrality. Degree describes the number of links that are sent to (in-degree) or sent by (out-degree) a node, and particularly in-degree works as a measure of popularity. In undirected networks, there is only one degree measure as no differentiation by in- or out-degree can be made (see e.g. Hämmerli et al. 2006). A measure of degree is used to test hypotheses R2, W2, V2, P3 and P4. If the measure refers to voters, I work with a relative definition of degree (i.e. I calculate a proportion).

While degree measures the number of connections a user has, it does not cover all ways to understand centrality. *Eigenvector centrality* is another popular measure developed by Bonacich (1972, 1987). Eigenvector centrality scores correspond to the values of the first eigenvector of the graph adjacency matrix and can be interpreted as arising from a reciprocal process in which the centrality of each user is proportional to the sum of the centralities of those users to whom ego is connected to. The measure thus assigns higher weights to links connecting a node to other central nodes. In practice, this means that in large networks, important nodes are those connected to other important nodes (see e.g. Fowler et al. 2007).

As a further network measure, I include whether a direct tie exists between two users, particularly between candidate and voter.

On Wikipedia, different networks can be thought of. My main interest lies in the effect of ties stemming from face-to-face meetings, however, I will simultaneously control for online network features. The conceptualisation of these networks will be described next.

The Offline Network Network measures regarding the offline network on Wikipedia are used to test the hypotheses. The meetup network that developed between Wikipedians has been discussed and described in section 3.3. Like in the analyses in the previous chapter 5, I consider the previous 12 months of meetup activity to calculate the network measures for any given point in time.

Online Networks: Collaboration and Communication on Wikipedia Network measures regarding different online networks on Wikipedia are taken into account to single out the effect of offline ties: collaboration ties and talk ties. A collaboration tie is based on the co-editing network. Co-editing is defined as users editing the same page directly after one another. Talk ties refer to leaving messages on users' talk pages, a form of directed but public messaging. See for a more in-depth discussion of collaboration ties subsection 3.1.2.1, and of talk ties subsection 3.1.2.2.

When focusing on offline ties, I take a user's offline meeting activity from the previous year into account. I take a shorter time frame when focusing on online networks, again in line with my approach in the previous chapter 5; however, I focus on the previous *two* months of online activity. This decision is made because the past two months of activity are of relevance in elections: users eligible to vote must have been registered for at least two months. Multiple ties are dropped which means that two users can only be connected by one (or no) edge. While both the talk and collaboration network are directed in nature, their direction is ignored when calculating centrality.

6.3.4.2 Further Variables

The main interest of this chapter lies in testing the hypotheses laid out in section 6.2 which is achieved with the network measures discussed previously. As this is the first study which looks at offline measures in an online election context, I will further explore the relationships of all offline measures with voting behaviours even if no specific hypothesis was previously theoretically derived.

Section 6.2.2 on the current state of research regarding elections on Wikipedia has highlighted numerous other determinants relevant for the success of candidates as well as for voting in elections. These other variables need to be controlled for to investigate whether (offline) ties have an effect beyond these online components, i.e., to isolate the statistical effects of the offline network, control variables are introduced.

Control variables include the previous total level of activity up to the time of the election as well as the recent activity before the election (see for details section 3.1). I measure recent activity as logged number of posts in the main article namespace in the past two months. Tenure is measured as years passed since a user's first edit.

I further control for features describing the relationship between voter and candidate in setups 3 and 4. With a dummy variable, I capture whether a voter has reverted or has been reverted by the candidate in the past two months. Reverting can be seen as a negative relationship (see chapter 5) as also highlighted in previous research (see e.g. Jankowski-Lorek et al. 2013; Turek et al. 2011). For setup 1, I control for the logged number of times a user has reverted others and has been reverted by others[209]; and for setup 2, I measure the proportion of voters who reverted the candidate and those who were reverted by the candidate.

For setups 1 and 2, I also control for the number of previous times a user has run as candidate. Lastly, I control for the year of the election, differentiating three equally long categories (before 2009, between 2009 and 2014, 2015 and after). Table 6.1 shows descriptive information on all (uncentred) variables in the complete dataset; table 6.2 refers to all independent and dependent variables included in the models on elections on the subsampled data (used in the models).

[209] For setup 1, I focus on the number of reverts in total and not in relation to specific users, as I assume running for administrator is more a function of general skill and less person-specific. It is not (necessarily) yet a situation in which other users make an assessment.

Table 6.1: Descriptive information on all variables.

Variable	Running as candidate Setup1	Winning elections Setup 2	Voting in election Setup 3	Voting supportively Setup 4
Number of meetups attended	0.17 (1.15) 0 / 40.3	1.76 (3.64) 0 / 38	0.28 (1.45) 0 / 47	1.75 (3.71) 0 / 46
Number of other users met (log)	0.12 (0.63) 0 / 5.56			
Met candidate			0.24%	3.41%
Proportion of voters met		2.52 (4.85) 0 / 41.67	0.21 (1.29) 0 / 80	1.71 (3.63) 0 / 80
Proportion of pro-voters met			0.22 (1.50) 0 / 100	1.86 (4.13) 0 / 100
Proportion of anti-voters met			0.15 (1.33) 0 / 100	1.10 (3.57) 0 / 100
Eigenvector centrality meetup network	0.0053 (0.045) 0 / 1	0.098 (0.22) 0 / 1	0.012 (0.076) 0 / 1	0.087 (0.21) 0 / 1
Number of other users collaborated with (log)	2.56 (1.74) 0 / 8.39			
Collaborated with candidate (direct collaboration tie, undirected)			4.97%	31.92%
Proportion of voters collaborated with		37.39 (24.41) 0 / 100	3.95 (9.29) 0 / 100	21.15 (17.34) 0 / 98.82
Proportion of pro-voters collaborated with			3.86 (9.48) 0 / 100	21.09 (17.73) 0 / 100
Proportion of anti-voters collaborated with			3.54 (9.39) 0 / 100	19.29 (18.42) 0 / 100
Eigenvector centrality collaboration network	0.038 (0.067) 0 / 1	0.29 (0.19) 0 / 1	0.045 (0.085) 0 / 1	0.20 (0.15) 0 / 1
Number of other users talked to (log)	0.29 (0.75) 0 / 7.45			
Talked to candidate (direct talk tie, undirected)			0.45%	6.27%
Proportion of voters talked to		7.63 (9.86) 0 / 100	0.38 (1.70) 0 / 100	3.22 (4.46) 0 / 100
Proportion of pro-voters talked to			0.37 (1.93) 0 / 100	3.30 (4.87) 0 / 100
Proportion of anti-voters talked to			0.32 (2.14) 0 / 100	2.90 (6.15) 0 / 100
Eigenvector centrality talk network	0.0055 (0.022) 0 / 0.97	0.12 (0.14) 0 / 1	0.010 (0.037) 0 / 1	0.072 (0.11) 0 / 1
Difference candidate-voter centrality meetup network			0.093 (0.24) -1 / 1	0.052 (0.32) -1 / 1
Difference candidate-voter centrality collaboration network			0.22 (0.19) -1 / 1	0.059 (0.20) -0.99 / 0.90
Difference candidate-voter centrality talk network			0.087 (0.12) -1 / 1	0.036 (0.15) -1 / 1
Number of times reverted others (log)	0.26 (0.75) 0 / 6.41			
Number of times got reverted (log)	0.28 (0.82) 0 / 7.44			
Proportion of voters reverted by candidate		1.54 (3.99) 0 / 100		
Proportion of voters reverted candidate		1.74 (4.32) 0 / 100		
Reverted candidate			0.12%	1.36%
Reverted by candidate			0.15%	1.42%
Number of previous elections candidated	0.018 (0.15) 0 / 4	0.58 (0.99) 0 / 8		
Mainspace edits, two months (log)	3.14 (1.88) 0 / 10.23	5.89 (1.56) 0 / 9.26	2.71 (2.20) 0 / 11.94	5.48 (1.55) 0 / 11.90
Total edits (log)	4.29 (2.66) 0 / 12.29	7.96 (1.55) 1.61 / 11.43	5.38 (2.10) 0 / 12.40	8.16 (1.46) 0.69 / 12.34
Difference candidate-voter total edits (cube root)			14.35 (11.35) - 62.28 / 45.12	5.71 (19.46) - 59.65 / 45.10
Years since first edit	4.48 (3.61) 0.00024 / 18.72	3.55 (3.42) 0.047 / 16.21	3.71 (2.80) 0.000004 / 18.73	4.62 (3.46) 0.0014 / 17.85
Year of meetup 03-08	29.73%	52.73%	40.38%	31.06%
Year of meetup 09-14	40.38%	32.66%	46.17%	45.50%
Year of meetup 15-20	29.89%	14.61%	13.45%	23.04%
Observations	123012	1191	6791107	183263
Observations realised (dependent variable = 1)	837	718	200852	135230
Number of groups	27294	756	30004	5022

Given are mean (standard deviation), minimum / maximum.

Table 6.2: Descriptive information on all variables included in the models, restricted dataset.

Variable	**Running as candidate Setup1**	**Voting Setup 3**	**Voting supportively Setup 4**
Number of meetups attended	2.26 (3.61) 0 / 40.3	1.88 (3.37) 0 / 47	2.78 (4.35) 0 / 46
Number of other users met (log)	1.61 (1.70) 0 / 5.56		
Met candidate		1.64%	5.41%
Proportion of voters met		1.43 (3.10) 0 / 80	2.71 (4.27) 0 / 80
Proportion of pro-voters met		1.50 (3.66) 0 / 100	2.94 (4.83) 0 / 100
Proportion of anti-voters met		1.04 (3.35) 0 / 100	1.74 (4.37) 0 / 100
Eigenvector centrality meetup network	0.069 (0.15) 0 / 1	0.080 (0.18) 0 / 1	0.14 (0.25) 0 / 1
Number of other users collaborated with (log)	4.03 (1.41) 0 / 7.92		
Collaborated with candidate (direct collaboration tie, undirected)		14.76%	36.91%
Proportion of voters collaborated with		11.85 (14.97) 0 / 100	24.76 (17.35) 0 / 94.79
Proportion of pro-voters collaborated with		11.57 (15.33) 0 / 100	24.70 (17.80) 0 / 100
Proportion of anti-voters collaborated with		10.96 (15.62) 0 / 100	22.80 (18.89) 0 / 100
Eigenvector centrality collaboration network	0.084 (0.094) 0 / 0.74	0.12 (0.13) 0 / 1	0.23 (0.15) 0.00024 / 1
Number of other users talked to (log)	1.19 (1.24) 0 / 6.96		
Talked to candidate (direct talk tie, undirected)		1.87%	7.74%
Proportion of voters talked to		1.50 (3.04) 0 / 100	4.02 (4.53) 0 / 100
Proportion of pro-voters talked to		1.49 (3.56) 0 / 100	4.13 (5.00) 0 / 100
Proportion of anti-voters talked to		1.34 (4.08) 0 / 100	3.62 (6.53) 0 / 100
Eigenvector centrality talk network	0.023 (0.038) 0 / 0.74	0.041 (0.077) 0 / 1	0.094 (0.12) 0 / 1
Difference candidate-voter centrality meetup network		0.027 (0.29) -1 / 1	0.0031 (0.35) -1 / 1
Difference candidate-voter centrality collaboration network		0.13 (0.20) -1 / 0.90	0.025 (0.20) -0.95 / 0.90
Difference candidate-voter centrality talk network		0.056 (0.13) -1 / 1	0.013 (0.15) -1 / 0.99
Number of times reverted others (log)	0.76 (1.18) 0 / 5.22		
Number of times got reverted (log)	0.92 (1.37) 0 / 7.13		
Reverted candidate		0.48%	1.68%
Reverted by candidate		0.49%	1.67%
Number of previous elections candidated	0.073 (0.30) 0 / 3.42		
Mainspace edits, two months (log)	4.46 (1.64) 0 / 9.62	4.47 (1.98) 0 / 11.21	5.79 (1.36) 0 / 11.05
Total edits (log)	6.88 (2.18) 0 / 12.29	7.63 (1.54) 1.10 / 12.40	8.74 (1.14) 2.89 / 12.11
Difference candidate-voter total edits (cube-root)		6.90 (17.45) -62.28 / 45.12	0.70 (20.28) -55.69 / 45.10
Years since first edit	6.30 (3.79) 0.20 / 18.61	4.71 (3.18) 0.0068 / 18.62	5.09 (3.41) 0.053 / 17.85
Year of meetup 03-08	14.07%	34.70%	30.81%
Year of meetup 09-14	45.26%	47.71%	48.28%
Year of meetup 15-20	40.67%	17.59%	20.91%
Observations	9014	996668	115608
Observations realised (dependent variable = 1)	247	126615	87519
Number of groups	3973	13979	2939

Given are mean (standard deviation), minimum / maximum.

6.3.5 Statistical Approach: Multilevel Within-Between Linear Probability Models

This chapter is concerned with the relationship between specific offline network measures and the voting behaviour of users. While the election process can be understood as a network—(signed) ties connecting users and candidates—and has also been so in the past (see the study of Putzke and Takeda 2017), this approach will not be followed up upon here. The election process will instead be understood as independent decisions of voters (how) to vote and of users deciding to run, however, the regression framework will be extended to include network statistics as covariates; this is a popular alternative approach to network models (Cranmer and Desmarais 2011).

The election data analysed exhibits a multilevel structure (Raudenbush and Bryk 2001). In the case of voting in elections, election (non-)participation is nested in users: each user and their behaviour are observed for each election they were eligible at. In the case of running for administrator, I observe eligible users in multiple years. Only in setup 2, I have a simpler data structure with fewer observations and only a few instances where users are observed multiple times. This does not require a multilevel model, but the inclusion of cluster robust standard errors.

Fixed effects (FE) models have been considered a gold-standard when aiming at making causal claims (Bell and Jones 2015). They help avoid omitted variable bias by controlling for time-invariant variables. FE models concentrate on the within differences of a cluster, excluding all between effects. This means, only variation across time is accounted for in a model. Time-invariant characteristics will difference out in FE models (Allison 2009; Mummolo and Peterson 2018; Wooldridge 2010). However, they ignore between-group variation, making them unable to estimate effects of variables which do not vary between clusters (Schunck 2013). All contextual (level two) information is discarded.

Within-between models are able to assess the drawbacks of the FE models. The general technique was proposed by Mundlak (1978) as a way to relax the assumption in the random effects (RE) estimator that the observed variables are uncorrelated with the unobserved variables (Perales 2013; Schunck 2013; Wooldridge 2010). In other words, the Mundlak device was developed to orthogonalise x_i (individuals i) and x_t (groups or times t) so that the effects of those variables on y can be modelled separately. In these models, RE regression models are estimated in which group means of variables are

included. This procedure forms the basis of many panel data models (such as the Hausman-Taylor model) and has been widely used in panel data econometrics in general but has not proliferated widely to applied economics or other social sciences. Bell and Jones (2015) recommend these models under the name of within-between RE models (REWB). They have also been proposed by Allison (2009) under the name of *hybrid models*, however, the name "within-between models" has since been preferred (Allison 2014; Bell et al. 2018). Other recent extensions in the same line are the so-called correlated random effects (CRE) models (Wooldridge 2019).
REWB models are RE models with decomposed variables. Each time-varying predictor is decomposed into two components:

- Between component: $\bar{x}_i = \frac{1}{T_i} \sum_{t=1}^{T_1} x_{it}$
- Within component: $x_{it} - \bar{x}_i$

The between component is the cluster-specific mean. Within each group, the mean for each independent time-varying variable is calculated. Group means will differ between clusters, but not within them. The within component is the demeaned variable; the mean of the group is subtracted from each time-varying variable. Putting both components into a RE model leads to the following formula:

$$y_{it} = \alpha + \beta(x_{it} - \bar{x}_i) + \gamma\bar{x}_i + \delta z_i + \alpha_i + \epsilon_{it}.$$

A RE model is then estimated which includes both the means of the variables and the difference-from-the-means variables. In this case, $\hat{\beta}$ reproduces exactly the FE (within) estimate, $\hat{\gamma}$ reproduces approximately the between estimate, and $\hat{\delta}$ is the effect of a time constant regressor. In essence, β_{it} are split apart in the same way the error terms are split apart.
Such REWB models allow to disentangle both within effects, i.e. how the behaviour of one person changes as the person's values change over time, and between effects, i.e. how different persons' behaviours differ due to different persons' features[210]. As I am interested in both within- and between effects, I run such REWB models. However, as FE models are simpler in their setup and preferred in Sociology, I present FE models in the appendix.

[210] There is some disagreement whether the coefficient of the cluster mean can be interpreted as the between effect. Schunck (2013: 66) argues so, but Paul Allison calls them "uninteresting or misleading" in a blog post (see here `https://statisticalhorizons.com/between-within-contextual-effects`). Paul Allison's argumentation is however based on geographic multilevel contexts, and I consider it more convincing to interpret them as between effects.

Given the very large number of observations in most of the data setups and the complex modelling structure, I will employ linear probability models (LPMs) (see also the discussion in section 4.3.7). Usage of the LPM has been discussed critically, but these models have been advocated for due to their interpretability and computational speed compared to the much more complex logistic regression (Mood 2009). The LPM can be employed in situations where the logit estimation fails, and Mood (2009) shows that LPM effect estimates are unbiased and consistent estimates of an independent variable's average effect (see also Wooldridge 2010: 454)[211]. I will address the essential issue of heteroscedasticity by using robust standard errors, employing the original form of the sandwich estimator (Liang and Zeger 1986). Logistic regressions (generalized linear models, GLM) are included in the appendix; however, they have raised convergence warnings in some instances.

Timoneda (2021) also argued that the LPM outperforms logistic regression in rare events data when estimating group FE in panel data with a binary dependent variable. FE LPM and FE GLM models are presented in the appendix. FE GLM models are run on the complete dataset as all observations without variation—which is the majority—are being discarded so that no computational hurdles due to big data arise.

For the main text, I estimate several models per explanandum. After assessing bivariate associations, I run models which include control variables and offline network measures separately to distinguish their effects. I then run a full model including all variables simultaneously. Model results will be discussed in the next section.

There can be instances of multicollinearity on the cluster mean variables in regard to a voter's centrality and the difference between a voter's and a candidate's centrality. A user who is, on average, not central at all tends to be, on average, much less central than any of the candidates. There is thus an association between the two cm values which can make them more difficult to interpret when they are included simultaneously in the model.

Statistical Software FE models were run using *plm* (Croissant and Millo 2008) and GLM FE models using *bife* (Stammann et al. 2016).

[211] The LPM has also been previously used in a multilevel context, see e.g. von Hippel and Workman (2016).

6.4 Results

This section will present the model results and test the hypotheses laid out in section 6.2. I will first discuss bivariate relationships before presenting the multivariate models. For all models, the following notation is used:

- cm: cluster mean (capturing the between effect).
- cwc: centred within clusters (capturing the within effect).

Given I use LPMs, the interpretation of the model coefficients is straightforward: a one-unit increase in an independent variable leads to a change in the probability of the outcome variable of $\beta * 100$ per cent.

6.4.1 Bivariate Relationships Between Meetup Participation and Voting Behaviour

The bivariate relationships presented in the first half of this section are based on the complete datasets including all observations as they are concerned with proportions. After subsampling, the proportion of eligible voters having attended meetups and not having attended meetups is split equally (meetup attendees are oversampled; the point of the matching procedure); a description based on the percentages would be rendered meaningless.

When looking at all observations of all eligible users at all elections, results show that in 7.3 per cent of cases, users have attended a meetup in the past year. This percentage sharply increases when looking at those users who have actually voted: in 35.8 per cent of cases, users that have voted in an election have also attended a meetup. In 35.8 per cent of cases[212], voters have met another voter in an election personally at one of those meetings, and in 3.2 per cent of cases, they have met the candidate personally (of those who partook in a meetup, 9.0 per cent have met the candidate).

Arguing from the perspective of candidates, I find that 36.5 per cent of candidates running to become administrator have attended a meetup. In 39.6 per cent of cases, eligible users who have met the candidate previously vote when this candidate runs for administrator. In 90.0 per cent of cases, users who know the candidate personally have voted in favour of them, while in 6.7 per cent of cases, they voted against them in the election (in the other

[212] The fact that the numbers are almost equal—there are difference hidden due to rounding with the latter number being slightly smaller—means that in almost 100 per cent of cases, users who have taken part in an election and a meetup have also met another voter. The latter number must be smaller or equal to the first number.

cases, they gave a neutral vote). Lastly, out of the successful candidates, 45.4 per cent have attended a meetup.

These associations in frequencies are all significant on a 1 per cent significance level according to χ^2 tests (using Yates' continuity correction, see Yates 1934). Overall, simply comparing these proportions suggests a large overlap between those Wikipedians that are voting in elections and those taking part in offline meetings.

In a second step, I use multilevel linear probability models with random intercepts for the user and one other variable—split up in a person's mean value, cm, and the person's within variation, cwc—as only predictor(s), using the subsampled datasets. The models suggest that the more meetings someone has attended (both cm and cwc), the more people they have met (both cm and cwc), and the more central they are in the meetup network (both cm and cwc), the more likely they are to run for administrator in a given year (see models in subsection A.4.1.1). The same pattern also holds for successful candidates of elections; attending more meetings, meeting more eligible users personally, and being more central in the meetup network increases the probability to be successful in an election (regression model with robust standard errors, see subsection A.4.2.1).

Regarding voting in elections (regression tables in subsection A.4.3.1), I find that users are more likely to vote when they have met the candidate (cm and cwc), when they have attended more meetings (cm and cwc), and the larger the proportion of other voters they have met (cm and cwc). Eligible users are also more likely to vote the more central they are in the meetup network (cm and cwc). Regarding the difference in centrality between candidate and voter, there is a negative between effect (cm), suggesting users that are less central on average than the candidates in elections are less likely to vote, and a positive within effect (cwc), suggesting that users are more likely to vote in an election where the candidate is more central than them in the meetup network compared to other candidates less central than them.

Lastly, users voting in elections are more likely to vote supportively when they have met the candidate (cm and cwc), when they are generally users attending meetups or more central in the network (cm only), the larger the proportion of other supporting voters they have met (cm and cwc), and they become less likely to vote supportively the higher the proportion the anti-voters they have met (cwc only). Regarding the difference in centrality between candidate and voter, there is the same relationship as on voting

generally: there is a negative between effect and a positive within effect. The model results can be found in the appendix, see subsection A.4.4.1.
Making bivariate comparisons without regard to any control variables, I find support for all hypotheses (R1, R2, R3, W1, W2, W3, V1, V2, P1, P2, P3, P4).

6.4.2 Multivariate Relationships

The following section will present LPMs for the four dependent variables: subsection 6.4.2.1 will try to explain who is running as administrator in a specific year, subsection 6.4.2.2 focuses on who wins elections, subsection 6.4.2.3 aims at explaining voting in elections, and lastly, subsection 6.4.2.4 looks at the direction of votes. As in the previous chapters, hypotheses-related results are presented in coefficient plots. Whenever effects are described, I mean statistical effects and do not necessarily imply causality. Full tables of all models can be found in the appendix in section A.4.

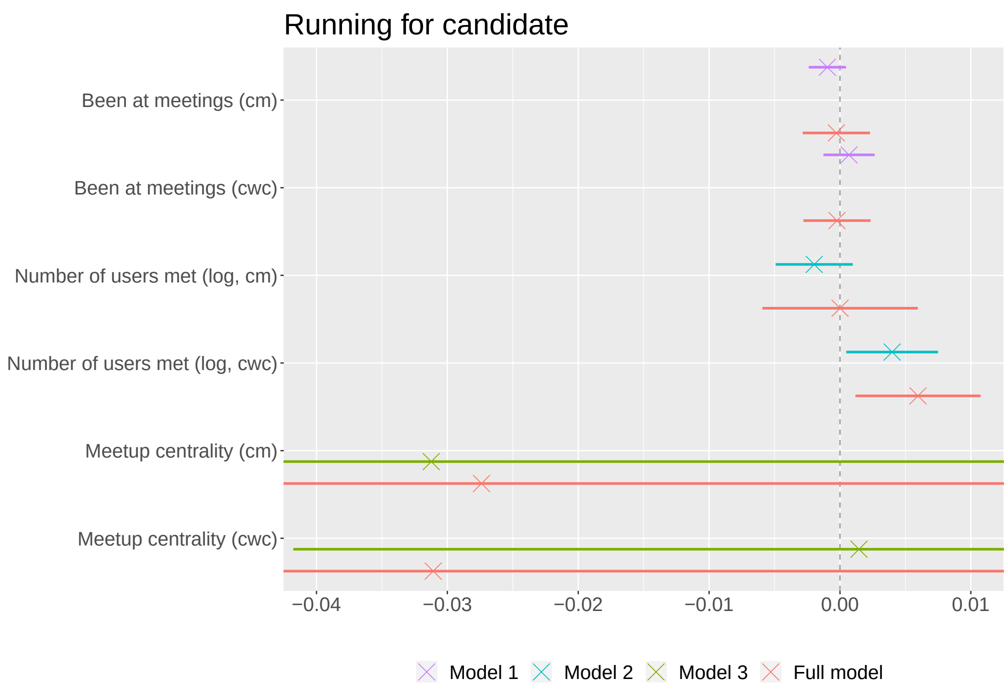
6.4.2.1 Running for Administrator

Who is most likely to run as a candidate in a given year and what role do offline networks play in this? This will be investigated in the following. Running an empty multilevel model including only random intercepts for the user IDs suggests that 33.5 per cent of variance is at the level of users, i.e. between users[213].
Model results are shown in the coefficient plot in figure 6.4; regression tables can be found in the appendix, see subsection A.4.1.2. Four models are estimated. Models 1, 2, and 3 include the control variables and different measures of offline meetup behaviour separately to distinguish effects of centrality, general meetup attendance, and the count of other users met. The last model includes all variables simultaneously.
There are no significant effects of offline interactions, except the within variation of the number of other users met. In models 2 and 4 when controlling for the number of meetings a user has attended and their position in the meetup network (as well as other important control variables), I find that the more users a user has met in the past year, the more likely the user is to run for administrator. There is no significant effect in the mean number of other users one has met throughout (no significant cm effect), but there

[213] When the complete dataset is used instead of the subsampled one on the basis of the matched non-attendees, 18.3 per cent of variance is found to be at the level of users.

is a positive effect of having an increasing number of people one got to know (significant cwc effect).

While the bivariate results show positive effects for all variables regarding hypotheses R1-R3, some of the effects disappear when controlling for other variables. Overall, there is no evidence supporting hypotheses R1 and R3, but there is support for hypothesis R2 in the multivariate models: the more other people a person meets, the more likely they are to run for administrator. When there is an increase of one in the logged number of users met, the probability to run as administrator in a given month increases 0.4 (Model 1) / 0.6 (Full model) per cent. This coefficient is small compared to the importance of having collaborated or talked with users (these coefficients are around 5 times larger) and also only significant on a five per cent level. Also, these effects are *not* robust when modelled as a multilevel GLM (which suggests the meetup centrality to matter) or FE LPM (see subsections A.4.1.3 and A.4.1.4); also, it is only significant on the 10 per cent level in the FE GLM (see subsection A.4.1.5).



Note: Horizontal line reflects 95 per cent confidence interval. The plot is cropped for better visibility of small effects.

Figure 6.4: Modelling running for administrator.

The control variables further suggest negative and significant effects of the within-change of recent two-month mainspace activity (i.e. those who have been more active in the mainspace recently than they usually are, are less likely to run for administrator), a negative effect of the between effect of total activity (i.e. those with more total edits are less likely to run for administrator), a positive effect of the within-change of total activity (i.e. those who have increased their cumulative number of edits more strongly are more probable to become administrator). Also, those users who have reverted more posts are less likely to run as administrators (cm). The within-change of tenure exhibits a positive effect, meaning users are more likely to run for administrator later in their Wikipedia career. If they tried to become administrator in the past, they are more likely to run again. Lastly, users who are collaborating and/or talking to more others (cm only for collaboration; cm and cwc for talking activity) and those who are more central in the talk or collaboration network (both cm and cwc) are more likely to run as administrator.

6.4.2.2 Winning Elections: Becoming Administrator

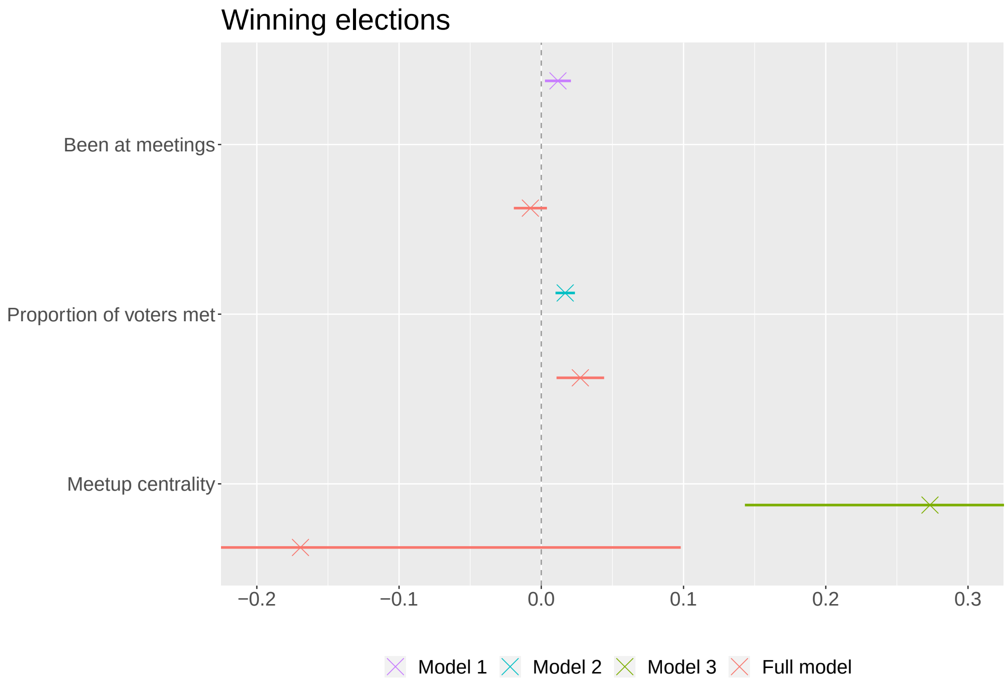
Who is most likely to be successful when running for administrator in an election and what role do offline networks play in this? This will be assessed in this subsection. Because only a few users run multiple times before being successful, multilevel models are not used here. Instead, cluster robust standard errors are employed. Given the setup and the smaller sample size, this dataset was not subsampled.

Model results are shown in the coefficient plot in figure 6.5; regression tables can be found in the appendix, see subsection A.4.2.2. Again, four models are estimated, with the first three models including different measures of the offline meetup network separately before presenting a full model which includes all variables simultaneously.

The models reveal a positive and significant effect of the proportion of voters met[214]. Both the effects of the bare number of meetups attended and the eigenvector centrality of a candidate are positive and significant, unless the number of voters met is included in the model simultaneously. The results suggest that attending meetups and being central in the network is helpful in winning an election, but it is particularly the meeting of those who then vote that plays a positive and significant role. Having met 1 per cent more of the voters leads to a 2.7 per cent increase in the probability to win the election. This lends support to hypothesis W2. While meetings are important, neither the bare number nor the meetup centrality matter beyond the proportion of

[214] Using the number of eligible users met instead of the proportion of voters met leads to the same results, not shown.

voters met (no support for hypotheses W1 or W3 in the full model). These results are stable when modelled as a GLM (see subsection A.4.2.3).



Note: Horizontal line reflects 95 per cent confidence interval. The plot is cropped for better visibility of small effects.

Figure 6.5: Modelling successful candidacy.

The control variables suggest that more active users and those who have been registered longer are more likely to win in elections (controlling for all other factors).

6.4.2.3 Voting in Elections

The previous analysis has shown that having met the people that vote increases the probability to win an election. Are users also more likely to vote if they have taken part in meetings recently? A subsample of all users was taken to investigate this and additional questions. Running an empty multilevel model including only random intercepts for the user IDs suggests that 18.0 per cent of variance is at the level of users[215].
Model results regarding the offline meetup measures are shown in a coefficient plot in figure 6.6. The corresponding regression tables can be found in the appendix, see subsection A.4.3.2. Five different models are estimated.
I find significant and positive effects of having met the candidate in all model specifications: users who have met candidates generally (cm) and also specifically the candidate of one election (cwc) are more likely to vote, while

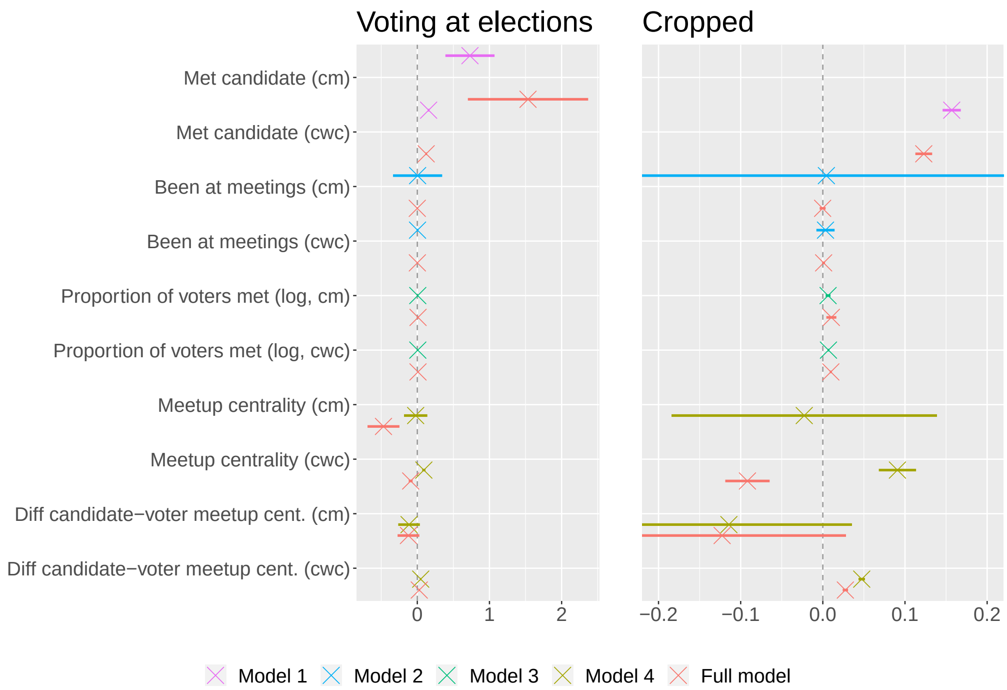
[215] When using the complete dataset, 20.0 per cent of variance is at the level of users.

there is no effect of the number of meetings attended. Having met a larger proportion of voters (cm and cwc) in an election significantly increases a user's probability to vote as well. The effect of a voter's centrality is more difficult to understand: when not including other network measures, there is a significant positive within effect of both a voter's own centrality and the difference between the candidate's centrality and the voter's centrality. This means, voters are more likely to vote if they are generally more central, but also if the candidate in an election is more central than them. If all other network measures are included, I find a significant negative effect of both the between and within effects of a voter's meetup centrality, suggesting that comparing different users, less central ones are more likely to vote, and a user is more likely to vote the less central they are on average across time. The positive effect of the relative centrality remains stable.

Regarding the hypotheses, there is support for both V1 and V2: the probability to vote increases if the user knows the candidate and the more other voters a user knows. If a user has not met any of the candidates at elections except the candidate at one specific election (meaning having a cm value very close to 0 and a cwc value very close to 1 for that specific election), they are 12.3 per cent more likely to vote in that case. Also, knowing 1 per cent more of the voters of the election (cwc) leads to an increase of 1.0 per cent in the probability to vote. These effects are robust across model specifications (modelled as REWB GLM in subsection A.4.3.3, as FE LPM in subsection A.4.3.4, and as FE GLM in subsection A.4.3.5).

The control variables further suggest that users who have made more edits are more likely to vote (total activity both cm and cwc, recent activity only cwc), and that users are more likely to vote if the candidate at the election has edited more than them (cwc). Those users that have been reverted by the candidate (cwc) or reverted the candidate themselves (cwc, partly also cm) are more likely to vote. Both having collaborated and talked with each other increases the probability to vote as well (captured by the cwc effect; the cm effect captures the average tendency of voters to collaborate or talk to candidates). Having talked to other voters further increases the probability to vote (cm and cwc), while having collaborated with a larger proportion of voters (cwc) decreases the probability to vote.

The effects of centrality are again more complex to understand. The more central a user is in the collaboration network (cwc), the more likely they are to vote. The more central a user is compared to others in the talk network, the more likely they are to vote as well (cm); however, across different elections,



Note: Horizontal line reflects 95 per cent confidence interval. The plot on the right is cropped for better visibility of small effects.

Figure 6.6: Modelling votes.

users are less likely to vote the more central they are in the talk network (cwc). Users are also less likely to vote if the candidates are on average more central than them in the collaboration or talk network (cm effects), and also less likely if this relative difference in collaboration centrality is even larger with a specific candidate (cwc effect); however, there is a positive within effect of the difference in talk centrality.

6.4.2.4 Voting Supportively in Elections

When do voters support a candidate in contrast to voting opposingly, i.e. how can the direction of votes be explained? This is the question guiding this subsection. Users casting a neutral vote were excluded from the analysis. An empty multilevel model including only random intercepts for the user IDs suggests that 20.1 per cent of the variance is at the level of users[216].
Figure 6.7 displays the model results in a coefficient plot; regression tables can be found in the appendix, see subsection A.4.4.2. I estimate five models. Models 1, 2, 3, and 4 include the control variables and different measures of offline meetup participation separately to distinguish the effects of centrality, general meetup attendance, having met the candidate and the proportion of other voters met; the last model includes all measures simultaneously.

[216] When using the complete dataset, 22.5 per cent of the variance is at the level of users.

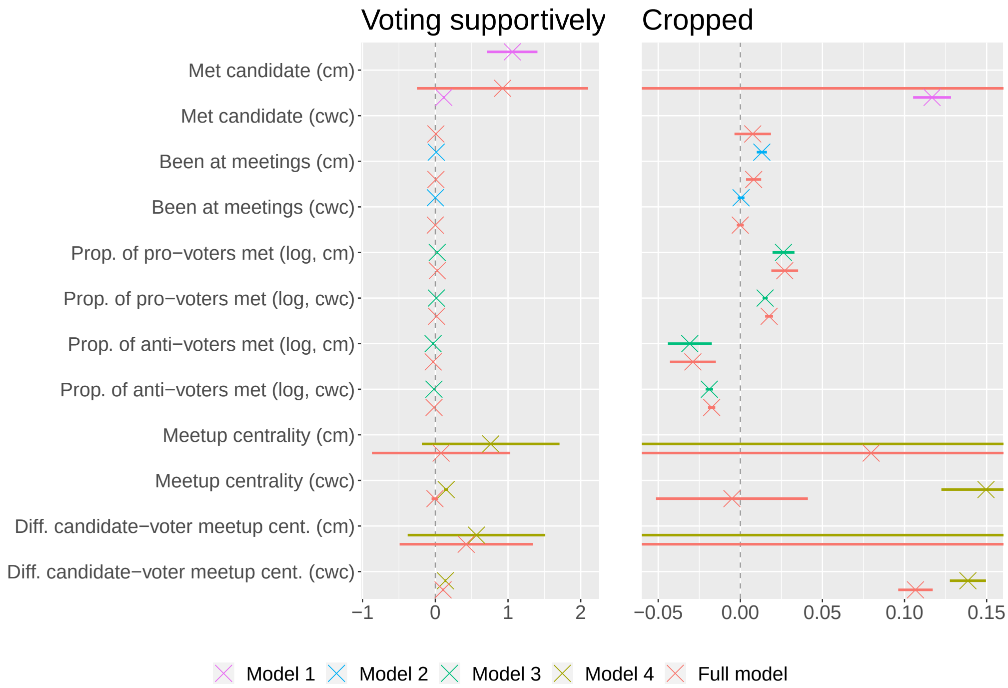
When not including any other measures of the offline network, I find significant and positive effects of having met the candidate (cm and cwc); however, the effects do not remain significant in the full model. Both, in model 2 and the full model, I find a significant between effect of attending meetings, suggesting users that have, on average, attended more meetings, are generally more likely to vote supportively. In all models, I find significant and positive effects of the proportion of supporting voters met (cm and cwc) and negative and significant effects of the proportion of opposing voters met (cm and cwc). Regarding the centrality of voters, I find positive within effects of both a voter's centrality and the difference between the candidate's and the voter's centrality (model 4), but only the positive effect of the difference between candidate and voter remains significant in the full model.

Overall, these results clearly support hypotheses P2, P3, and P4: voters are more likely to support candidates which are more central than themselves, they are more likely to vote supportively if they know a high proportion of pro-voters, and they are less likely to vote supportively if they know a high percentage of anti-voters. Knowing 1 per cent more pro-voters in an election leads to a 1.8 per cent increase in the probability of also voting supportively and similarly, knowing 1 per cent more anti-voters in an election leads to a 1.7 per cent decrease in the probability to vote supportively (within variation only, i.e. average level is held constant). In the full model, when controlling for other network measures, there is no support for P1.

These effects are robust across model specifications (modelled as REWB GLM in subsection A.4.4.3, as FE LPM in subsection A.4.4.4, and as FE GLM in subsection A.4.4.5). Additionally, there is support for P1, i.e. users who have met the candidate are more likely to support them when the relationship is modelled as a GLM (both in a REWB GLM in subsection A.4.4.3 and the FE GLM model in subsection A.4.4.5).

The control variables further suggest that the editing behaviour of the voter does only play a small role; there is only a significant effect of the recent mainspace activity (cwc); however, there is a significant and positive within effect of the difference in the number of total edits with users being more likely to vote supportively if the candidate has more edits than they themselves.

Also, users registered for longer are more likely to vote positively (cwc); those that have been reverted by the candidate or themselves reverted the candidate are less likely to support them (cm and cwc), while both having collaborated and talked with each other increases the probability to vote supportively (captured by the cwc effect; the cm effect captures the average



Note: Horizontal line reflects 95 per cent confidence interval. The plot is cropped for better visibility of small effects.

Figure 6.7: Modelling supportive votes.

tendency to collaborate or talk to candidates by voters). Having collaborated with or talked to other voters generally exhibits the same effects as having met voters; there is a positive effect of sharing ties with pro-voters and a negative effect of sharing ties with anti-voters. There are significant effects of all variables related to talk ties (pro and anti, cm and cwc) and effects of collaboration ties to pro-voters in all model specifications. Sharing collaborative ties with a larger proportion of anti-voters exhibits a significant negative effect, but only if the meeting ties are not included in the model (thus not in model 3 or the full model). The more central a user is in the collaboration or talk network (both cwc), the less likely they are to vote supportively in an election; additionally, voters are also less likely to vote supportively if the candidate is more central in the talk network than them (cwc), but they are more likely to vote supportively if the candidate is more central in the collaboration network than them (cwc).

6.5 Conclusions

This chapter has focused on elections on Wikipedia and tried to explain which users are most likely to run for administrator and subsequently successfully become one, as well as who is participating in elections as a (pro-)voter.

Particularly, the study focused on the role of offline meetups to explain this behaviour.
The results presented show significant and stable statistical effects of the offline network of both election candidates and users who vote: partaking in the offline space of Wikipedia clearly matters to explain election participation, both actively and passively. An overview of the hypotheses supported is given in table 6.3. On a bivariate level, all hypotheses presented in section 6.2 could be supported; however, as the full models including further covariates revealed, some associations were explained away by other factors such as the general activity of Wikipedians which influences both, meetup and election participation. In the full models including all covariates and additionally all network characteristics simultaneously, some effects further disappeared; this points towards mediation effects. For example, in regard to successful candidacy, the attendance of meetings affects the proportion of voters met and the centrality in the offline network which in turn affects the probability of winning the election.

Table 6.3: Overview of supported hypotheses regarding elections.

Hypothesis: User is more likely to...		**Bivariate**	**Multivariate (controls)**	**Multivariate (full model)**
run as administrator if..	R1: attended more meetups	YES	NO	NO
	R2: met more users	YES	YES	YES
	R3: more central in network	YES	NO	NO
be elected as administrator if..	W1: attended more meetups	YES	YES	NO
	W2: met more voters	YES	YES	YES
	W3: more central in network	YES	YES	NO
vote if..	V1: met the candidate	YES	YES	YES
	V2: met more voters	YES	YES	YES
vote supportively if..	P1: met the candidate	YES	YES	NO
	P2: less central than candidate	YES	YES	YES
	P3: met more supportive voters	YES	YES	YES
	P4: met fewer opposing voters	YES	YES	YES

When focusing on the full models including all covariates and network characteristics simultaneously, I find weak evidence for hypothesis R2, and strong evidence for hypotheses W2, V1 and V2, as well as P2, P3, and P4. My results show only weak evidence for the importance of offline meetups in the decision to run for administrator. I do not find that users who have attended more meetings or are more central in the meetup network are more likely to run as an administrator. I do find weak evidence that the more users someone has met, the more likely they are to run as administrator. However, the effect is small and not robust across different model specifications. Even though offline participation seems to play only a negligible role in deciding whether one runs for administrator or not, it does matter when explaining election success: users that have met a high proportion of the voters face-to-face are significantly more likely to become administrators. The bare number of meetups attended by a candidate does not show a significant effect in the full model, it thus does not seem like attending meetings signals more commitment and a better ability as administrator. The significant relationship is also reflected when taking the voter's perspective: an eligible user is much more likely to vote if they have met the candidate in the past, and they are also more likely to vote if they have met other voters. These offline ties do not only influence the probability to vote, but also affect the direction of the vote: users are more likely to vote supportively if they have met a high proportion of other pro-voters, are less likely to vote supportively if they have met a high proportion of anti-voters, and are more likely to support candidates that are more central in the meetup network than they themselves. While the offline component does matter in explaining supporting votes, the results do not show that users who have met a candidate are more likely to support them.

In summary, this chapter has shown quantitatively that the offline component matters in the domain of elections: users who have met more users are more likely to run as administrators; users who have met more voters are more likely to win elections; users who met the candidate of an election and who have met more other voters are more likely to vote in an election; and users who are less central than the candidate, who met more supportive voters and who met fewer opposing voters are more likely to vote supportively (controlling for all other variables). While causal claims cannot be made, the community of Wikimedia needs to reflect on the election process and be aware of a potential influence of face-to-face meetings. While having an open process is in the spirit of the platform, such public elections exhibit specific dynamics which can be considered negative when neutrality is the aim (Manin 2015).

This chapter continued in the tradition of Lazarsfeld et al. (1944) and highlighted how social contacts matter for voting decisions—even in the online space. Offline social capital is supportive when people run for administrator: it makes a successful candidacy more likely. Personal voting decisions are also influenced by the ties to the candidate and to other voters. In a next step, it is important to ask why the offline network matters and whether the relationships uncovered are causal: are users discussing upcoming or current elections at the meetups they attend and potentially come to a consensus, or are users voting like their friends or even feel pressured to vote in line with them? Are strong ties restricting a flow of information or even restricting what is considered a valid opinion within a group, clearly negative aspects of social capital (Portes 1998)? Are candidates of current or upcoming elections using meetups to campaign? Are popular users setting the agenda during interactions at meetups (see on informal agenda setting Rossiter 2021)? Are users voting like other voters because they have met, or potentially also because of reasons of homophily—the tendency of similar actors to form connections to one another (McPherson et al. 2001)? These are questions that this study cannot answer but which are important to explore in future work. Anecdotal evidence reported in the study of Stegbauer (2009 chapter 15) suggested that upcoming elections are a topic of discussion at meetups, but such evidence could not be easily inferred from meetup minutes collected as part of the present study.

My findings provide evidence for the ideas that voters are fulfilling their obligations towards their friends (one aspect of social capital) or that these direct ties provide cheap information to the person voting (see also Sinclair 2012). Given that users who have met the candidate are more likely to vote but not to vote supportively (when controlling for all network characteristics), it seems less likely to expect that obligations are driving the decision but rather that it is the additional (offline) information about a user which makes one vote.

Future research should aim at bettering the understanding of the causal relationships behind the associations uncovered. Potential mediation effects could be made explicit and systematically tested with the help of directed acyclic graphs (see on this e.g. Elwert and Winship 2014). Interviews with Wikipedians, who have voted or ran for administrator, can further help to shed light on users' motivations. Going beyond Wikipedia, it is important to understand the mechanism at play in public voting situations. Disadvantages in non-secret voting situations regarding the potential pressure and influence present of one's immediate environment do not receive much attention in the Swiss towns and cantons still regularly holding public votes—in these regions, public assembly voting has a long tradition and forms an almost sacrosanct institution. Still, given that personal contacts even affect the voting behaviour in an online community, it is important to better understand how contacts affect offline (public) voting. Web data used in this study has shown that social capital matters. Beyond this data from an online community, more controlled laboratory studies can offer a setting which is more appropriate to understand the many moving parts within a public election process. The uncovering of social mechanisms will allow to go beyond the identification of factors which are of explanatory relevance, and instead offer a clear description of the constellation of entities and activities which bring forward specific events (Hedström 2005 chapter 2). This will allow to understand the decision-making processes in public elections. In such laboratory studies, single properties of the situation can be purposely varied.

This study has limitations which must be discussed (for general limitations affecting all chapters of this thesis, see also section 7.3). Methodologically, this study is working with very large datasets and employed techniques to decrease computational load. First of all, the data was subsampled by reducing it to the users attending a meetup and their matched non-attendees. While this leads to an oversampling of meetup attendees and a dataset which is not representative of (eligible) Wikipedians, it allows me to estimate effects of offline features. Still, subsampling discards information contained in the complete dataset. Also, while this study modelled binary outcomes, it employed linear probability models. LPMs have their known shortcomings and their popularity is discipline-specific, but their faster and simpler estimation becomes particularly advantageous in the case of large datasets. Other strategies of analysis are also feasible; for example, the transition to candidacy and to successful candidacy could also be modelled with an event history approach.

Also, this study did not model the election/voting process as a network but assigned a number of network values to users. Other values than those I included could also be included in future work; for example, betweenness describes the extent to which a node lies between other nodes. A high value of betweenness implies that other nodes are dependent on one to access information (see e.g. Kolaczyk et al. 2009); however, the computational cost of calculating betweenness is high (Brandes 2001). Generally, with this non-network setup, I assume that the decision to vote is more or less independent of other users in the network (i.e. other users voting). However, there could also be reciprocity across time (i.e. when one user voted for another one opposingly, they might do so too) and other network interdependencies in place. This would suggest the usage of a stochastic actor-oriented model. Such an approach has for example been followed up by Putzke and Takeda (2017). While such network approaches are computationally more expensive, they can reveal interesting insights. In their study, Putzke and Takeda (2017) have focused on neutral votes cast in elections which occur less frequently. With a more restricted frame of analysis, such an approach could also be applied to the present data.

Notwithstanding its limitations, this study was the first one to bring offline relationships into the context of an online election setting. It has highlighted the importance of social capital in this context. Using data from Wikipedia and framing it as a public assembly vote, this study is unique in employing classical voting theory in the context of an online election. Additionally, it is the first time a public voting process has been researched in such detail. Extending previous research on elections on Wikipedia, it was also the first to take such a large time span into account and the first to use the German Wikipedia as a case study. With this, a new dataset for future research is created now allowing comparisons of elections across more language versions and thus, cultural contexts. This study is also the first one which has looked at who is running for administrator by setting up eligible users for each month. Power in Wikipedia derives from community recognition and respect; it is important to understand who is being granted this trust and how the public voting process functions.

7 Discussion and Conclusion: Does the Offline Matter?

This thesis asked to what extent online behaviour in a large online community is affected by offline meetings between the members of the community. The thesis took Wikipedia as a case study, an online free-content encyclopaedia; one of the largest and most successful examples of online peer-production. Wikipedia celebrated its twentieth birthday in 2021 and has developed into a key figure in the internet landscape. Known by most internet users, it provides the backbone of many information technologies, gives the answers to Alexia, Google, and Siri, and is also a phenomenon that has attracted considerable attention from researchers. Not only does Wikipedia provide a rich and valuable source of data, but it is also a peculiar community to research in itself—a fact often unknown to the end-user.

In this thesis, I have focused on one of the most unknown facts of the Wikipedia community: Wikipedians meet offline, often, regularly, and across the globe. In the typical spirit of Wikipedia, these meetings are organised publicly and are well-documented with lists of attendees, minutes, and photo evidence. *To what extent is online behaviour on Wikipedia affected by offline meetings between Wikipedians?* This question was investigated in the previous chapters. Three realms of online behaviour were researched: productive contribution behaviour, norm-relevant behaviour, and behaviour related to elections. The results will be summarised briefly in the next section.

7.1 Summary of Findings

Do Offline Meetings Matter for the Productivity on Wikipedia? Chapter 4 explored whether there are effects of meetup participation on the extent of contribution and collaboration on Wikipedia. A control group of similar other users was constructed so that a difference-in-differences could be calculated, assessing an effect of the meetup in both the short and long term (quasi-experimental setup). I find that attending an offline meetup has a positive effect on the contribution behaviour of users. Users who have not made any edits in the time frame before the meetup are more likely to start editing after taking part in an offline meeting. Further, while it is not necessarily the case that users increase their contributions after a meetup in comparison to before the meetup, their reduction in contributions is less than the reduction a comparable control group experiences in the same time frame. Concerning collaboration, I find that attendees become slightly more likely to collaborate with each other, but there is no evidence of shifting the extent of the collaboration to the users that have attended a meetup with a user in favour of those that have not been met. Theoretically, these findings highlight the positive effects of social capital: developing ties to others and committing more strongly to the online project increases users' contribution and the strengthening of bonds between meetup attendees increases their collaboration (slightly). While potential negative effects of social capital are important to consider (Portes 1998), this chapter did not reveal any in terms of productive behaviour.

Does the Offline Meetup Network Affect Norm Enforcing Behaviour on Wikipedia? Building upon the theoretical arguments put forward by Coleman (1988, 1990), chapter 5 tested to what extent the density of a user's offline network is important in explaining their norm-relevant behaviour. The chapter conceptually replicated and extended the study of Piskorski and Gorbatâi (2017) who tested to what extent the density of a user's online collaboration network is relevant in regard to norms. I tested the same set of hypotheses as Piskorski and Gorbatâi (2017) but diverged from their variable operationalisations in several ways due to their language-specific and somewhat unconvincing setup. Overall, I found only very limited support for the argument put forward by Coleman (1990) when focusing on the online network measures and only limited importance of the offline network. Users who attend meetups tend to both experience and conduct fewer norm violations, and they give and receive more rewards. However, the density of the offline network does not play a noteworthy role in explaining online norm violation and norm enforcement, except that those in high-density offline networks generally give, unexpectedly, fewer rewards. There is thus no support for Coleman's mechanism based on the offline network, but the results do suggest that those taking part in meetups behave somewhat differently online than those who do not meet up.

Do Offline Meetings Affect Elections on Wikipedia? Focusing on elections to become administrator, chapter 6 investigated whether participation in offline meetings influences 1) whether users run to become administrator in a given year, 2) whether users are successful when running for administrator, 3) whether users vote in elections, and 4) whether users vote supportively in elections. I found that offline participation measures only weakly influence whether a user runs for administrator in a given year. To a greater extent, the offline network affects whether one is successful as a candidate, whether one votes, and whether one votes supportively: the larger the proportion of voters a candidate has met, the more likely they are to win and the higher the proportion of other voters a user has met, the more likely they are to vote themselves (this also holds true for the direction of votes: the more pro-voters a user knows, the more likely they also vote supportively, and the more anti-voters they have met, the less likely they vote supportively). Users are also more likely to vote if they have met the candidate, and they tend to support those more central in the meetup network. While not all hypotheses tested could be supported—for example, having met the candidate does not increase the likelihood to vote supportively in an election—the chapter still highlighted that taking part in elections, either passively as a voter or actively as a candidate, is influenced, among many other things, by meetup participation. This is in line with the long-lasting strand of research started by Lazarsfeld et al. (1944) which highlights the importance of social contacts in explaining voting behaviour and extends it to an online setting. Offline social capital is supportive when people run for administrator and personal voting decisions are also influenced by the ties to the candidate and to other voters. The findings support the idea that voters are fulfilling their obligations towards their friends or that these direct ties provide cheap information to the person voting. While social mechanisms cannot be tested, this chapter highlighted the importance of social capital in the context of a public election.

Does the Offline Matter? Regarding the three realms of online behaviour investigated, the offline activities contributors take part in are shown to matter and affect their online behaviour to some extent. The conclusions of this thesis aimed at developing an overarching understanding that offline meetup participation affects how a community functions online. Those taking part in meetups are a very self-selected group and there are differences between those taking part and those who do not. Taking part in meetings has been shown to be positive for the community in terms of productivity and collaboration and those taking part experience and conduct fewer norm violations, and do give and receive more rewards. Having face-to-face ties to others also influences the probability that someone is successful when running to become an administrator and when deciding to vote (supportively) in these elections. Thus, to answer the main question: yes, the offline matters. The overarching research question of this thesis asked to what extent online behaviour on Wikipedia is affected by offline meetings between Wikipedians. This thesis has clearly shown that online behaviour is affected by offline meetings, with the extent depending on the specific domain and the identification of causality being an important question for future research. The social capital and the identification with the community which develop and increase at such meetings suggest to make people contribute more, collaborate with each other, and change their voting behaviour. In contrast to many other online communities as well as to many other collective goods in general, Wikipedia is an example of sustained cooperation—the offline meetings which enrich the community and remove it from being something purely virtual play an important part in this.

7.2 Impact and Contributions to Knowledge

What impact does this thesis have and how does it contribute to human knowledge? Firstly, the study offers findings of interest to the Wikimedia community and Foundation. It extends their previous, anecdotal evidence of the importance of offline meetups[217]. The informal meetups analysed in this study are generally open to all, but a certain reluctance to join them is observable on the organisation pages (as discussed in section 2.4.2): in many cases, editors who are or consider themselves to be part of a minority on Wikipedia are hesitant to join local meetups, while other active users have attended hundreds of meetings and can be considered "stars" in the network of Wikipedians. Reading the discussion pages of meetups further reveals that

[217] For example, when learning about new editors in the New Editor Experiences project, the Wikimedia Foundation (2017) suggested the "Joiner Inner Helena" to be one of six personas new editors can correspond to—Helena is seen as a person who starts to edit Wikipedia for the experience, to learn something new, be part of the offline community of editors, and meet new people (https://www.mediawiki.org/wiki/File:New_editors_personas,_Joiner-Inner,_Helena.pdf). Further, some of the public answers in the Wikimania 2006 Wikipedian Survey mention the role of friendships on Wikipedia (see https://en.wikipedia.org/wiki/User:Linuxbeak/Wikimania_2006/Wikipedian_Survey).

they are not neutral spaces, but that tensions and cliques can develop. The three quantitative chapters have shed light on the question of whether offline meetups are a negligible factor or whether they affect the online community. My results show that offline meetups matter and affect the online behaviour of users. This evidence-based research allows to conclude that offline meetups are a relevant factor in the German Wikipedia. These conclusions are made on empirical facts instead of speculative thoughts. This makes it even more important that such meetups are inclusive to all to foster a more diverse and fair community, enhancing the sustainability of the Wikipedia project. While this research project did not yet directly suggest implementable solutions, it will allow for informed decisions regarding the organisation of offline meetups. The results highlight that the Foundation's and community's efforts spent regarding their offline organisation are important. The Wikimedia community should continue to strive to make meetups inviting to newcomers and reduce the perception of a closed-off clique, for example by friendly introductions and offline versions of their "adopt-a-user program". In summary, the output of this research can raise awareness in the community of Wikipedia. If changes in the way meetups are organised are implemented, their impact must be carefully evaluated. The data collected as part of this research project can work as a baseline.

Besides the impact of the study on the community of Wikipedians, it has further contributed to sociological knowledge on (online) communities and collective goods and shed light on the interplay of online and offline behaviour. Collectively, my analytical chapters also set out some broader contributions to the literature on social capital and social networks that I unpacked in chapter 2, and discussed the role of (offline) network ties in contributing behaviour, norm enforcement, and election participation. The study was the first to assess the effects of twenty years of offline activity on an online community. Online communities surviving for such a long time are a rarity in themselves, and Wikipedia's sustainability shows that it might serve as a prime example other communities can learn from. Showing the positive effects of offline meetups on contribution and collaboration has shown that the inclusion of an offline component can be one helpful piece to the puzzle of an active online community. This study was also the first to go beyond activity levels of Wikipedians and further assessed offline network effects on norm-relevant behaviour as well as on voting behaviour, thus highlighting a more complex understanding of the potential effects of offline meetings. I aimed at identifying causal effects by using a difference-in-differences design and by studying within variations of users across time in more complex multi-level setups to conclude the actual effects of meetup participation. However, with the observational digital trace data, the possibilities of such an identification are limited and mechanisms could not be identified with my study setup. Still, my thesis revealed patterns suggesting an influence of meetup participation and highlighted avenues for future research.

These findings are useful to better understand not only Wikipedia—one of the most important websites world wide—but online communities in general. Offline ties between members of online communities affect their online behaviour and knowing this is important in a world which increasingly relies on digital platforms and communities and aims at inclusivity. While the specifics of the Wikipedian context must be acknowledged and kept in mind (see on different types of online communities e.g. González-Anta et al. 2021), the results of this thesis highlight relationships which are important beyond its immediate context. Across the different chapters, social capital has shown to matter and primarily so in a positive way by increasing people's activity within the community and making them contribute, collaborate, enforce norms and reward, and take part in election processes. The dark side of social capital should, however, not be neglected and needs to be considered, for example when future research will focus on the mechanisms at work which make users vote (in a certain direction).

Beyond the context of online communities, this thesis has also highlighted the core of Sociology: people act and interact within a social environment. Social acts like public votes must be understood as such and the influence of social contacts cannot be ignored. Editing an online article is also not an individualistic act removed from the social environment, but decisions of contribution and collaboration are affected by interactions. Norm-relevant behaviour is by definition an interaction between people reacting towards actions conducted by one another. In this realm, testing the important theoretical considerations on norms put forward by Coleman (1988, 1990), this thesis highlighted specific circumstances in which his propositions are not supported. Taken together, this thesis studied how the contribution towards the online collective good and how an online group's organisation is affected by offline interaction between members; these are variants of core questions of the social sciences.

As a last contribution, I hope to make Wikipedia a more popular source of data for computational social scientists. While Wikipedia is often used as a data source by computer scientists, making use of its data in combination with sociological theories offers much potential. Understanding Wikipedia's dynamics and pre-processing the data can be a complex undertaking. I aimed for extensive methods sections in each chapter, giving rich descriptions of Wikipedia and its twenty years of history. Further, to make this research topic in particular more accessible to Wikipedia researchers and to allow for replication and scalability across different Wikipedia language versions, I shared much of it in the form of guidelines on Wikipedia itself[218]. Also, given the basic values and principles of Wikipedia, not only the results of this research and this thesis itself will be shared, but also the data collected and analysed will be made accessible to other researchers after an embargo period given my impending publication plans. The pre-processed data will be shared on the OpenScienceFoundation platform. Using data from Wikipedia for social science research allows for a new and very different context than for example the very frequently studied Twitter data.

7.3 Overall Limitations and Future Research

Like any other study, this thesis comes with limitations which must be considered. Limitations were already given in the concluding sections of each chapter; this section will thus not repeat the previously discussed challenges and limitations but highlight the most important points and raise more general issues.

This thesis took a broad view of Wikipedia and generally made use of the twenty years of history and data produced. It did not focus on specific cases, time frames or users. While this is a strength, it also raises limitations. Section 3.3 has given a rich description of anecdotes of the meeting culture of Wikipedians. This could be followed up to investigate small-scale dynamics in-depth. The network of offline meetups could be analysed in more detail, and cliques and communities could be better understood. It would also be of interest to focus on different (regional) cliques of the network and explore potential features of self-similarity. A focus on small parts of the meetup network could also allow to track negative relationships developed at meetups; the fact that different sorts of relationships can develop at such meetings has largely been ignored in this study.

[218] See https://meta.wikimedia.org/w/index.php?title=Learning_patterns/Collecting_data_on_offline_meetups, https://meta.wikimedia.org/w/index.php?title=Learning_patterns/Collecting_data_on_requests_for_adminship and https://meta.wikimedia.org/w/index.php?title=Learning_patterns/Analysing_effects_of_offline_meetups.

Also, methodologically, the present analyses might gain from a network analytical approach. However, the sheer size of the data did not make it feasible to follow this. Sub-analyses of parts of the data in future research can exploit their richness and model the dependency structures more explicitly. This could account for the fact that independence of observations is not always given. Future research can also combine geographical meeting attendance with geographical attributes of the articles edited to understand whether places, where meetings took place, are relevant in subsequently edited content (see for a study about locating Wikipedia contributors through their editing histories Lieberman and Lin 2009).

Future studies might further aim at explaining meetup participation. For example, event history models could be insightful in explaining when users take part in their first meetup and what characteristics are relevant in explaining this. It would complement this thesis well; this thesis followed a different approach and tried to show what effects attendance at a meetup has on subsequent online behaviour. A study explaining meetup participation could also have significant impact: while this study showed that the offline matters, such a study can focus for example on the inequality of meeting access (a topic briefly touched upon in section 2.4.2). As this thesis showed, the offline network is important to Wikipedians and to their online behaviour; it is thus also important to understand who is and who is not taking part in this sphere. Further, different meetup trajectories could be analysed then: for example, are those users who take part in meetings before ever editing Wikipedia different from people who first edit and then attend a meetup?

Across all chapters and analyses, this research study made use of generally very large datasets. This *big data* comes with challenges. Throughout all quantitative pre-processing steps and analyses, computational costs had to be considered. Data was often reduced, simplified, and subsampled in the most meaningful way possible, however, this comes with a loss of information. The matching and subsampling procedures which rely on a 1:1-matching might not be the most efficient and discard information, but they were chosen sensibly. However, I am aware that discussions around any sort of matching are very present in the literature and that these approaches must be justified (see e.g. Jann 2017; King and Nielsen 2019).

The large number of observations often led to significant results. Given this, it becomes particularly important to pay attention to the size of effects and be wary that significant differences can also be (irrelevantly) small. Further, I also aimed to collect complete information about Wikipedians and their behaviour; given this, the effect sizes calculated can be true effect sizes of the behaviour of the population of Wikipedians without an error. When using the complete data, it could be discussed whether the use of significance tests is necessary (see e.g. Rubin 1985). I have decided to use general significance tests under the assumption that there will be more data in the future and I only have a sample of all the data Wikipedians will ever produce, as well as just a sample of the current data due to errors and problems in data collection (see below), excluded data (e.g. on large meetings), deleted edits, etc. and necessarily through the process of subsampling and matching.

Concerning the data used in this thesis, several limitations arise. First, the data collected is merely observational which makes the establishing of causal relations difficult. Further, meetup attendance was collected from protocols written after the meetup if possible; in most cases, however, attendance is taken from the registration of interest written before the meetup took place. It is, of course, not mandatory to sign up for a meeting before attending; it is also not mandatory to attend after registering. In the ideal case, these errors occur at random and do not affect the results. Concerning meetings, I have further decided to exclude community spaces and large meetups so that the assumption of actually having met at meetings holds. However, such meetings are not any less important than the meetups researched in this thesis: community spaces exhibit a very different dynamic than informal meetups and global, large meetings are important events for the community. Future research could focus on these events. Particularly, community spaces can reflect strong and close clusters of small groups of people which deserve more attention.

Affecting all parts of this project, one of the most difficult and error-prone but also most central parts is the user identification. The facts that a person can have multiple usernames and that users can change their names (and other users can take the name in the future) make it difficult to assign a person-specific ID to all usernames. This is generally less of an issue in other Wikipedia research which is based solely on the online part; such a study can justifiably rely on the user ID assigned by Wikipedia. In my case, however, I try to merge user-written text (i.e. meetup sign-ups) with online activity. This complicates the issue. I spent significant effort and time on identifying and linking users, however, there were still some users who got “lost” when combining activity data with the person-user-IDs. Future research effort can be spent on identifying better methods for such person-user-linking. Also, in my thesis, I have focused on registered users only; this is in line with the majority of other user-focused research conducted with and on Wikipedia. Contributions of unregistered users however also make up a substantial part of Wikipedia and matter (see for an example discussing anonymous contributions Champion et al. 2019).

Furthermore, I want to highlight the limitations concerning my measure of collaboration. Defining collaboration is not straight-forward and comes with a number of arbitrary decisions which need to be made: I restrict my analysis in chapter 4 to collaboration based on edits in the article mainspace as the article mainspace represents the most productive form of editing. When measuring collaboration in chapters 5 and 6, I take any form of co-editing into account as these chapters focus less on the writing of new articles but more on contributors being in general exchange with one another. Co-editing in other namespaces is reflective of not just collaboration, but can also cover forms of communication, the answering of questions, or the statement of opinions. My co-editing also only takes directly following edits into account while dropping edits made by unregistered users. This definition is narrow in the sense that only directly following edits were considered, but at the same time broad as the time between those edits was ignored. Instead of focusing on only the very direct pair-editing neighbours, collaboration could be defined differently. More advanced and fine-grained measures of collaboration using more complex algorithms might further distinguish between fruitful, productive collaboration or destructive edit-wars; a differentiation I have ignored. With this, interactions could be understood as signed—users can interact positively or negatively with each other. Such an approach has shown to be useful (see Lerner and Lomi 2020) but comes with extensive computational costs.

In an ideal case, robustness checks could test for the sensitivity of operationalisations. However, computational constraints limit the possibilities of conducting such robustness checks easily. Somewhat arbitrary decisions were taken multiple times across the data pre-processing, particularly when time frames or relevant variables and weights for matching were selected. While the most informed choices were tried to be made and transparency is my priority, additional robustness and sensitivity checks are warranted; however, such checks require fewer constraints, both computationally and timewise.

A general problem with user data from Wikipedia is that only little is known about the users. In contrast to traditional surveys or other data sources, there is no information about socio-demographics or attitudes. The only information available is the username and what users write about themselves on their user page. Given the difficulties and the computational costs of working with this text data, it was not used in this project. Also, it must be kept in mind that it is only a selective subset of users who give (a lot of) information about themselves. Studies have tried to retrieve additional information (see e.g. Brückner et al. 2021) and this can be a promising avenue for further research; keeping in mind ethical constraints.

Finally, this study was a case study of one online community: the German Wikipedia. Offline meetups can affect different online communities in different ways, depending on the context, the content, and the userbase of the community. Future research should test the generalisability of these results to other online communities. A particularly fruitful avenue might be the comparison between different language versions of Wikipedia: as a researcher, one is in the lucky situation to be able to make use of several projects which are very much alike and share their goals and rules but vary in some others like length of existence and size. While the differences and idiosyncrasies between different Wikipedia language versions must be understood and cannot be ignored, they still offer a setup in which the effect of somewhat isolated features can be studied.

Notwithstanding these limitations and potentials for future research, this study was the first large-scale analysis of the effect of informal meetups on different domains of online behaviour on Wikipedia. It bridged the gap between offline and online behaviour. Wikipedia provides a special context; it is written by a self-selected group of people interested in the project and willing to spend their time pursuing the goal of sharing free knowledge with the world. Assessing the generalisability to other online communities is the task of future research.

7.4 The Future of Offline Meetups

Wikipedia and the community around it were not unaffected by the Covid-19 pandemic. The lively culture of face-to-face meetings in the German speaking area came to a stark halt in March 2020 when all meetings became temporarily forbidden due to governmental measures taken to fight the outbreak of the disease. As large gatherings were disallowed by the national governments in Germany, Austria, and Switzerland and many public spaces such as restaurants but also the community spaces had to temporarily shut down, Wikipedians could not meet offline anymore.

The way regional portals handled the pandemic varied. Some cities have moved their meetups to an online space. From a first anecdotal view, online meetings have not proven to be very successful or long-lasting. For example, Tyrol introduced an online meetup, however, after only two occurrences, they moved back to face-to-face meetings at the end of May 2020, even though it required necessary adaptions (wearing masks, highly restricted number of attendees). Several other cities have also reinitiated face-to-face meetings quite early. For example, Munich Wikipedians began meeting again in outdoor spaces of restaurants in July 2020. Independent from regional groups, a "digital topic discussion round" was also established[219] as an alternative for cancelled offline meetings. However, this still needs to stand the test of time. This is, however, just a first anecdotal view of the effects of Covid-19 on offline meetings of Wikipedians. Future research should explore the determinants of sustainability and success of offline meetings, especially in light of such disruptions. The data made available as part of this PhD thesis cover all meetings up to the outbreak of Covid-19 in Germany. It will be the task of another researcher to collect the meetings after March 2020 to assess how local communities have dealt with the forced stop of social life and whether there has been a discontinuity in other measures. The major changes related to the Covid-19 outbreak offer possibilities for experimental research designs including and beyond offline meetups.

[219] See https://de.wikipedia.org/wiki/Wikipedia:Digitaler_Themenstammtisch.

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A Appendix

The appendix includes tables referring to the models estimated in the main text as well as additional model specification as robustness checks. For all models, the following notation is used:

- cm: cluster mean (capturing the between effect)
- cwc: centred within clusters (capturing the within effect).

A.1 Models on Productivity

A.1.1 Main LPM

Table A1: Changes in editing behaviour, 7 days.

	Mainspace binary	Mainspace binary	Mainspace continuous	Mainspace cont.	Total binary	Total binary	Total cont.	Total cont.
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Intercept	0.1580 (0.0045)***	−0.0607 (0.0125)***	−0.3176 (0.0198)***	−1.1636 (0.0884)***	0.1540 (0.0048)***	−0.0824 (0.0174)***	−0.3977 (0.0218)***	−1.4135 (0.0884)***
Treatment group (Ref.: Control)	0.2039 (0.0092)***	0.1928 (0.0110)***	0.0754 (0.0274)**	0.1259 (0.0363)***	0.3778 (0.0113)***	0.3974 (0.0150)***	0.3870 (0.0299)***	0.3353 (0.0384)***
First meetup (Ref.: Later meetup)		0.0257 (0.0094)**		0.0215 (0.0611)		0.0122 (0.0108)		0.0002 (0.0639)
First meetup * Treatment		−0.0216 (0.0162)		0.1058 (0.0827)		−0.0461 (0.0235)*		0.2466 (0.0842)**
Was ever admin (Ref.: Never)		−0.0528 (0.0269)+		0.1607 (0.0690)*		−0.0443 (0.0293)		0.2334 (0.0758)**
Was ever admin * Treatment		0.0917 (0.0380)*		−0.4066 (0.0813)***		0.0133 (0.0463)		−0.4251 (0.0895)***
Work meetup (Ref.: Social)		−0.0048 (0.0069)		−0.0448 (0.0409)		−0.0048 (0.0075)		−0.0892 (0.0436)*
Work meetup * Treatment		0.0817 (0.0142)***		0.0130 (0.0553)		0.0450 (0.0213)*		0.1743 (0.0578)**
Mainspace edits up to meeting (log, cwc)		0.0264 (0.0105)*		0.1659 (0.0305)***				
Mainspace edits up to meeting (log, cm)		0.0517 (0.0017)***		0.3251 (0.0147)***				
Total edits up to meeting (log, cwc)						0.0284 (0.0175)		0.1815 (0.0315)***
Total edits up to meeting (log, cm)						0.0456 (0.0023)***		0.3548 (0.0141)***
Mainspace edits 7 days before (cube-root, cwc)				−1.0710 (0.0111)***				
Mainspace edits 7 days before (cube-root, cm)				−0.4339 (0.0156)***				
Total edits 7 days before (cube-root, cwc)								−1.0611 (0.0109)***
Total edits 7 days before (cube-root, cm)								−0.4503 (0.0153)***
Year of meetup: 09-14 (Ref.: 03-08)		0.0150 (0.0127)		0.0571 (0.0499)		0.0128 (0.0146)		0.1382 (0.0516)**
Year of meetup: 15-20 (Ref.: 03-08)		−0.0115 (0.0113)		−0.2053 (0.0339)***		0.0022 (0.0141)		−0.1371 (0.0358)***
Years since first edit (cwc)		−0.0294 (0.0023)***		−0.1486 (0.0080)***		−0.0264 (0.0026)***		−0.1851 (0.0085)***
Years since first edit (cm)		−0.0121 (0.0014)***		−0.0644 (0.0069)***		−0.0086 (0.0016)***		−0.0661 (0.0072)***
AIC	19941.7376	18675.5160	250524.2299	241892.5737	12600.5306	12002.1531	294450.4854	285460.8344
BIC	19973.6679	18803.2365	250559.6461	242051.9465	12631.0055	12124.0517	294486.3819	285622.3688
Log Likelihood	−9966.8688	−9321.7580	−125258.1149	−120928.2869	−6296.2653	−5985.0765	−147221.2427	−142712.4172
Num. obs.	21646	21645	51743	51743	15044	15043	58345	58345
Num. groups: id	7160	7160	7122	7122	5720	5720	8319	8319
Var: id (Intercept)	0.0455	0.0349	0.0608	0.1535	0.0504	0.0450	0.1112	0.1972
Var: Residual	0.1218	0.1175	7.3623	6.1523	0.1064	0.1028	9.0114	7.6478

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$.

Table A2: Changes in editing behaviour, 1 month.

	Mainspace binary	Mainspace binary	Mainspace continuous	Mainspace cont.	Total binary	Total binary	Total cont.	Total cont.
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Intercept	0.1427 (0.0054)***	−0.0130 (0.0173)	−0.5523 (0.0262)***	−1.5179 (0.1086)***	0.1393 (0.0061)***	−0.0024 (0.0226)	−0.7216 (0.0288)***	−1.9431 (0.1149)***
Treatment group (Ref.: Control)	0.2301 (0.0121)***	0.2537 (0.0152)***	0.3839 (0.0363)***	0.3237 (0.0487)***	0.3604 (0.0184)***	0.4179 (0.0253)***	0.5969 (0.0395)***	0.4600 (0.0528)***
First meetup (Ref.: Later meetup)		0.0287 (0.0113)*		−0.0437 (0.0807)		−0.0044 (0.0129)		0.0069 (0.0864)
First meetup * Treatment		−0.0628 (0.0205)**		0.1835 (0.1089)$^{+}$		−0.0737 (0.0373)*		0.2556 (0.1137)*
Was ever admin (Ref.: Never)		−0.0060 (0.0402)		0.1324 (0.0948)		0.0262 (0.0405)		0.3151 (0.1044)**
Was ever admin * Treatment		0.0623 (0.0609)		−0.3208 (0.1121)**		−0.1178 (0.1017)		−0.3786 (0.1237)**
Work meetup (Ref.: Social)		0.0037 (0.0076)		−0.1104 (0.0552)*		0.0026 (0.0077)		−0.0825 (0.0606)
Work meetup * Treatment		0.0744 (0.0172)***		0.1936 (0.0748)**		0.0086 (0.0329)		0.2802 (0.0810)***
Mainspace edits up to meeting (log, cwc)		−0.0059 (0.0128)		−0.1031 (0.0413)*				
Mainspace edits up to meeting (log, cm)		0.0435 (0.0022)***		0.3508 (0.0193)***				
Total edits up to meeting (log, cwc)						−0.0025 (0.0215)		−0.0529 (0.0446)
Total edits up to meeting (log, cm)						0.0321 (0.0029)***		0.3816 (0.0195)***
Mainspace edits 1 month before (cube-root, cwc)				−1.0812 (0.0111)***				
Mainspace edits 1 month before (cube-root, cm)				−0.3075 (0.0139)***				
Total edits 1 month before (cube-root, cwc)								−1.0431 (0.0112)***
Total edits 1 month before (cube-root, cm)								−0.3108 (0.0137)***
Year of meetup: 09-14 (Ref.: 03-08)		0.0033 (0.0178)		0.0932 (0.0662)		0.0238 (0.0202)		0.1924 (0.0707)**
Year of meetup: 15-20 (Ref.: 03-08)		−0.0086 (0.0163)		−0.2832 (0.0460)***		0.0050 (0.0172)		−0.1938 (0.0501)***
Years since first edit (cwc)		−0.0247 (0.0029)***		−0.2137 (0.0109)***		−0.0237 (0.0034)***		−0.2609 (0.0121)***
Years since first edit (cm)		−0.0108 (0.0018)***		−0.0455 (0.0093)***		−0.0103 (0.0020)***		−0.0428 (0.0098)***
AIC	9721.1635	9154.0140	336391.3802	327252.4392	4508.5429	4325.1597	376040.5144	367446.3875
BIC	9751.1118	9273.8070	336427.4020	327414.5369	4536.8429	4438.3593	376076.8217	367609.7700
Log Likelihood	−4856.5818	−4561.0070	−168191.6901	−163608.2196	−2250.2715	−2146.5798	−188016.2572	−183705.1938
Num. obs.	13188	13188	60201	60200	8734	8734	64655	64654
Num. groups: id	4767	4767	8586	8586	3167	3167	9868	9868
Var: id (Intercept)	0.0630	0.0546	0.1050	0.3024	0.0693	0.0673	0.1420	0.3581
Var: Residual	0.0909	0.0882	15.5448	13.1933	0.0673	0.0652	19.5240	16.9119

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$.

Table A3: Changes in editing behaviour, 2 months.

	Mainspace binary	Mainspace binary	Mainspace continuous	Mainspace cont.	Total binary	Total binary	Total cont.	Total cont.
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Intercept	0.0900 (0.0048)***	0.0066 (0.0168)	−0.7512 (0.0323)***	−1.6452 (0.1266)***	0.0848 (0.0055)***	0.0281 (0.0214)	−0.9482 (0.0355)***	−2.1227 (0.1381)***
Treatment group (Ref.: Control)	0.2003 (0.0124)***	0.2118 (0.0161)***	0.4640 (0.0453)***	0.4054 (0.0599)***	0.3087 (0.0230)***	0.3568 (0.0339)***	0.6522 (0.0494)***	0.5219 (0.0657)***
First meetup (Ref.: Later meetup)		0.0167 (0.0100)$^{+}$		0.0121 (0.0944)		−0.0149 (0.0111)		0.0808 (0.1024)
First meetup * Treatment		−0.0538 (0.0194)**		0.0398 (0.1279)		−0.0726 (0.0434)$^{+}$		0.1066 (0.1357)
Was ever admin (Ref.: Never)		0.0191 (0.0378)		0.2346 (0.1214)$^{+}$		0.0241 (0.0366)		0.3726 (0.1344)**
Was ever admin * Treatment		0.0513 (0.0787)		−0.4552 (0.1436)**		−0.2299 (0.1357)		−0.4721 (0.1594)**
Work meetup (Ref.: Social)		−0.0063 (0.0063)		−0.0837 (0.0650)		−0.0093 (0.0060)		−0.0795 (0.0721)
Work meetup * Treatment		0.0875 (0.0177)***		0.1848 (0.0885)*		0.0294 (0.0397)		0.2250 (0.0971)*
Mainspace edits up to meeting (log, cwc)		−0.0238 (0.0132)$^{+}$		−0.5275 (0.0492)***				
Mainspace edits up to meeting (log, cm)		0.0267 (0.0021)***		0.3112 (0.0234)***				
Total edits up to meeting (log, cwc)						−0.0203 (0.0240)		−0.5764 (0.0539)***
Total edits up to meeting (log, cm)						0.0165 (0.0026)***		0.3419 (0.0243)***
Mainspace edits 2 months before (cube-root, cwc)				−1.1415 (0.0114)***				
Mainspace edits 2 months before (cube-root, cm)				−0.2548 (0.0141)***				
Total edits 2 months before (cube-root, cwc)								−1.0804 (0.0116)***
Total edits 2 months before (cube-root, cm)								−0.2529 (0.0141)***
Year of meetup: 09-14 (Ref.: 03-08)		0.0015 (0.0174)		0.2615 (0.0792)***		0.0063 (0.0191)		0.3743 (0.0858)***
Year of meetup: 15-20 (Ref.: 03-08)		−0.0067 (0.0154)		−0.2431 (0.0551)***		−0.0041 (0.0165)		−0.1340 (0.0608)*
Years since first edit (cwc)		−0.0136 (0.0027)***		−0.2282 (0.0131)***		−0.0121 (0.0024)***		−0.2603 (0.0148)***
Years since first edit (cm)		−0.0073 (0.0017)***		−0.0017 (0.0114)		−0.0056 (0.0019)**		0.0031 (0.0122)
AIC	4102.2402	3912.5396	374654.9706	364492.2159	263.6104	255.9040	412183.9778	402955.7907
BIC	4131.3365	4028.9247	374691.1570	364655.0547	291.0353	365.6037	412220.3899	403119.6447
Log Likelihood	−2047.1201	−1940.2698	−187323.4853	−182228.1080	−127.8052	−111.9520	−206087.9889	−201459.8953
Num. obs.	10658	10658	62731	62730	7018	7018	66371	66370
Num. groups: id	3899	3899	9084	9084	2365	2365	10300	10300
Var: id (Intercept)	0.0505	0.0468	0.2633	0.6011	0.0541	0.0531	0.3296	0.7169
Var: Residual	0.0618	0.0608	22.7546	19.0951	0.0401	0.0395	28.8688	24.8209

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$.

Table A4: Changes in editing behaviour, 1 year.

	Mainspace binary	Mainspace binary	Mainspace continuous	Mainspace cont.	Total cont.	Total cont.
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Intercept	0.0595 (0.0058)***	0.1205 (0.0244)***	−2.3199 (0.0668)***	−0.7142 (0.2089)***	−2.7273 (0.0745)***	−1.3211 (0.2420)***
Treatment group (Ref.: Control)	0.2502 (0.0183)***	0.2095 (0.0290)***	0.7578 (0.1030)***	1.0204 (0.1193)***	1.0139 (0.1141)***	1.3121 (0.1320)***
First meetup (Ref.: Later meetup)		0.0055 (0.0086)		0.4546 (0.1402)**		0.6331 (0.1557)***
First meetup * Treatment		−0.0302 (0.0281)		−1.0231 (0.1934)***		−1.3796 (0.2119)***
Was ever admin (Ref.: Never)		−0.0127 (0.0259)		−0.1696 (0.2960)		−0.3068 (0.3274)
Was ever admin * Treatment		−0.1294 (0.1098)		−0.5131 (0.3517)		−0.4641 (0.3897)
Work meetup (Ref.: Social)		−0.0049 (0.0034)		−0.1697 (0.0951)+		−0.2018 (0.1075)+
Work meetup * Treatment		0.0315 (0.0241)		0.0357 (0.1320)		0.1531 (0.1486)
Mainspace edits up to meeting (log, cwc)		−0.1707 (0.0261)***		−4.2646 (0.0779)***		
Mainspace edits up to meeting (log, cm)		0.0077 (0.0025)**		−0.3451 (0.0462)***		
Total edits up to meeting (log, cwc)						−5.0936 (0.0888)***
Total edits up to meeting (log, cm)						−0.2749 (0.0504)***
Mainspace edits 1 year before (cube-root, cwc)				−1.2202 (0.0125)***		
Mainspace edits 1 year before (cube-root, cm)				−0.0709 (0.0185)***		
Total edits 1 year before (cube-root, cwc)						−1.1628 (0.0127)***
Total edits 1 year before (cube-root, cm)						−0.1053 (0.0185)***
Year of meetup: 09-14 (Ref.: 03-08)		−0.0431 (0.0259)+		1.5116 (0.1315)***		1.8094 (0.1454)***
Year of meetup: 15-20 (Ref.: 03-08)		−0.0559 (0.0223)*		0.1755 (0.0890)*		0.2913 (0.0999)**
Years since first edit (cwc)		−0.0014 (0.0026)		−0.0879 (0.0214)***		−0.0993 (0.0250)***
Years since first edit (cm)		−0.0081 (0.0020)***		0.2253 (0.0217)***		0.2294 (0.0237)***
AIC	−1849.6175	−2146.7224	468363.1381	448372.0122	502242.5657	481839.6428
BIC	−1822.8055	−2039.4743	468399.6098	448536.1345	502279.1608	482004.3206
Log Likelihood	928.8088	1089.3612	−234177.5691	−224168.0061	−251117.2828	−240901.8214
Num. obs.	6021	6021	67368	67367	69479	69478
Num. groups: id	2206	2206	10108	10108	11031	11031
Var: id (Intercept)	0.0783	0.0722	6.6014	7.2262	8.4361	8.6866
Var: Residual	0.0210	0.0198	57.8883	42.2524	76.3483	56.0703

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$.

A.1.1.1 QQ-Plots

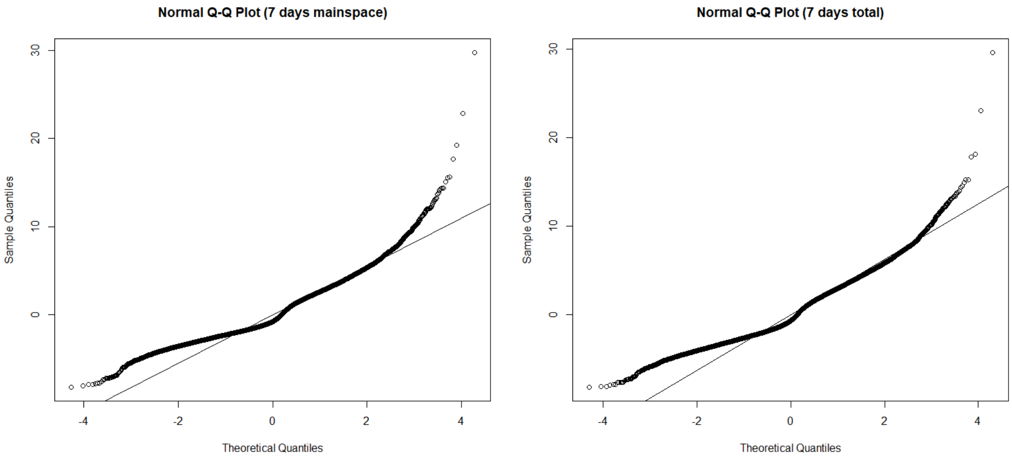

Figure A.1: Quantile-quantile plot for the full main LPMs, 7 days.

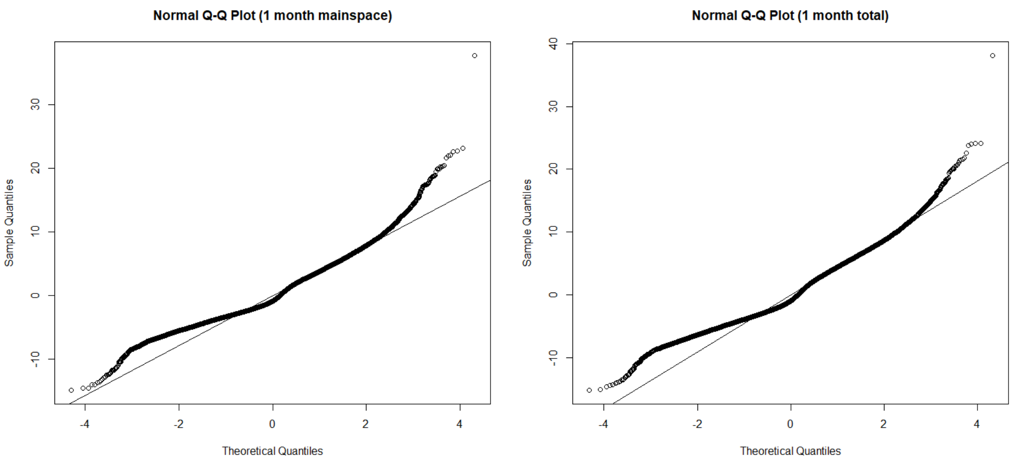

Figure A.2: Quantile-quantile plot for the full main LPMs, 1 month.

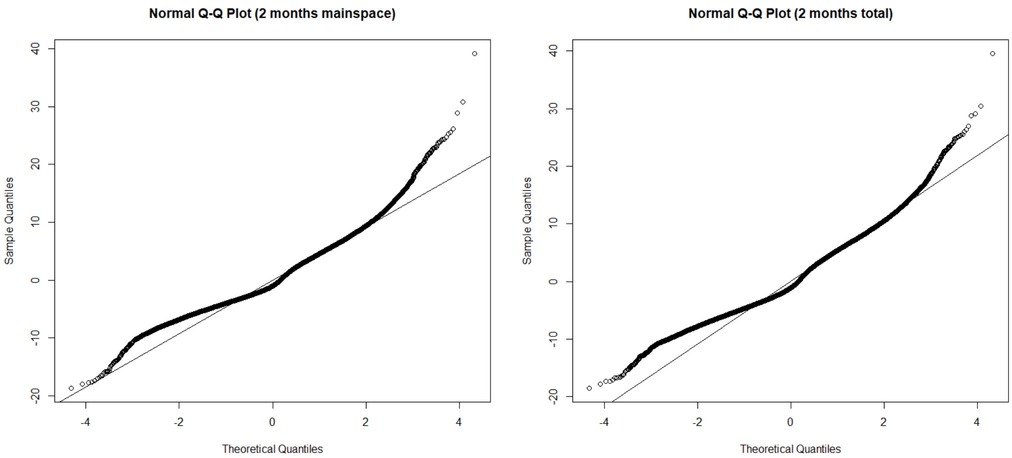

Figure A.3: Quantile-quantile plot for the full main LPMs, 2 months.

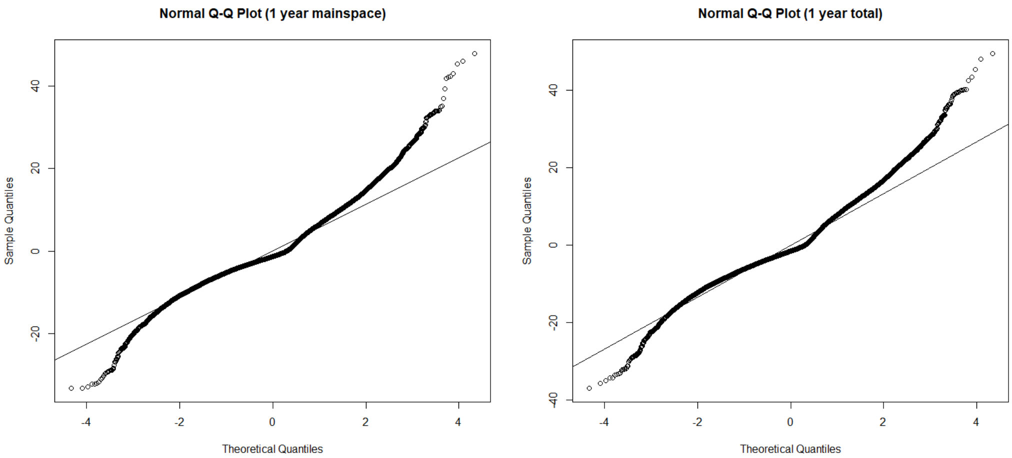

Figure A.4: Quantile-quantile plot for the full main LPMs, 1 year.

A.1.1.2 Posterior Predictive Checks

Table A5: Comparison of descriptive information of observed and simulated change in editing behaviour.

	7 days		1 month		2 months		1 year	
Edits	**Observed**	**Simulated**	**Observed**	**Simulated**	**Observed**	**Simulated**	**Observed**	**Simulated**
	-0.26 (2.72)	-0.25 (1.13)	-0.33 (3.96)	-0.31 (1.58)	0.47 (4.80)	-0.51 (1.96)	-1.97 (8.06)	-1.96 (4.67)
Mainspace	02.29 / -1 / 2.08	-0.85 / -0.19 / 0.44	-3.27 / -1.26 / 2.88	-1.13 / -0.26 / 0.61	- 4.04 / -1.44 / 3.42	- 1.48 / -0.47 / 0.59	- 7.61 / -3.63 / 4.51	-4.58 / -1.88 / 0.58
	-14.29 / 23.77	-14.69 / 6.57	-26.40 / 35.34	-24.77 / 10.82	-29.64 / 37.83	-29.24 / 11.38	-67.21 / 42.02	- 71.06 / 43.30
	-0.17 (3.02	-0.14 (1.21)	-0.37 (4.44)	-0.36 (1.69)	-0.55 (5.41)	-0.62 (2.10)	-2.35 (9.28)	-2.51 (5.28)
Total	-2.52 / -1 / 2.41	-0.84 / -0.10 / 0.62	-3.78 / -1.44 / 3.33	-1.32 / -0.35 / 0.64	-4.67 / -1.71 / 3.94	-1.67 / -0.60 / 0.54	-9.04 / -4.22 / 5.30	-5.42 / -2.45 / 0.21
	-14.63 / 23.77	-13.73 / 6.37	-25.32 / 35.34	-23.12 / 10.71	-29.67 / 37.83	-30.39 / 13.73	-67.25 / 42.13	-72.40 / 44.12

Given are mean (standard deviation), 1st/2nd/3rd quantile, minimum / maximum.

A.1.2 LPM (Without Interactions)

Table A6: Changes in editing behaviour, 7 days (no interaction effects).

	Mainspace binary	Mainspace continuous	Total binary	Total continuous
	Model 1	Model 2	Model 3	Model 4
Intercept	-0.0675 (0.0124)***	-1.1624 (0.0000)***	-0.0803 (0.0177)***	-1.4402 (0.0000)***
Treatment group (Ref.: Control)	0.2163 (0.0083)***	0.0800 (0.0074)**	0.3973 (0.0107)***	0.3528 (0.0000)***
First meetup (Ref.: Later meetup)	0.0154 (0.0086)$^{+}$	0.0822 (0.0638)$^{+}$	-0.0044 (0.0115)	0.1373 (0.0027)**
Was ever admin (Ref.: Never)	-0.0044 (0.0206)	-0.1202 (0.0039)**	-0.0365 (0.0240)	-0.0620 (0.1760)
Work meetup (Ref.: Social)	0.0278 (0.0067)***	-0.0395 (0.1635)	0.0065 (0.0076)	0.0070 (0.8117)
Mainspace edits up to meeting (log, cwc)	0.0291 (0.0103)**	0.1652 (0.0000)***		
Mainspace edits up to meeting (log, cm)	0.0515 (0.0017)***	0.3310 (0.0000)***		
Total edits up to meeting (log, cwc)			0.0335 (0.0168)*	0.1747 (0.0000)***
Total edits up to meeting (log, cm)			0.0453 (0.0023)***	0.3614 (0.0000)***
Mainspace edits 7 days before (cube-root, cwc)		-1.0696 (0.0000)***		
Mainspace edits 7 days before (cube-root, cm)		-0.4445 (0.0000)***		
Total edits 7 days before (cube-root, cwc)				-1.0596 (0.0000)***
Total edits 7 days before (cube-root, cm)				-0.4634 (0.0000)***
Year of meetup: 09-14 (Ref.: 03-08)	0.0143 (0.0127)	0.0615 (0.2187)	0.0137 (0.0147)	0.1430 (0.0057)**
Year of meetup: 15-20 (Ref.: 03-08)	-0.0118 (0.0113)	-0.2062 (0.0000)***	0.0024 (0.0141)	-0.1369 (0.0001)***
Years since first edit (cwc)	-0.0294 (0.0023)***	-0.1492 (0.0000)***	-0.0267 (0.0026)***	-0.1848 (0.0000)***
Years since first edit (cm)	-0.0122 (0.0014)***	-0.0653 (0.0000)***	-0.0087 (0.0016)***	-0.0672 (0.0000)***
AIC	18701.3829	241903.8983	11991.3419	285487.8006
BIC	18805.1558	242036.7090	12090.3846	285622.4125
Log Likelihood	-9337.6915	-120936.9492	-5982.6710	-142728.9003
Num. obs.	21645	51743	15043	58345
Num. groups: id	7160	7122	5720	8319
Var: id (Intercept)	0.0352	0.1622	0.0455	0.2101
Var: Residual	0.1177	6.1502	0.1027	7.6458

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$.

Table A7: Changes in editing behaviour, 1 month (no interaction effects).

	Mainspace binary	Mainspace continuous	Total binary	Total continuous
	Model 1	Model 2	Model 3	Model 4
Intercept	−0.0104 (0.0170)	−1.5503 (0.0000)***	0.0065 (0.0226)	−2.4831 (0.0000)***
Treatment group (Ref.: Control)	0.2590 (0.0113)***	0.3445 (0.0000)***	0.3900 (0.0180)***	0.5172 (0.0000)***
First meetup (Ref.: Later meetup)	0.0011 (0.0104)	0.0555 (0.3437)	−0.0237 (0.0138)+	0.1285 (0.0605)+
Was ever admin (Ref.: Never)	0.0216 (0.0319)	−0.0902 (0.1143)	0.0013 (0.0385)	0.0074 (0.9126)
Work meetup (Ref.: Social)	0.0274 (0.0076)***	−0.0080 (0.8339)	0.0035 (0.0078)	0.0507 (0.2544)
Mainspace edits up to meeting (log, cwc)	−0.0003 (0.0125)	−0.1067 (0.0094)**		
Mainspace edits up to meeting (log, cm)	0.0429 (0.0022)***	0.3570 (0.0000)***		
Total edits up to meeting (log, cwc)			0.0056 (0.0211)	−0.0696 (0.1505)
Total edits up to meeting (log, cm)			0.0316 (0.0029)***	0.4811 (0.0000)***
Mainspace edits 1 month before (cube-root, cwc)		−1.0805 (0.0000)***		
Mainspace edits 1 month before (cube-root, cm)		−0.3139 (0.0000)***		
Total edits 1 month before (cube-root, cwc)				−1.0743 (0.0000)***
Total edits 1 month before (cube-root, cm)				−0.3537 (0.0000)***
Year of meetup: 09-14 (Ref.: 03-08)	0.0037 (0.0178)	0.0943 (0.1554)	0.0226 (0.0202)	0.1868 (0.0156)*
Year of meetup: 15-20 (Ref.: 03-08)	−0.0087 (0.0164)	−0.2847 (0.0000)***	0.0042 (0.0172)	−0.2233 (0.0000)***
Years since first edit (cwc)	−0.0248 (0.0029)***	−0.2135 (0.0000)***	−0.0238 (0.0034)***	−0.2613 (0.0000)***
Years since first edit (cm)	−0.0110 (0.0018)***	−0.0463 (0.0000)***	−0.0102 (0.0020)***	−0.0592 (0.0000)***
AIC	9164.5531	327256.6659	4313.1678	345391.3436
BIC	9261.8849	327391.7473	4405.1426	345526.4250
Log Likelihood	−4569.2766	−163613.3330	−2143.5839	−172680.6718
Num. obs.	13188	60200	8734	60200
Num. groups: id	4767	8586	3167	8586
Var: id (Intercept)	0.0551	0.3102	0.0676	0.4262
Var: Residual	0.0883	13.1921	0.0651	17.8265

***$p < 0.001$; **$p < 0.01$; *$p < 0.05$; +$p < 0.1$.

Table A8: Changes in editing behaviour, 2 months (no interaction effects).

	Mainspace binary	Mainspace continuous	Total binary	Total continuous
	Model 1	Model 2	Model 3	Model 4
Intercept	0.0073 (0.0165)	−1.6573 (0.0000)***	0.0353 (0.0216)	−2.1465 (0.0000)***
Treatment group (Ref.: Control)	0.2241 (0.0122)***	0.3920 (0.0000)***	0.3329 (0.0231)***	0.5334 (0.0000)***
First meetup (Ref.: Later meetup)	−0.0064 (0.0095)	0.0388 (0.5729)	−0.0306 (0.0131)*	0.1425 (0.0562)+
Was ever admin (Ref.: Never)	0.0338 (0.0344)	−0.0753 (0.3005)	0.0002 (0.0361)	0.0512 (0.5288)
Work meetup (Ref.: Social)	0.0186 (0.0070)**	0.0124 (0.7846)	−0.0067 (0.0064)	0.0406 (0.4152)
Mainspace edits up to meeting (log, cwc)	−0.0188 (0.0131)	−0.5242 (0.0000)***		
Mainspace edits up to meeting (log, cm)	0.0261 (0.0020)***	0.3171 (0.0000)***		
Total edits up to meeting (log, cwc)			−0.0133 (0.0242)	−0.5770 (0.0000)***
Total edits up to meeting (log, cm)			0.0159 (0.0026)***	0.3488 (0.0000)***
Mainspace edits 2 months before (cube-root, cwc)		−1.1408 (0.0000)***		
Mainspace edits 2 months before (cube-root, cm)		−0.2604 (0.0000)***		
Total edits 2 months before (cube-root, cwc)				−1.0795 (0.0000)***
Total edits 2 months before (cube-root, cm)				−0.2593 (0.0000)***
Year of meetup: 09-14 (Ref.: 03-08)	0.0030 (0.0174)	0.2622 (0.0009)***	0.0064 (0.0191)	0.3769 (0.0000)***
Year of meetup: 15-20 (Ref.: 03-08)	−0.0063 (0.0154)	−0.2458 (0.0000)***	−0.0041 (0.0165)	−0.1354 (0.0260)*
Years since first edit (cwc)	−0.0138 (0.0027)***	−0.2288 (0.0000)***	−0.0122 (0.0024)***	−0.2605 (0.0000)***
Years since first edit (cm)	−0.0074 (0.0017)***	−0.0026 (0.8205)	−0.0056 (0.0019)**	0.0019 (0.8755)
AIC	3930.8300	364493.7532	247.4338	402958.5773
BIC	4025.3928	364629.4521	336.5648	403095.1223
Log Likelihood	−1952.4150	−182231.8766	−110.7169	−201464.2886
Num. obs.	10658	62730	7018	66370
Num. groups: id	3899	9084	2365	10300
Var: id (Intercept)	0.0471	0.6125	0.0536	0.7299
Var: Residual	0.0610	19.0926	0.0394	24.8183

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$.

Table A9: Changes in editing behaviour, 1 year (no interaction effects).

	Mainspace binary	Mainspace continuous	Total continuous
	Model 1	Model 2	Model 3
Intercept	$0.1267\ (0.0256)^{***}$	$-0.5597\ (0.0067)^{**}$	$-1.1074\ (0.0000)^{***}$
Treatment group (Ref.: Control)	$0.2041\ (0.0196)^{***}$	$0.7486\ (0.0000)^{***}$	$0.9719\ (0.0000)^{***}$
First meetup (Ref.: Later meetup)	$-0.0102\ (0.0151)$	$-0.0474\ (0.6446)$	$-0.0492\ (0.6680)$
Was ever admin (Ref.: Never)	$-0.0311\ (0.0284)$	$-0.4600\ (0.0082)^{**}$	$-0.5403\ (0.0055)^{**}$
Work meetup (Ref.: Social)	$0.0020\ (0.0058)$	$-0.1518\ (0.0243)^{*}$	$-0.1249\ (0.1004)$
Mainspace edits up to meeting (log, cwc)	$-0.1694\ (0.0260)^{***}$	$-4.2143\ (0.0000)^{***}$	
Mainspace edits up to meeting (log, cm)	$0.0067\ (0.0027)^{*}$	$-0.3517\ (0.0000)^{***}$	
Total edits up to meeting (log, cwc)			$-5.0140\ (0.0000)^{***}$
Total edits up to meeting (log, cm)			$-0.2878\ (0.0000)^{***}$
Mainspace edits 1 year before (cube-root, cwc)		$-1.2203\ (0.0000)^{***}$	
Mainspace edits 1 year before (cube-root, cm)		$-0.0702\ (0.0001)^{***}$	
Total edits 1 year before (cube-root, cwc)			$-1.1631\ (0.0000)^{***}$
Total edits 1 year before (cube-root, cm)			$-0.1025\ (0.0000)^{***}$
Year of meetup: 09-14 (Ref.: 03-08)	$-0.0421\ (0.0258)$	$1.5032\ (0.0000)^{***}$	$1.7931\ (0.0000)^{***}$
Year of meetup: 15-20 (Ref.: 03-08)	$-0.0551\ (0.0221)^{*}$	$0.1651\ (0.0635)^{+}$	$0.2735\ (0.0062)^{**}$
Years since first edit (cwc)	$-0.0013\ (0.0026)$	$-0.0928\ (0.0000)^{***}$	$-0.1078\ (0.0000)^{***}$
Years since first edit (cm)	$-0.0080\ (0.0020)^{***}$	$0.2240\ (0.0000)^{***}$	$0.2283\ (0.0000)^{***}$
AIC	−2159.4301	448391.1734	481873.9452
BIC	−2072.2909	448527.9420	482011.1767
Log Likelihood	1092.7150	−224180.5867	−240921.9726
Num. obs.	6021	67367	69478
Num. groups: id	2206	10108	11031
Var: id (Intercept)	0.0723	7.2439	8.6937
Var: Residual	0.0198	42.2645	56.1025

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$.

A.1.3 GLM

Table A10: Changes in editing behaviour, 7 days (GLM).

	Mainspace binary (logit)	Mainspace binary (logit)	Total binary (logit)	Total binary (logit)
	Model 1	Model 2	Model 3	Model 4
Intercept	$-2.4529\ (0.0608)^{***}$	$-4.6906\ (0.1459)^{***}$	$-2.4644\ (0.0676)^{***}$	$-4.9098\ (0.2040)^{***}$
Treatment group (Ref.: Control)	$1.5848\ (0.0721)^{***}$	$1.5464\ (0.0894)^{***}$	$2.6499\ (0.0928)^{***}$	$2.9602\ (0.1232)^{***}$
First meetup (Ref.: Later meetup)		0.0650 (0.1188)		−0.0723 (0.1371)
First meetup * Treatment		0.2156 (0.1499)		0.1151 (0.1821)
Was ever admin (Ref.: Never)		$-0.5582\ (0.2066)^{**}$		$-0.5041\ (0.2442)^{*}$
Was ever admin * Treatment		0.3614 (0.2720)		−0.0441 (0.3573)
Work meetup (Ref.: Social)		−0.1083 (0.0798)		−0.0920 (0.0909)
Work meetup * Treatment		$0.6833\ (0.1084)^{***}$		$0.4324\ (0.1440)^{**}$
Mainspace edits up to meeting (log, cwc)		$0.3159\ (0.0511)^{***}$		
Mainspace edits up to meeting (log, cm)		$0.5017\ (0.0193)^{***}$		
Total edits up to meeting (log, cwc)				$0.4317\ (0.0733)^{***}$
Total edits up to meeting (log, cm)				$0.4385\ (0.0252)^{***}$
Year of meetup: 09-14 (Ref.: 03-08)		0.1111 (0.1007)		0.0899 (0.1249)
Year of meetup: 15-20 (Ref.: 03-08)		−0.0917 (0.0767)		0.0362 (0.0984)
Years since first edit (cwc)		$-0.2411\ (0.0143)^{***}$		$-0.2604\ (0.0192)^{***}$
Years since first edit (cm)		$-0.1243\ (0.0139)^{***}$		$-0.0922\ (0.0161)^{***}$
AIC	19888.1302	18479.0295	13029.4724	12337.3903
BIC	19912.0779	18598.7675	13052.3286	12451.6703
Log Likelihood	−9941.0651	−9224.5148	−6511.7362	−6153.6952
Num. obs.	21646	21645	15044	15043
Num. groups: id	7160	7160	5720	5720
Var: id (Intercept)	2.5657	2.2092	2.3725	2.7361

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$.

Table A11: Changes in editing behaviour, 1 month (GLM).

	Mainspace binary (logit)	Mainspace binary (logit)	Total binary (logit)	Total binary (logit)
	Model 1	Model 2	Model 3	Model 4
Intercept	-7.4264 (0.2528)***	-5.7158 (0.3277)***	-6.2287 (0.2939)***	-8.4879 (0.6035)***
Treatment group (Ref.: Control)	2.2043 (0.2257)***	2.8178 (0.2051)***	6.3473 (0.5317)***	7.2050 (0.6000)***
First meetup (Ref.: Later meetup)		0.2823 (0.1845)		0.0963 (0.3054)
First meetup * Treatment		-0.4793 (0.2418)*		-1.3979 (0.5721)*
Was ever admin (Ref.: Never)		-0.1285 (0.4209)		0.4649 (0.7943)
Was ever admin * Treatment		0.1882 (0.6310)		-2.1683 (1.9917)
Work meetup (Ref.: Social)		0.0069 (0.1218)		0.0939 (0.1622)
Work meetup * Treatment		0.7587 (0.1810)***		-0.1783 (0.4396)
Mainspace edits up to meeting (log, cwc)		0.1484 (0.0771)$^+$		
Mainspace edits up to meeting (log, cm)		0.5415 (0.0360)***		
Total edits up to meeting (log, cwc)				0.6040 (0.2117)**
Total edits up to meeting (log, cm)				0.5599 (0.0667)***
Year of meetup: 09-14 (Ref.: 03-08)		0.0607 (0.1785)		0.4542 (0.3287)
Year of meetup: 15-20 (Ref.: 03-08)		-0.0426 (0.1428)		0.1091 (0.2654)
Years since first edit (cwc)		-0.2881 (0.0247)***		-0.5159 (0.0461)***
Years since first edit (cm)		-0.1378 (0.0242)***		-0.1927 (0.0454)***
AIC	10435.0540	9876.6784	5881.2760	5618.6419
BIC	10457.5152	9988.9844	5902.5010	5724.7666
Log Likelihood	-5214.5270	-4923.3392	-2937.6380	-2794.3210
Num. obs.	13188	13188	8734	8734
Num. groups: id	4767	4767	3167	3167
Var: id (Intercept)	78.3791	7.5602	38.9362	31.7321

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$.

Table A12: Changes in editing behaviour, 2 months (GLM).

	Mainspace binary (logit)	Mainspace binary (logit)	Total binary (logit)	Total binary (logit)
	Model 1	Model 2	Model 3	Model 4
Intercept	-8.7520 (0.2715)***	-9.7734 (0.5258)***	-9.3249 (0.3590)***	-9.8249 (0.8194)***
Treatment group (Ref.: Control)	2.0195 (0.2602)***	2.8067 (0.4014)***	2.9433 (0.4015)***	3.9641 (0.6767)***
First meetup (Ref.: Later meetup)		0.3664 (0.4265)		-0.3851 (0.7224)
First meetup * Treatment		-0.7242 (0.5021)		-0.4047 (0.9285)
Was ever admin (Ref.: Never)		-0.0410 (1.0062)		-0.4771 (1.2233)
Was ever admin * Treatment		1.1957 (2.2042)		-1.0368 (2.8164)
Work meetup (Ref.: Social)		-0.3014 (0.2181)		-0.3194 (0.2678)
Work meetup * Treatment		1.2895 (0.3035)***		-0.0014 (0.6225)
Mainspace edits up to meeting (log, cwc)		0.1375 (0.1140)		
Mainspace edits up to meeting (log, cm)		0.4053 (0.0671)***		
Total edits up to meeting (log, cwc)				0.5544 (0.2977)$^{+}$
Total edits up to meeting (log, cm)				0.2267 (0.1008)*
Year of meetup: 09-14 (Ref.: 03-08)		-0.0457 (0.3426)		0.2410 (0.5413)
Year of meetup: 15-20 (Ref.: 03-08)		-0.1416 (0.2722)		-0.1008 (0.4522)
Years since first edit (cwc)		-0.2665 (0.0397)***		-0.4800 (0.0690)***
Years since first edit (cm)		-0.1121 (0.0496)*		-0.1315 (0.0712)$^{+}$
AIC	6127.2988	6007.9692	3054.7031	2988.4513
BIC	6149.1210	6117.0802	3075.2718	3091.2948
Log Likelihood	-3060.6494	-2988.9846	-1524.3515	-1479.2257
Num. obs.	10658	10658	7018	7018
Num. groups: id	3899	3899	2365	2365
Var: id (Intercept)	112.7542	87.0489	140.5565	137.5908

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$.

Table A13: Changes in editing behaviour, 1 year (GLM).

	Mainspace binary (logit)	Mainspace binary (logit)
	Model 1	Model 2
Intercept	$-12.1283\ (0.5377)^{***}$	$-10.5834\ (1.1574)^{***}$
Treatment group (Ref.: Control)	$2.6223\ (0.5656)^{***}$	$2.8117\ (1.0316)^{**}$
First meetup (Ref.: Later meetup)		1.0955 (1.0704)
First meetup * Treatment		−1.8260 (1.1476)
Was ever admin (Ref.: Never)		−1.5703 (2.9980)
Was ever admin * Treatment		1.5496 (5.2566)
Work meetup (Ref.: Social)		−0.4600 (0.7941)
Work meetup * Treatment		0.9374 (0.8910)
Mainspace edits up to meeting (log, cwc)		$-5.7325\ (0.6714)^{***}$
Mainspace edits up to meeting (log, cm)		0.2183 (0.1640)
Year of meetup: 09-14 (Ref.: 03-08)		−0.7999 (0.7165)
Year of meetup: 15-20 (Ref.: 03-08)		$-2.2879\ (0.7477)^{**}$
Years since first edit (cwc)		−0.0707 (0.1052)
Years since first edit (cm)		$-0.2541\ (0.1398)^{+}$
AIC	1742.2391	1623.8875
BIC	1762.3481	1724.4326
Log Likelihood	−868.1195	−796.9437
Num. obs.	6021	6021
Num. groups: id	2206	2206
Var: id (Intercept)	521.4467	466.7738

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$.

A.1.4 LDV

Table A14: Changes in editing behaviour, 7 days (LDV).

	Mainspace continuous	Mainspace continuous	Total continuous	Total continuous
	Model 1	Model 2	Model 3	Model 4
Intercept	0.3903 (0.0160)***	−1.3931 (0.0396)***	0.3052 (0.0157)***	−1.3965 (0.0361)***
Treatment group (Ref.: Control)	0.1952 (0.0190)***	0.1283 (0.0188)***	0.3760 (0.0188)***	0.2990 (0.0182)***
First meetup (Ref.: Later meetup)		0.0528 (0.0255)*		0.0472 (0.0241)$^{+}$
First meetup * Treatment		0.0334 (0.0349)		0.0781 (0.0321)*
Was ever admin (Ref.: Never)		−0.0857 (0.0409)*		−0.0058 (0.0421)
Was ever admin * Treatment		0.0283 (0.0482)		−0.0064 (0.0495)
Work meetup (Ref.: Social)		−0.0106 (0.0170)		−0.0183 (0.0163)
Work meetup * Treatment		0.0004 (0.0231)		0.0726 (0.0218)***
Mainspace edits up to meeting (log, cwc)		0.0575 (0.0125)***		
Mainspace edits up to meeting (log, cm)		0.3054 (0.0058)***		
Total edits up to meeting (log, cwc)				0.0588 (0.0116)***
Total edits up to meeting (log, cm)				0.2900 (0.0051)***
Mainspace edits 7 days before (cube-root)	0.7073 (0.0039)***	0.6292 (0.0042)***		
Total edits 7 days before (cube-root)			0.7449 (0.0034)***	0.6598 (0.0037)***
Year of meetup: 09-14 (Ref.: 03-08)		0.0595 (0.0227)**		0.0825 (0.0213)***
Year of meetup: 15-20 (Ref.: 03-08)		−0.0711 (0.0149)***		−0.0367 (0.0142)**
Years since first edit (cwc)		−0.0599 (0.0034)***		−0.0659 (0.0032)***
Years since first edit (cm)		−0.0628 (0.0033)***		−0.0582 (0.0032)***
AIC	153188.1354	150168.2370	173386.9666	169572.9642
BIC	153232.4056	150318.7557	173431.8373	169725.5244
Log Likelihood	−76589.0677	−75067.1185	−86688.4833	−84769.4821
Num. obs.	51743	51743	58345	58345
Num. groups: id	7122	7122	8319	8319
Var: id (Intercept)	0.2436	0.1060	0.2957	0.1209
Var: Residual	1.0352	1.0098	1.0355	1.0095

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$.

Table A15: Changes in editing behaviour, 1 month (LDV).

	Mainspace continuous	Mainspace continuous	Total continuous	Total continuous
	Model 1	Model 2	Model 3	Model 4
Intercept	$0.4326\ (0.0184)^{***}$	$-1.6271\ (0.0423)^{***}$	$0.2528\ (0.0185)^{***}$	$-1.7449\ (0.0408)^{***}$
Treatment group (Ref.: Control)	$0.3651\ (0.0225)^{***}$	$0.2757\ (0.0228)^{***}$	$0.5077\ (0.0223)^{***}$	$0.4138\ (0.0225)^{***}$
First meetup (Ref.: Later meetup)		$0.0773\ (0.0290)^{**}$		$0.0690\ (0.0285)^{*}$
First meetup * Treatment		$-0.0029\ (0.0395)$		$0.0433\ (0.0381)$
Was ever admin (Ref.: Never)		$-0.0617\ (0.0533)$		$0.0389\ (0.0544)$
Was ever admin * Treatment		$0.0529\ (0.0630)$		$0.0484\ (0.0641)$
Work meetup (Ref.: Social)		$-0.0118\ (0.0195)$		$-0.0085\ (0.0197)$
Work meetup * Treatment		$0.0622\ (0.0267)^{*}$		$0.0979\ (0.0266)^{***}$
Mainspace edits up to meeting (log, cwc)		$-0.0875\ (0.0143)^{***}$		
Mainspace edits up to meeting (log, cm)		$0.3789\ (0.0066)^{***}$		
Total edits up to meeting (log, cwc)				$-0.0782\ (0.0141)^{***}$
Total edits up to meeting (log, cm)				$0.3621\ (0.0061)^{***}$
Mainspace edits 1 month before (cube-root)	$0.7623\ (0.0031)^{***}$	$0.6686\ (0.0034)^{***}$		
Total edits 1 month before (cube-root)			$0.8035\ (0.0027)^{***}$	$0.7049\ (0.0031)^{***}$
Year of meetup: 09-14 (Ref.: 03-08)		$0.1361\ (0.0263)^{***}$		$0.1650\ (0.0258)^{***}$
Year of meetup: 15-20 (Ref.: 03-08)		$-0.0459\ (0.0175)^{**}$		$-0.0101\ (0.0175)$
Years since first edit (cwc)		$-0.0660\ (0.0039)^{***}$		$-0.0723\ (0.0040)^{***}$
Years since first edit (cm)		$-0.0695\ (0.0040)^{***}$		$-0.0614\ (0.0039)^{***}$
AIC	205329.6467	201198.9614	225555.7926	220876.1750
BIC	205374.6739	201352.0537	225601.1768	221030.4807
Log Likelihood	−102659.8233	−100582.4807	−112772.8963	−110421.0875
Num. obs.	60201	60200	64655	64654
Num. groups: id	8586	8586	9868	9868
Var: id (Intercept)	0.4107	0.2080	0.4626	0.2165
Var: Residual	1.6166	1.5542	1.7397	1.6748

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$.

Table A16: Changes in editing behaviour, 2 months (LDV).

	Mainspace continuous	Mainspace continuous	Total continuous	Total continuous
	Model 1	Model 2	Model 3	Model 4
Intercept	0.5261 (0.0215)***	−1.7309 (0.0486)***	0.3093 (0.0216)***	−1.9042 (0.0483)***
Treatment group (Ref.: Control)	0.4288 (0.0270)***	0.3495 (0.0281)***	0.5654 (0.0265)***	0.4832 (0.0280)***
First meetup (Ref.: Later meetup)		0.0987 (0.0331)**		0.0995 (0.0332)**
First meetup * Treatment		−0.0579 (0.0453)		−0.0072 (0.0447)
Was ever admin (Ref.: Never)		−0.0582 (0.0694)		0.0717 (0.0703)
Was ever admin * Treatment		0.1305 (0.0820)		0.1380 (0.0831)$^{+}$
Work meetup (Ref.: Social)		−0.0100 (0.0223)		−0.0102 (0.0229)
Work meetup * Treatment		0.0429 (0.0306)		0.0725 (0.0312)*
Mainspace edits up to meeting (log, cwc)		−0.2731 (0.0164)***		
Mainspace edits up to meeting (log, cm)		0.4204 (0.0079)***		
Total edits up to meeting (log, cwc)				−0.2774 (0.0166)***
Total edits up to meeting (log, cm)				0.3993 (0.0074)***
Mainspace edits 2 months before (cube-root)	0.7586 (0.0029)***	0.6628 (0.0034)***		
Total edits 2 months before (cube-root)			0.8039 (0.0026)***	0.7045 (0.0032)***
Year of meetup: 09-14 (Ref.: 03-08)		0.1865 (0.0308)***		0.2359 (0.0308)***
Year of meetup: 15-20 (Ref.: 03-08)		−0.0319 (0.0204)		0.0224 (0.0208)
Years since first edit (cwc)		−0.0577 (0.0045)***		−0.0622 (0.0047)***
Years since first edit (cm)		−0.0646 (0.0048)***		−0.0538 (0.0047)***
AIC	233548.3225	229089.7366	254293.8218	249511.3172
BIC	233593.5555	229243.5287	254339.3369	249666.0682
Log Likelihood	−116769.1612	−114527.8683	−127141.9109	−124738.6586
Num. obs.	62731	62730	66371	66370
Num. groups: id	9084	9084	10300	10300
Var: id (Intercept)	0.6691	0.3959	0.6956	0.3996
Var: Residual	2.1840	2.0857	2.4389	2.3304

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$.

Table A17: Changes in editing behaviour, 1 year (LDV).

	Mainspace continuous	Mainspace continuous	Total continuous	Total continuous
	Model 1	Model 2	Model 3	Model 4
Intercept	$0.9050\ (0.0363)^{***}$	$-1.9378\ (0.0787)^{***}$	$0.6849\ (0.0380)^{***}$	$-2.2975\ (0.0846)^{***}$
Treatment group (Ref.: Control)	$0.7914\ (0.0496)^{***}$	$0.7647\ (0.0537)^{***}$	$1.0155\ (0.0507)^{***}$	$0.9756\ (0.0556)^{***}$
First meetup (Ref.: Later meetup)		$0.2946\ (0.0495)^{***}$		$0.3852\ (0.0529)^{***}$
First meetup * Treatment		$-0.4308\ (0.0681)^{***}$		$-0.5555\ (0.0721)^{***}$
Was ever admin (Ref.: Never)		$0.0018\ (0.1562)$		$0.0660\ (0.1620)$
Was ever admin * Treatment		$0.4334\ (0.1847)^{*}$		$0.6550\ (0.1916)^{***}$
Work meetup (Ref.: Social)		$-0.0823\ (0.0320)^{*}$		$-0.0993\ (0.0350)^{**}$
Work meetup * Treatment		$0.1082\ (0.0443)^{*}$		$0.1415\ (0.0484)^{**}$
Mainspace edits up to meeting (log, cwc)		$-1.9175\ (0.0251)^{***}$		
Mainspace edits up to meeting (log, cm)		$0.4479\ (0.0137)^{***}$		
Total edits up to meeting (log, cwc)				$-2.2531\ (0.0275)^{***}$
Total edits up to meeting (log, cm)				$0.4197\ (0.0141)^{***}$
Mainspace edits 1 year before (cube-root)	$0.7058\ (0.0029)^{***}$	$0.6650\ (0.0037)^{***}$		
Total edits 1 year before (cube-root)			$0.7432\ (0.0028)^{***}$	$0.7085\ (0.0036)^{***}$
Year of meetup: 09-14 (Ref.: 03-08)		$0.6379\ (0.0490)^{***}$		$0.7560\ (0.0521)^{***}$
Year of meetup: 15-20 (Ref.: 03-08)		$0.1468\ (0.0317)^{***}$		$0.2450\ (0.0343)^{***}$
Years since first edit (cwc)		$0.0441\ (0.0072)^{***}$		$0.0724\ (0.0080)^{***}$
Years since first edit (cm)		$-0.0199\ (0.0087)^{*}$		$-0.0011\ (0.0090)$
AIC	314396.5396	301618.1008	340017.3678	325580.0313
BIC	314442.1293	301773.1053	340063.1117	325735.5603
Log Likelihood	−157193.2698	−150792.0504	−170003.6839	−162773.0156
Num. obs.	67368	67367	69479	69478
Num. groups: id	10108	10108	11031	11031
Var: id (Intercept)	3.1505	2.6144	3.3169	2.7590
Var: Residual	5.3461	4.4161	6.7846	5.4943

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$.

A.1.5 DiD Without Lagged Activity

Table A18: Changes in editing behaviour, 7 days (without previous activity).

	Mainspace continuous	Total continuous
	Model 1	Model 2
Intercept	-0.8041 (0.0837)***	-0.9343 (0.0870)***
Treatment group (Ref.: Control)	0.1173 (0.0352)***	0.4005 (0.0380)***
First meetup (Ref.: Later meetup)	-0.1843 (0.0657)**	-0.2715 (0.0683)***
First meetup * Treatment	0.1466 (0.0891)$^{+}$	0.2998 (0.0901)***
Was ever admin (Ref.: Never)	0.0203 (0.0611)	0.0230 (0.0701)
Was ever admin * Treatment	-0.2193 (0.0718)**	-0.3096 (0.0821)***
Work meetup (Ref.: Social)	-0.0128 (0.0443)	-0.0653 (0.0469)
Work meetup * Treatment	-0.0075 (0.0594)	0.1133 (0.0618)$^{+}$
Mainspace edits up to meeting (log, cwc)	-0.1552 (0.0330)***	
Mainspace edits up to meeting (log, cm)	0.0650 (0.0107)***	
Total edits up to meeting (log, cwc)		-0.2055 (0.0338)***
Total edits up to meeting (log, cm)		0.0610 (0.0106)***
Year of meetup: 09-14 (Ref.: 03-08)	0.0238 (0.0510)	0.1110 (0.0531)*
Year of meetup: 15-20 (Ref.: 03-08)	0.0223 (0.0354)	0.1118 (0.0374)**
Years since first edit (cwc)	0.0261 (0.0084)**	0.0291 (0.0088)***
Years since first edit (cm)	-0.0081 (0.0063)	-0.0037 (0.0067)
AIC	250520.7982	294389.6141
BIC	250662.4629	294533.2002
Log Likelihood	-125244.3991	-147178.8071
Num. obs.	51743	58345
Num. groups: id	7122	8319
Var: id (Intercept)	0.0564	0.1027
Var: Residual	7.3543	8.9962

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$.

Table A19: Changes in editing behaviour, 1 month (without previous activity).

	Mainspace continuous	Total continuous
	Model 1	Model 2
Intercept	$-0.8734\ (0.1013)^{***}$	$-1.1397\ (0.1091)^{***}$
Treatment group (Ref.: Control)	$0.3640\ (0.0466)^{***}$	$0.5614\ (0.0507)^{***}$
First meetup (Ref.: Later meetup)	$-0.3808\ (0.0858)^{***}$	$-0.4087\ (0.0908)^{***}$
First meetup * Treatment	$0.2340\ (0.1159)^{*}$	$0.3161\ (0.1198)^{**}$
Was ever admin (Ref.: Never)	$0.0379\ (0.0822)$	$0.1372\ (0.0917)$
Was ever admin * Treatment	$-0.2055\ (0.0969)^{*}$	$-0.3270\ (0.1079)^{**}$
Work meetup (Ref.: Social)	$-0.0688\ (0.0591)$	$-0.0461\ (0.0643)$
Work meetup * Treatment	$0.1538\ (0.0793)^{+}$	$0.1829\ (0.0853)^{*}$
Mainspace edits up to meeting (log, cwc)	$-0.7713\ (0.0439)^{***}$	
Mainspace edits up to meeting (log, cm)	$0.0227\ (0.0131)^{+}$	
Total edits up to meeting (log, cwc)		$-0.8223\ (0.0467)^{***}$
Total edits up to meeting (log, cm)		$0.0176\ (0.0133)$
Year of meetup: 09-14 (Ref.: 03-08)	$0.0583\ (0.0670)$	$0.1703\ (0.0714)^{*}$
Year of meetup: 15-20 (Ref.: 03-08)	$0.1435\ (0.0474)^{**}$	$0.2485\ (0.0513)^{***}$
Years since first edit (cwc)	$0.1174\ (0.0110)^{***}$	$0.1257\ (0.0120)^{***}$
Years since first edit (cm)	$0.0219\ (0.0083)^{**}$	$0.0303\ (0.0089)^{***}$
AIC	336087.9590	375695.8587
BIC	336232.0459	375841.0876
Log Likelihood	−168027.9795	−187831.9293
Num. obs.	60200	64654
Num. groups: id	8586	9868
Var: id (Intercept)	0.0989	0.1299
Var: Residual	15.4545	19.4103

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$.

Table A20: Changes in editing behaviour, 2 months (without previous activity).

	Mainspace continuous	Total continuous
	Model 1	Model 2
Intercept	-0.9985 (0.1177)***	-1.3058 (0.1295)***
Treatment group (Ref.: Control)	0.4772 (0.0570)***	0.6352 (0.0624)***
First meetup (Ref.: Later meetup)	-0.3682 (0.1003)***	-0.3788 (0.1073)***
First meetup * Treatment	0.0759 (0.1359)	0.1724 (0.1423)
Was ever admin (Ref.: Never)	0.1165 (0.1048)	0.1525 (0.1166)
Was ever admin * Treatment	-0.3219 (0.1237)**	-0.3717 (0.1375)**
Work meetup (Ref.: Social)	-0.0236 (0.0696)	-0.0269 (0.0763)
Work meetup * Treatment	0.1001 (0.0940)	0.0874 (0.1020)
Mainspace edits up to meeting (log, cwc)	-1.5509 (0.0518)***	
Mainspace edits up to meeting (log, cm)	-0.0355 (0.0153)*	
Total edits up to meeting (log, cwc)		-1.7239 (0.0559)***
Total edits up to meeting (log, cm)		-0.0379 (0.0159)*
Year of meetup: 09-14 (Ref.: 03-08)	0.2830 (0.0801)***	0.4136 (0.0862)***
Year of meetup: 15-20 (Ref.: 03-08)	0.3769 (0.0566)***	0.5013 (0.0620)***
Years since first edit (cwc)	0.2373 (0.0130)***	0.2717 (0.0144)***
Years since first edit (cm)	0.0629 (0.0101)***	0.0735 (0.0109)***
AIC	373694.3453	411114.3984
BIC	373839.0908	411260.0464
Log Likelihood	-186831.1726	-205541.1992
Num. obs.	62730	66370
Num. groups: id	9084	10300
Var: id (Intercept)	0.2338	0.2880
Var: Residual	22.4058	28.4090

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$.

Table A21: Changes in editing behaviour, 1 year (without previous activity).

	Mainspace continuous	Total continuous
	Model 1	Model 2
Intercept	-0.6887 (0.1945)***	-1.0604 (0.2232)***
Treatment group (Ref.: Control)	1.2495 (0.1187)***	1.5231 (0.1312)***
First meetup (Ref.: Later meetup)	0.2111 (0.1480)	0.3444 (0.1629)*
First meetup * Treatment	-1.1016 (0.2044)***	-1.4963 (0.2219)***
Was ever admin (Ref.: Never)	-0.3064 (0.2842)	-0.4711 (0.3159)
Was ever admin * Treatment	-0.2569 (0.3370)	-0.2924 (0.3747)
Work meetup (Ref.: Social)	-0.0996 (0.1014)	-0.1364 (0.1135)
Work meetup * Treatment	-0.1555 (0.1406)	-0.0907 (0.1568)
Mainspace edits up to meeting (log, cwc)	-7.7313 (0.0743)***	
Mainspace edits up to meeting (log, cm)	-0.5628 (0.0271)***	
Total edits up to meeting (log, cwc)		-9.0209 (0.0827)***
Total edits up to meeting (log, cm)		-0.5849 (0.0294)***
Year of meetup: 09-14 (Ref.: 03-08)	1.8708 (0.1361)***	2.2241 (0.1496)***
Year of meetup: 15-20 (Ref.: 03-08)	1.5615 (0.0921)***	1.7351 (0.1027)***
Years since first edit (cwc)	0.9853 (0.0194)***	1.1349 (0.0221)***
Years since first edit (cm)	0.2441 (0.0198)***	0.2702 (0.0217)***
AIC	457157.9850	489697.9326
BIC	457303.8716	489844.3128
Log Likelihood	-228562.9925	-244832.9663
Num. obs.	67367	69478
Num. groups: id	10108	11031
Var: id (Intercept)	6.0609	7.4284
Var: Residual	48.8238	63.5583

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$.

A.2 Models on Collaboration

A.2.1 Main LPM

Table A22: Changes in collaboration behaviour, 7 days.

	Mainspace binary	Mainspace binary
	Model 1	Model 2
Intercept	0.00016 (0.00004)***	0.00005 (0.00008)
After meeting (Ref.: Before)	−0.00002 (0.00004)	−0.00004 (0.00005)
Treatment group (Ref.: Control)	0.00053 (0.00009)***	−0.00009 (0.00010)
After meeting * Treatment	0.00052 (0.00011)***	0.00035 (0.00011)**
Was ever admin (Ref.: Never)		−0.00071 (0.00024)**
Was ever admin * Treatment		0.00029 (0.00029)
Was ever admin * After meeting		0.00023 (0.00022)
Was ever admin * Treatment * After meeting		−0.00024 (0.00031)
Work meetup (Ref.: Social)		0.00005 (0.00007)
Work meetup * Treatment		0.00011 (0.00016)
Work meetup * After meeting		−0.00003 (0.00007)
Work meetup * Treatment * After meeting		0.00062 (0.00024)*
Collaborations up to meeting (log, cwc)		0.02966 (0.00233)***
Collaborations up to meeting (log, cm)		0.04637 (0.00533)***
Year of meetup: 09-14 (Ref.: 03-08)		0.00004 (0.00011)
Year of meetup: 15-20 (Ref.: 03-08)		−0.00012 (0.00011)
Years since first edit (cwc)		−0.00011 (0.00003)***
Years since first edit (cm)		−0.00005 (0.00001)***
AIC	−3796381.91738	−3852195.97550
BIC	−3796312.21721	−3851963.64162
Log Likelihood	1898196.95869	1926117.98775
Num. obs.	819700	819700
Num. groups: userofinterest	11102	11102
Var: userofinterest (Intercept)	0.00000	0.00000
Var: Residual	0.00057	0.00053

***$p < 0.001$; **$p < 0.01$; *$p < 0.05$; $^{+}p < 0.1$.

Table A23: Changes in collaboration behaviour, 1 month.

	Mainspace binary	Mainspace binary
	Model 1	Model 2
Intercept	0.00044 (0.00007)***	0.00028 (0.00014)$^{+}$
After meeting (Ref.: Before)	−0.00004 (0.00007)	−0.00019 (0.00008)*
Treatment group (Ref.: Control)	0.00162 (0.00021)***	0.00016 (0.00017)
After meeting * Treatment	0.00080 (0.00018)***	0.00055 (0.00019)**
Was ever admin (Ref.: Never)		−0.00096 (0.00041)*
Was ever admin * Treatment		0.00052 (0.00053)
Was ever admin * After meeting		0.00025 (0.00029)
Was ever admin * Treatment * After meeting		0.00017 (0.00049)
Work meetup (Ref.: Social)		0.00009 (0.00013)
Work meetup * Treatment		−0.00002 (0.00028)
Work meetup * After meeting		0.00034 (0.00013)**
Work meetup * Treatment * After meeting		0.00048 (0.00038)
Collaborations up to meeting (log, cwc)		0.07998 (0.00376)***
Collaborations up to meeting (log, cm)		0.11083 (0.00856)***
Year of meetup: 09-14 (Ref.: 03-08)		0.00001 (0.00020)
Year of meetup: 15-20 (Ref.: 03-08)		−0.00058 (0.00020)**
Years since first edit (cwc)		−0.00035 (0.00005)***
Years since first edit (cm)		−0.00011 (0.00002)***
AIC	−2934843.73708	−3079896.22287
BIC	−2934774.03692	−3079663.88900
Log Likelihood	1467427.86854	1539968.11143
Num. obs.	819700	819700
Num. groups: userofinterest	11102	11102
Var: userofinterest (Intercept)	0.00003	0.00001
Var: Residual	0.00162	0.00136

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$.

Table A24: Changes in collaboration behaviour, 2 months.

	Mainspace binary	Mainspace binary
	Model 1	Model 2
Intercept	0.00078 (0.00010)***	0.00074 (0.00018)***
After meeting (Ref.: Before)	−0.00016 (0.00010)	−0.00033 (0.00012)**
Treatment group (Ref.: Control)	0.00249 (0.00030)***	0.00018 (0.00021)
After meeting * Treatment	0.00077 (0.00019)***	0.00060 (0.00024)*
Was ever admin (Ref.: Never)		−0.00118 (0.00056)*
Was ever admin * Treatment		0.00101 (0.00069)
Was ever admin * After meeting		0.00014 (0.00036)
Was ever admin * Treatment * After meeting		−0.00011 (0.00052)
Work meetup (Ref.: Social)		−0.00002 (0.00018)
Work meetup * Treatment		−0.00001 (0.00035)
Work meetup * After meeting		0.00046 (0.00015)**
Work meetup * Treatment * After meeting		0.00054 (0.00040)
Collaborations up to meeting (log, cwc)		0.11372 (0.00431)***
Collaborations up to meeting (log, cm)		0.15974 (0.00964)***
Year of meetup: 09-14 (Ref.: 03-08)		−0.00002 (0.00024)
Year of meetup: 15-20 (Ref.: 03-08)		−0.00096 (0.00023)***
Years since first edit (cwc)		−0.00048 (0.00006)***
Years since first edit (cm)		−0.00017 (0.00003)***
AIC	−2609567.07501	−2812642.45657
BIC	−2609497.37484	−2812410.12270
Log Likelihood	1304789.53750	1406341.22829
Num. obs.	819700	819700
Num. groups: userofinterest	11102	11102
Var: userofinterest (Intercept)	0.00008	0.00001
Var: Residual	0.00240	0.00189

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$.

Table A25: Changes in collaboration behaviour, 1 year.

	Mainspace binary	Mainspace binary
	Model 1	Model 2
Intercept	$0.00262\ (0.00023)^{***}$	$0.00224\ (0.00032)^{***}$
After meeting (Ref.: Before)	$-0.00091\ (0.00017)^{***}$	$-0.00109\ (0.00021)^{***}$
Treatment group (Ref.: Control)	$0.00529\ (0.00057)^{***}$	$0.00076\ (0.00032)^{*}$
After meeting * Treatment	0.00037 (0.00030)	0.00053 (0.00035)
Was ever admin (Ref.: Never)		0.00039 (0.00091)
Was ever admin * Treatment		0.00117 (0.00104)
Was ever admin * After meeting		−0.00103 (0.00074)
Was ever admin * Treatment * After meeting		−0.00026 (0.00097)
Work meetup (Ref.: Social)		−0.00049 (0.00033)
Work meetup * Treatment		−0.00058 (0.00056)
Work meetup * After meeting		$0.00094\ (0.00038)^{*}$
Work meetup * Treatment * After meeting		0.00021 (0.00059)
Collaborations up to meeting (log, cwc)		$0.23583\ (0.00521)^{***}$
Collaborations up to meeting (log, cm)		$0.30867\ (0.01418)^{***}$
Year of meetup: 09-14 (Ref.: 03-08)		0.00027 (0.00043)
Year of meetup: 15-20 (Ref.: 03-08)		$-0.00170\ (0.00040)^{***}$
Years since first edit (cwc)		$-0.00098\ (0.00008)^{***}$
Years since first edit (cm)		$-0.00025\ (0.00004)^{***}$
AIC	−1864256.54140	−2247386.92763
BIC	−1864186.84124	−2247154.59376
Log Likelihood	932134.27070	1123713.46381
Num. obs.	819700	819700
Num. groups: userofinterest	11102	11102
Var: userofinterest (Intercept)	0.00035	0.00003
Var: Residual	0.00593	0.00375

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$.

A.2.2 LPM (Without Interactions)

Table A26: Changes in collaboration behaviour (no interactions).

	Mainspace binary, 7 days	Mainspace binary, 1 month	Mainspace binary, 2 months	Mainspace binary, 1 year
	Model 1	Model 2	Model 3	Model 4
Intercept	-0.00004 (0.00008)	0.00015 (0.00015)	0.00057 (0.00018)**	0.00218 (0.00031)***
After meeting (Ref.: Before)	-0.00002 (0.00004)	-0.00004 (0.00007)	-0.00016 (0.00010)	-0.00091 (0.00017)***
Treatment group (Ref.: Control)	-0.00002 (0.00008)	0.00016 (0.00014)	0.00027 (0.00017)	0.00078 (0.00025)**
After meeting * Treatment	0.00052 (0.00011)***	0.00080 (0.00018)***	0.00077 (0.00019)***	0.00037 (0.00030)
Was ever admin (Ref.: Never)	-0.00047 (0.00018)**	-0.00042 (0.00032)	-0.00045 (0.00038)	0.00060 (0.00058)
Work meetup (Ref.: Social)	0.00024 (0.00009)**	0.00037 (0.00016)*	0.00035 (0.00018)$^{+}$	-0.00025 (0.00027)
Collaborations up to meeting (log, cwc)	0.02966 (0.00233)***	0.07998 (0.00376)***	0.11372 (0.00431)***	0.23583 (0.00521)***
Collaborations up to meeting (log, cm)	0.04635 (0.00534)***	0.11083 (0.00856)***	0.15973 (0.00964)***	0.30870 (0.01419)***
Year of meetup: 09-14 (Ref.: 03-08)	0.00004 (0.00011)	0.00001 (0.00020)	-0.00002 (0.00024)	0.00028 (0.00043)
Year of meetup: 15-20 (Ref.: 03-08)	-0.00012 (0.00011)	-0.00058 (0.00020)**	-0.00096 (0.00023)***	-0.00170 (0.00040)***
Years since first edit (cwc)	-0.00011 (0.00003)***	-0.00035 (0.00005)***	-0.00048 (0.00006)***	-0.00098 (0.00008)***
Years since first edit (cm)	-0.00005 (0.00001)***	-0.00011 (0.00002)***	-0.00017 (0.00003)***	-0.00025 (0.00004)***
AIC	-3852271.53886	-3079976.32912	-2812720.25487	-2247448.80925
BIC	-3852108.90515	-3079813.69541	-2812557.62116	-2247286.17554
Log Likelihood	1926149.76943	1540002.16456	1406374.12744	1123738.40462
Num. obs.	819700	819700	819700	819700
Num. groups: userofinterest	11102	11102	11102	11102
Var: userofinterest (Intercept)	0.00000	0.00001	0.00001	0.00003
Var: Residual	0.00053	0.00136	0.00189	0.00375

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$.

A.2.3 GLM

Table A27: Changes in collaboration behaviour, 7 days (GLM).

	Mainspace binary (logit)	Mainspace binary (logit)
	Model 1	Model 2
Intercept	$-13.37406\ (0.35580)^{***}$	$-10.97342\ (0.42036)^{***}$
After meeting (Ref.: Before)	$-0.10033\ (0.22089)$	$-0.30429\ (0.30714)$
Treatment group (Ref.: Control)	$1.06075\ (0.34547)^{**}$	$0.39485\ (0.33132)$
After meeting * Treatment	$0.66325\ (0.24502)^{**}$	$0.89087\ (0.36161)^{*}$
Was ever admin (Ref.: Never)		$0.14369\ (0.58377)$
Was ever admin * Treatment		$0.08582\ (0.66449)$
Was ever admin * After meeting		$0.78182\ (0.51451)$
Was ever admin * Treatment * After meeting		$-0.99698\ (0.57662)^{+}$
Work meetup (Ref.: Social)		$-0.93837\ (0.53299)^{+}$
Work meetup * Treatment		$0.88926\ (0.58252)$
Work meetup * After meeting		$-0.87222\ (0.86043)$
Work meetup * Treatment * After meeting		$1.59513\ (0.89756)^{+}$
Collaborations up to meeting (log, cwc)		$1.81295\ (0.04610)^{***}$
Collaborations up to meeting (log, cm)		$4.28680\ (0.42958)^{***}$
Year of meetup: 09-14 (Ref.: 03-08)		$-0.05626\ (0.29736)$
Year of meetup: 15-20 (Ref.: 03-08)		$-0.44880\ (0.19577)^{*}$
Years since first edit (cwc)		$-0.17292\ (0.03471)^{***}$
Years since first edit (cm)		$-0.01907\ (0.03704)$
AIC	6697.98113	4666.54340
BIC	6756.06460	4887.26058
Log Likelihood	-3343.99056	-2314.27170
Num. obs.	819700	819700
Num. groups: userofinterest	11102	11102
Var: userofinterest (Intercept)	37.93345	7.78097

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$.

Table A28: Changes in collaboration behaviour, 1 month (GLM).

	Mainspace binary (logit)	Mainspace binary (logit)
	Model 1	Model 2
Intercept	-11.75399 $(0.25003)^{***}$	-9.42954 $(0.23682)^{***}$
After meeting (Ref.: Before)	-0.06439 (0.11896)	-0.35835 $(0.17972)^{*}$
Treatment group (Ref.: Control)	1.03099 $(0.22090)^{***}$	0.59488 $(0.19392)^{**}$
After meeting * Treatment	0.37035 $(0.13472)^{**}$	0.63840 $(0.21512)^{**}$
Was ever admin (Ref.: Never)		0.96615 $(0.32662)^{**}$
Was ever admin * Treatment		-0.54338 (0.37859)
Was ever admin * After meeting		0.35096 (0.27643)
Was ever admin * Treatment * After meeting		-0.33244 (0.31894)
Work meetup (Ref.: Social)		-0.85877 $(0.28436)^{**}$
Work meetup * Treatment		0.53096 $(0.32201)^{+}$
Work meetup * After meeting		0.87669 $(0.34861)^{*}$
Work meetup * Treatment * After meeting		-0.20755 (0.39087)
Collaborations up to meeting (log, cwc)		2.07218 $(0.03182)^{***}$
Collaborations up to meeting (log, cm)		5.30915 $(0.31529)^{***}$
Year of meetup: 09-14 (Ref.: 03-08)		0.10204 (0.18441)
Year of meetup: 15-20 (Ref.: 03-08)		-0.28577 $(0.11748)^{*}$
Years since first edit (cwc)		-0.22702 $(0.02155)^{***}$
Years since first edit (cm)		-0.00984 (0.02258)
AIC	16945.92407	10748.48995
BIC	17004.00754	10969.20713
Log Likelihood	-8467.96204	-5355.24497
Num. obs.	819700	819700
Num. groups: userofinterest	11102	11102
Var: userofinterest (Intercept)	26.33079	3.61909

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$.

Table A29: Changes in collaboration behaviour, 2 months (GLM).

	Mainspace binary (logit)	Mainspace binary (logit)
	Model 1	Model 2
Intercept	-11.36178 (0.00088)***	-9.06898 (0.21073)***
After meeting (Ref.: Before)	-0.14066 (0.00088)***	-0.39118 (0.14356)**
Treatment group (Ref.: Control)	0.97880 (0.11490)***	0.52631 (0.16774)**
After meeting * Treatment	0.31429 (0.05248)***	0.56517 (0.17604)**
Was ever admin (Ref.: Never)		0.98655 (0.30152)**
Was ever admin * Treatment		-0.37997 (0.35084)
Was ever admin * After meeting		0.27939 (0.22707)
Was ever admin * Treatment * After meeting		-0.39008 (0.26590)
Work meetup (Ref.: Social)		-0.70901 (0.22234)**
Work meetup * Treatment		0.41224 (0.25787)
Work meetup * After meeting		0.64895 (0.28015)*
Work meetup * Treatment * After meeting		-0.05008 (0.32055)
Collaborations up to meeting (log, cwc)		2.29583 (0.02999)***
Collaborations up to meeting (log, cm)		6.11409 (0.31666)***
Year of meetup: 09-14 (Ref.: 03-08)		0.13447 (0.16329)
Year of meetup: 15-20 (Ref.: 03-08)		-0.31012 (0.10248)**
Years since first edit (cwc)		-0.23857 (0.01890)***
Years since first edit (cm)		-0.01610 (0.02049)
AIC	23694.49084	14448.53267
BIC	23752.57431	14669.24985
Log Likelihood	-11842.24542	-7205.26633
Num. obs.	819700	819700
Num. groups: userofinterest	11102	11102
Var: userofinterest (Intercept)	26.45147	3.92974

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$.

Table A30: Changes in collaboration behaviour, 1 year (GLM).

	Mainspace binary (logit)	Mainspace binary (logit)
	Model 1	Model 2
Intercept	-10.41172 (0.16879)***	-8.47418 (0.16346)***
After meeting (Ref.: Before)	-0.25701 (0.05206)***	-0.50299 (0.08943)***
Treatment group (Ref.: Control)	0.82431 (0.14890)***	0.41705 (0.12460)***
After meeting * Treatment	0.18944 (0.06240)**	0.37788 (0.11478)***
Was ever admin (Ref.: Never)		1.27799 (0.26196)***
Was ever admin * Treatment		-0.30245 (0.30841)
Was ever admin * After meeting		0.08118 (0.14536)
Was ever admin * Treatment * After meeting		-0.26204 (0.17587)
Work meetup (Ref.: Social)		-0.45831 (0.12060)***
Work meetup * Treatment		0.21173 (0.14767)
Work meetup * After meeting		0.30504 (0.16421)$^{+}$
Work meetup * Treatment * After meeting		-0.03520 (0.19844)
Collaborations up to meeting (log, cwc)		3.16039 (0.02964)***
Collaborations up to meeting (log, cm)		8.07456 (0.32818)***
Year of meetup: 09-14 (Ref.: 03-08)		0.29985 (0.12116)*
Year of meetup: 15-20 (Ref.: 03-08)		-0.16101 (0.07293)*
Years since first edit (cwc)		-0.25356 (0.01358)***
Years since first edit (cm)		-0.00081 (0.01666)
AIC	51258.07704	28710.45423
BIC	51316.16051	28931.17141
Log Likelihood	-25624.03852	-14336.22712
Num. obs.	819700	819700
Num. groups: userofinterest	11102	11102
Var: userofinterest (Intercept)	25.73010	4.79096

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$.

A.2.4 LPM (All Meetups)

Table A31: Changes in collaboration behaviour, 7 days (all meetups).

	Mainspace binary	Mainspace binary
	Model 1	Model 2
Intercept	0.00025 (0.00003)***	0.00018 (0.00010)+
After meeting (Ref.: Before)	−0.00002 (0.00004)	0.00001 (0.00004)
Treatment group (Ref.: Control)	0.00115 (0.00012)***	0.00012 (0.00011)
After meeting * Treatment	0.00065 (0.00012)***	0.00055 (0.00015)***
Was ever admin (Ref.: Never)		−0.00066 (0.00022)**
Was ever admin * Treatment		0.00075 (0.00032)*
Was ever admin * After meeting		0.00001 (0.00015)
Was ever admin * Treatment * After meeting		−0.00031 (0.00030)
Work meetup (Ref.: Social)		0.00042 (0.00010)***
Work meetup * Treatment		−0.00016 (0.00021)
Work meetup * After meeting		−0.00012 (0.00008)
Work meetup * Treatment * After meeting		0.00075 (0.00029)*
Collaborations up to meeting (log, cwc)		0.03327 (0.00169)***
Collaborations up to meeting (log, cm)		0.03859 (0.00210)***
Year of meetup: 09-14 (Ref.: 03-08)		−0.00018 (0.00014)
Year of meetup: 15-20 (Ref.: 03-08)		−0.00054 (0.00014)***
Years since first edit (cwc)		−0.00026 (0.00003)***
Years since first edit (cm)		−0.00009 (0.00001)***
AIC	−6842970.97374	−7019574.60330
BIC	−6842896.46816	−7019326.25136
Log Likelihood	3421491.48687	3509807.30165
Num. obs.	1825924	1825924
Num. groups: userofinterest	11666	11666
Var: userofinterest (Intercept)	0.00001	0.00000
Var: Residual	0.00138	0.00125

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$.

Table A32: Changes in collaboration behaviour, 1 month (all meetups).

	Mainspace binary	Mainspace binary
	Model 1	Model 2
Intercept	0.00070 (0.00007)***	0.00078 (0.00019)***
After meeting (Ref.: Before)	−0.00009 (0.00006)	−0.00015 (0.00007)*
Treatment group (Ref.: Control)	0.00297 (0.00027)***	0.00067 (0.00020)***
After meeting * Treatment	0.00088 (0.00018)***	0.00069 (0.00022)**
Was ever admin (Ref.: Never)		−0.00111 (0.00047)*
Was ever admin * Treatment		0.00114 (0.00063)$^{+}$
Was ever admin * After meeting		−0.00001 (0.00026)
Was ever admin * Treatment * After meeting		0.00003 (0.00045)
Work meetup (Ref.: Social)		0.00052 (0.00019)**
Work meetup * Treatment		−0.00032 (0.00041)
Work meetup * After meeting		0.00021 (0.00013)
Work meetup * Treatment * After meeting		0.00067 (0.00040)$^{+}$
Collaborations up to meeting (log, cwc)		0.08136 (0.00272)***
Collaborations up to meeting (log, cm)		0.09565 (0.00361)***
Year of meetup: 09-14 (Ref.: 03-08)		−0.00043 (0.00025)$^{+}$
Year of meetup: 15-20 (Ref.: 03-08)		−0.00153 (0.00027)***
Years since first edit (cwc)		−0.00067 (0.00006)***
Years since first edit (cm)		−0.00020 (0.00003)***
AIC	−5054071.45557	−5475041.24383
BIC	−5053996.94999	−5474792.89189
Log Likelihood	2527041.72778	2737540.62191
Num. obs.	1825924	1825924
Num. groups: userofinterest	11666	11666
Var: userofinterest (Intercept)	0.00006	0.00001
Var: Residual	0.00366	0.00291

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$.

Table A33: Changes in collaboration behaviour, 2 months (all meetups).

	Mainspace binary	Mainspace binary
	Model 1	Model 2
Intercept	$0.00120\ (0.00010)^{***}$	$0.00122\ (0.00025)^{***}$
After meeting (Ref.: Before)	$-0.00018\ (0.00009)^{*}$	$-0.00021\ (0.00011)^{*}$
Treatment group (Ref.: Control)	$0.00428\ (0.00038)^{***}$	$0.00092\ (0.00025)^{***}$
After meeting * Treatment	$0.00082\ (0.00020)^{***}$	$0.00067\ (0.00025)^{**}$
Was ever admin (Ref.: Never)		$-0.00139\ (0.00066)^{*}$
Was ever admin * Treatment		$0.00171\ (0.00082)^{*}$
Was ever admin * After meeting		$-0.00028\ (0.00032)$
Was ever admin * Treatment * After meeting		$-0.00012\ (0.00052)$
Work meetup (Ref.: Social)		$0.00057\ (0.00024)^{*}$
Work meetup * Treatment		$-0.00042\ (0.00051)$
Work meetup * After meeting		$0.00029\ (0.00017)^{+}$
Work meetup * Treatment * After meeting		$0.00091\ (0.00043)^{*}$
Collaborations up to meeting (log, cwc)		$0.11466\ (0.00296)^{***}$
Collaborations up to meeting (log, cm)		$0.13916\ (0.00503)^{***}$
Year of meetup: 09-14 (Ref.: 03-08)		$-0.00049\ (0.00033)$
Year of meetup: 15-20 (Ref.: 03-08)		$-0.00203\ (0.00034)^{***}$
Years since first edit (cwc)		$-0.00095\ (0.00008)^{***}$
Years since first edit (cm)		$-0.00029\ (0.00003)^{***}$
AIC	-4328197.03542	-4914000.71135
BIC	-4328122.52984	-4913752.35942
Log Likelihood	2164104.51771	2457020.35568
Num. obs.	1825924	1825924
Num. groups: userofinterest	11666	11666
Var: userofinterest (Intercept)	0.00012	0.00002
Var: Residual	0.00544	0.00396

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$.

Table A34: Changes in collaboration behaviour, 1 year (all meetups).

	Mainspace binary	Mainspace binary
	Model 1	Model 2
Intercept	0.00403 (0.00023)***	0.00326 (0.00045)***
After meeting (Ref.: Before)	−0.00159 (0.00019)***	−0.00149 (0.00022)***
Treatment group (Ref.: Control)	0.00834 (0.00072)***	0.00195 (0.00042)***
After meeting * Treatment	0.00022 (0.00035)	0.00022 (0.00040)
Was ever admin (Ref.: Never)		0.00130 (0.00111)
Was ever admin * Treatment		0.00067 (0.00138)
Was ever admin * After meeting		−0.00264 (0.00084)**
Was ever admin * Treatment * After meeting		0.00119 (0.00108)
Work meetup (Ref.: Social)		0.00010 (0.00049)
Work meetup * Treatment		−0.00031 (0.00089)
Work meetup * After meeting		0.00118 (0.00042)**
Work meetup * Treatment * After meeting		0.00029 (0.00070)
Collaborations up to meeting (log, cwc)		0.22058 (0.00350)***
Collaborations up to meeting (log, cm)		0.26948 (0.00744)***
Year of meetup: 09-14 (Ref.: 03-08)		−0.00059 (0.00062)
Year of meetup: 15-20 (Ref.: 03-08)		−0.00340 (0.00063)***
Years since first edit (cwc)		−0.00180 (0.00012)***
Years since first edit (cm)		−0.00037 (0.00005)***
AIC	−2787131.54285	−3830512.86293
BIC	−2787057.03726	−3830264.51099
Log Likelihood	1393571.77142	1915276.43146
Num. obs.	1825924	1825924
Num. groups: userofinterest	11666	11666
Var: userofinterest (Intercept)	0.00047	0.00007
Var: Residual	0.01263	0.00716

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$; + $p < 0.1$.

A.2.5 LDV

Table A35: Changes in collaboration behaviour, 7 days (LDV).

	Mainspace binary	Mainspace binary
	Model 1	Model 2
Intercept	0.00009 (0.00003)***	0.00002 (0.00010)
Treatment group (Ref.: Control)	0.00090 (0.00010)***	0.00029 (0.00010)**
Collaborated 7 days before	0.26240 (0.03414)***	0.19348 (0.03259)***
Was ever admin (Ref.: Never)		−0.00036 (0.00023)
Was ever admin * Treatment		0.00005 (0.00028)
Work meetup (Ref.: Social)		0.00002 (0.00007)
Work meetup * Treatment		0.00066 (0.00022)**
Collaborations up to meeting (log, cwc)		0.02509 (0.00244)***
Collaborations up to meeting (log, cm)		0.03724 (0.00513)***
Year of meetup: 09-14 (Ref.: 03-08)		0.00002 (0.00015)
Year of meetup: 15-20 (Ref.: 03-08)		−0.00016 (0.00013)
Years since first edit (cwc)		−0.00009 (0.00003)**
Years since first edit (cm)		−0.00005 (0.00002)**
AIC	−1838216.09421	−1853927.60310
BIC	−1838161.47647	−1853763.74990
Log Likelihood	919113.04710	926978.80155
Num. obs.	409850	409850
Num. groups: userofinterest	11102	11102
Var: userofinterest (Intercept)	0.00000	0.00000
Var: Residual	0.00066	0.00063

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$.

Table A36: Changes in collaboration behaviour, 1 month (LDV).

	Mainspace binary	Mainspace binary
	Model 1	Model 2
Intercept	0.00027 (0.00005)***	0.00000 (0.00015)
Treatment group (Ref.: Control)	0.00173 (0.00016)***	0.00063 (0.00017)***
Collaborated 1 month before	0.37868 (0.02452)***	0.24103 (0.02216)***
Was ever admin (Ref.: Never)		−0.00062 (0.00040)
Was ever admin * Treatment		0.00064 (0.00051)
Work meetup (Ref.: Social)		0.00038 (0.00013)**
Work meetup * Treatment		0.00039 (0.00035)
Collaborations up to meeting (log, cwc)		0.05797 (0.00356)***
Collaborations up to meeting (log, cm)		0.09022 (0.00804)***
Year of meetup: 09-14 (Ref.: 03-08)		−0.00001 (0.00023)
Year of meetup: 15-20 (Ref.: 03-08)		−0.00055 (0.00021)**
Years since first edit (cwc)		−0.00024 (0.00005)***
Years since first edit (cm)		−0.00008 (0.00003)**
AIC	−1474579.04266	−1505844.26159
BIC	−1474524.42493	−1505680.40840
Log Likelihood	737294.52133	752937.13080
Num. obs.	409850	409850
Num. groups: userofinterest	11102	11102
Var: userofinterest (Intercept)	0.00001	0.00001
Var: Residual	0.00160	0.00148

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$.

Table A37: Changes in collaboration behaviour, 2 months (LDV).

	Mainspace binary	Mainspace binary
	Model 1	Model 2
Intercept	0.00038 (0.00007)***	0.00011 (0.00018)
Treatment group (Ref.: Control)	0.00205 (0.00019)***	0.00082 (0.00020)***
Collaborated 2 months before	0.41084 (0.01925)***	0.24179 (0.01806)***
Was ever admin (Ref.: Never)		−0.00067 (0.00048)
Was ever admin * Treatment		0.00068 (0.00058)
Work meetup (Ref.: Social)		0.00029 (0.00015)+
Work meetup * Treatment		0.00040 (0.00038)
Collaborations up to meeting (log, cwc)		0.07667 (0.00410)***
Collaborations up to meeting (log, cm)		0.11483 (0.00989)***
Year of meetup: 09-14 (Ref.: 03-08)		0.00022 (0.00027)
Year of meetup: 15-20 (Ref.: 03-08)		−0.00074 (0.00024)**
Years since first edit (cwc)		−0.00034 (0.00005)***
Years since first edit (cm)		−0.00011 (0.00003)**
AIC	−1352185.33810	−1389064.11837
BIC	−1352130.72037	−1388900.26518
Log Likelihood	676097.66905	694547.05919
Num. obs.	409850	409850
Num. groups: userofinterest	11102	11102
Var: userofinterest (Intercept)	0.00002	0.00001
Var: Residual	0.00215	0.00197

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$; + $p < 0.1$.

Table A38: Changes in collaboration behaviour, 1 year (LDV).

	Mainspace binary	Mainspace binary
	Model 1	Model 2
Intercept	0.00071 (0.00012)***	0.00024 (0.00029)
Treatment group (Ref.: Control)	0.00284 (0.00027)***	0.00161 (0.00031)***
Collaborated 1 year before	0.49238 (0.01186)***	0.28021 (0.01380)***
Was ever admin (Ref.: Never)		−0.00008 (0.00086)
Was ever admin * Treatment		0.00120 (0.00100)
Work meetup (Ref.: Social)		0.00019 (0.00032)
Work meetup * Treatment		−0.00039 (0.00058)
Collaborations up to meeting (log, cwc)		0.11832 (0.00574)***
Collaborations up to meeting (log, cm)		0.16858 (0.01267)***
Year of meetup: 09-14 (Ref.: 03-08)		0.00043 (0.00044)
Year of meetup: 15-20 (Ref.: 03-08)		−0.00097 (0.00037)**
Years since first edit (cwc)		−0.00067 (0.00009)***
Years since first edit (cm)		−0.00004 (0.00005)
AIC	−1081483.29468	−1112347.81848
BIC	−1081428.67695	−1112183.96528
Log Likelihood	540746.64734	556188.90924
Num. obs.	409850	409850
Num. groups: userofinterest	11102	11102
Var: userofinterest (Intercept)	0.00003	0.00002
Var: Residual	0.00416	0.00386

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$.

A.3 Models on Norms

A.3.1 Bivariate Main Negative Binomial Models

Table A39: Explaining norm violations (bivariate).

	Experience norm violation	Experience norm violation	Violate norms	Violate norms
	Model 1	Model 2	Model 3	Model 4
Intercept	$-2.2614\ (0.0162)^{***}$	$-2.3577\ (0.0203)^{***}$	$-2.4613\ (0.0199)^{***}$	$-2.4671\ (0.0244)^{***}$
Egocentric offline network density	$0.1334\ (0.2119)$		$-0.5171\ (0.2176)^{*}$	
Meetup attendee	$-0.0305\ (0.1783)$		$1.0795\ (0.1859)^{***}$	
Egocentric online network density		$0.1919\ (0.0237)^{***}$		$0.0572\ (0.0264)^{*}$
AIC	137993.7135	137928.6347	146409.4525	146540.7569
Log Likelihood	−68991.8567	−68960.3173	−73199.7263	−73266.3785
Num. obs.	140016	140016	140016	140016
Num. groups: id	33204	33204	33204	33204
Var: id (Intercept)	0.9716	0.9796	1.6705	1.6943

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$.

Table A40: Explaining norm violations (bivariate).

	Experience norm violation	Experience norm violation	Violate norms	Violate norms
	Model 1	Model 2	Model 3	Model 4
Intercept	-2.2613 (0.0162)***	-2.1956 (0.0169)***	-2.4596 (0.0199)***	-2.3378 (0.0208)***
Alter offline network density	0.5327 (0.3128)$^{+}$		0.1559 (0.3102)	
Meetup attendee	-0.0256 (0.0803)		0.6286 (0.0829)***	
Alter online network density		-0.7905 (0.0802)***		-1.1704 (0.0917)***
AIC	137991.2375	137890.3504	146414.8472	146367.9708
Log Likelihood	-68990.6187	-68941.1752	-73202.4236	-73179.9854
Num. obs.	140016	140016	140016	140016
Num. groups: id	33204	33204	33204	33204
Var: id (Intercept)	0.9712	0.9348	1.6683	1.5990

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$.

Table A41: Explaining norm punishments (bivariate).

	Experience norm pun.	Experience norm pun.	Punishing norm violators	Punishing norm violators
	Model 1	Model 2	Model 3	Model 4
Intercept	$-2.4497\ (0.0172)^{***}$	$-2.5697\ (0.0215)^{***}$	$-5.5221\ (0.0651)^{***}$	$-5.5629\ (0.0653)^{***}$
Egocentric offline network density	0.3432 (0.2232)		$-0.6534\ (0.1339)^{***}$	
Meetup attendee	-0.2601 (0.1871)		$0.8596\ (0.1328)^{***}$	
Egocentric online network density		$0.2330\ (0.0250)^{***}$		$-0.0988\ (0.0287)^{***}$
AIC	114987.6862	114901.6512	176176.8916	176223.5991
Log Likelihood	-57488.8431	-57446.8256	-88083.4458	-88107.7996
Num. obs.	140016	140016	140016	140016
Num. groups: id	33204	33204	33204	33204
Var: id (Intercept)	0.8314	0.8362	16.5636	17.4531

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$.

Table A42: Explaining rewards (bivariate).

	Receiving rewards	Receiving rewards	Rewarding others	Rewarding others
	Model 1	Model 2	Model 3	Model 4
Intercept	-4.0641 $(0.0440)^{***}$	-4.1748 $(0.0484)^{***}$	-6.9689 $(0.0717)^{***}$	-6.9585 $(0.0713)^{***}$
Egocentric offline network density	-1.3736 $(0.1369)^{***}$		-1.0678 $(0.1742)^{***}$	
Meetup attendee	1.9088 $(0.1352)^{***}$		1.3681 $(0.1728)^{***}$	
Egocentric online network density		-0.1578 $(0.0280)^{***}$		-0.2450 $(0.0373)^{***}$
AIC	177592.4164	177866.7589	140011.2792	140048.1184
Log Likelihood	-88791.2082	-88929.3795	-70000.6396	-70020.0592
Num. obs.	140016	140016	140016	140016
Num. groups: id	33204	33204	33204	33204
Var: id (Intercept)	7.2168	8.3629	29.5997	31.4490

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$.

Table A43: Explaining rewards (restricted; bivariate).

	Receiving rewards	Receiving rewards	Rewarding others	Rewarding others
	Model 1	Model 2	Model 3	Model 4
Intercept	-8.7517 (0.1138)***	-8.7679 (0.1244)***	-9.1206 (0.1233)***	-8.9676 (0.1290)***
Egocentric offline network density	-0.8069 (0.6787)		-2.1817 (0.4116)***	
Meetup attendee	1.5906 (0.5821)**		2.9256 (0.3952)***	
Egocentric online network density		-0.0192 (0.1157)		-0.6904 (0.1203)***
AIC	27960.9554	27982.8759	24956.4239	24994.9394
Log Likelihood	-13975.4777	-13987.4380	-12473.2120	-12493.4697
Num. obs.	140016	140016	140016	140016
Num. groups: id	33204	33204	33204	33204
Var: id (Intercept)	34.8101	36.4698	35.5127	40.7483

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$.

A.3.2 Bivariate Logit Models

Table A44: Explaining norm violations (binary, bivariate).

	Experience norm violation	Experience norm violation	Violate norms	Violate norms
	Model 1	Model 2	Model 3	Model 4
Intercept	$-2.3375\ (0.0153)^{***}$	$-2.4636\ (0.0191)^{***}$	$-2.5453\ (0.0179)^{***}$	$-2.5515\ (0.0217)^{***}$
Egocentric offline network density	$0.5520\ (0.2208)^{*}$		$-0.3312\ (0.2125)$	
Meetup attendee	$-0.5184\ (0.1861)^{**}$		$0.7811\ (0.1797)^{***}$	
Egocentric online network density		$0.2461\ (0.0226)^{***}$		$0.0507\ (0.0244)^{*}$
AIC	103645.4229	103533.7043	101662.4714	101745.1213
Log Likelihood	-51818.7115	-51763.8522	-50827.2357	-50869.5606
Num. obs.	140016	140016	140016	140016
Num. groups: id	33204	33204	33204	33204
Var: id (Intercept)	0.8828	0.8813	1.3489	1.3621

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$.

Table A45: Explaining norm violations (binary, bivariate).

	Experience norm violation	Experience norm violation	Violate norms	Violate norms
	Model 1	Model 2	Model 3	Model 4
Intercept	-2.3377 (0.0153)***	-2.3079 (0.0160)***	-2.5446 (0.0178)***	-2.4457 (0.0185)***
Alter offline network density	0.7114 (0.3209)*		0.1041 (0.3111)	
Meetup attendee	-0.2117 (0.0824)*		0.4939 (0.0811)***	
Alter online network density		-0.4559 (0.0752)***		-1.0135 (0.0896)***
AIC	103646.9443	103612.8424	101664.7844	101605.5072
Log Likelihood	-51819.4721	-51803.4212	-50828.3922	-50799.7536
Num. obs.	140016	140016	140016	140016
Num. groups: id	33204	33204	33204	33204
Var: id (Intercept)	0.8826	0.8694	1.3480	1.2886

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$.

Table A46: Explaining norm punishments (binary, bivariate).

	Experience norm pun.	Experience norm pun.	Punishing norm violators	Punishing norm violators
	Model 1	Model 2	Model 3	Model 4
Intercept	$-2.5356\ (0.0164)^{***}$	$-2.6768\ (0.0204)^{***}$	$-6.7644\ (0.0732)^{***}$	$-6.9515\ (0.0717)^{***}$
Egocentric offline network density	$0.6614\ (0.2334)^{**}$		$-3.3819\ (0.4146)^{***}$	
Meetup attendee	$-0.6416\ (0.1966)^{**}$		$4.4569\ (0.4028)^{***}$	
Egocentric online network density		$0.2738\ (0.0239)^{***}$		$-0.0674\ (0.0413)$
AIC	90987.5086	90867.8695	82154.2790	82358.5974
Log Likelihood	−45489.7543	−45430.9348	−41073.1395	−41176.2987
Num. obs.	140016	140016	140016	140016
Num. groups: id	33204	33204	33204	33204
Var: id (Intercept)	0.7960	0.7883	34.1902	39.1776

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$.

Table A47: Explaining rewards (binary, bivariate).

	Receiving rewards	Receiving rewards	Rewarding others	Rewarding others
	Model 1	Model 2	Model 3	Model 4
Intercept	-4.5318 (0.0643)***	-5.2031 (0.0764)***	-7.5665 (0.0763)***	-7.6500 (0.0755)***
Egocentric offline network density	-4.0779 (0.3256)***		-3.3212 (0.4023)***	
Meetup attendee	5.6899 (0.3041)***		4.1481 (0.3910)***	
Egocentric online network density		-0.0797 (0.0358)*		-0.2351 (0.0490)***
AIC	92399.3082	93006.2164	65174.0243	65315.5954
Log Likelihood	-46195.6541	-46500.1082	-32583.0122	-32654.7977
Num. obs.	140016	140016	140016	140016
Num. groups: id	33204	33204	33204	33204
Var: id (Intercept)	10.1521	16.4453	41.4096	46.8266

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$.

Table A48: Explaining rewards (restricted; binary, bivariate)

	Receiving rewards	Receiving rewards	Rewarding others	Rewarding others
	Model 1	Model 2	Model 3	Model 4
Intercept	-7.1436 (0.1670)***	-7.3558 (0.1513)***	-9.1419 (0.1247)***	-9.0294 (0.1309)***
Egocentric offline network density	-0.6980 (0.5000)		-2.5401 (0.4701)***	
Meetup attendee	1.4302 (0.4368)**		3.4119 (0.4432)***	
Egocentric online network density		-0.0102 (0.0824)		-0.6504 (0.1247)***
AIC	22061.1606	22093.8360	19392.3012	19446.9972
Log Likelihood	-11026.5803	-11043.9180	-9692.1506	-9720.4986
Num. obs.	140016	140016	140016	140016
Num. groups: id	33204	33204	33204	33204
Var: id (Intercept)	12.0784	14.4252	35.6114	41.8747

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$.

A.3.3 Main Negative Binomial Models

Table A49: Explaining norm violations (main negative binomial).

	Exp. norm violation	Exp. norm violation	Exp. norm violation	Violate norms	Violate norms	Violate norms
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Intercept	−2.8350 (0.0425)***	−3.1116 (0.0444)***	−3.1138 (0.0444)***	−2.7396 (0.0426)***	−2.8821 (0.0449)***	−2.8838 (0.0450)***
Egocentric offline network density	0.4074 (0.3004)		0.3861 (0.2979)	0.4428 (0.2732)		0.4495 (0.2709)+
Offline network size	−0.0037 (0.0025)		−0.0009 (0.0025)	−0.0006 (0.0023)		0.0007 (0.0022)
Meetup attendee	−0.7165 (0.3001)*	−0.4292 (0.0511)***	−0.7153 (0.2971)*	−0.5576 (0.2728)*	−0.1976 (0.0488)***	−0.5757 (0.2703)*
Egocentric online network density		0.0936 (0.0246)***	0.0930 (0.0246)***		−0.0292 (0.0266)	−0.0301 (0.0266)
Online network size		−0.0044 (0.0002)***	−0.0044 (0.0002)***		−0.0022 (0.0001)***	−0.0022 (0.0001)***
Edits this month (log)	0.3776 (0.0071)***	0.4437 (0.0075)***	0.4439 (0.0075)***	0.7059 (0.0077)***	0.7438 (0.0080)***	0.7440 (0.0080)***
Total edits (log)	0.0123 (0.0074)+	0.0535 (0.0076)***	0.0536 (0.0076)***	−0.1233 (0.0078)***	−0.0958 (0.0080)***	−0.0955 (0.0080)***
Years since first edit	−0.0165 (0.0048)***	−0.0214 (0.0048)***	−0.0212 (0.0048)***	−0.0329 (0.0050)***	−0.0367 (0.0050)***	−0.0366 (0.0050)***
Was administrator	−1.5185 (0.1189)***	−1.2118 (0.1185)***	−1.1955 (0.1191)***	−0.9199 (0.1026)***	−0.7505 (0.1009)***	−0.7366 (0.1016)***
Month of year: May-Aug (Ref.: Jan-Apr)	−0.0987 (0.0198)***	−0.1062 (0.0199)***	−0.1065 (0.0199)***	−0.0041 (0.0206)	−0.0055 (0.0206)	−0.0059 (0.0206)
Month of year: Sep-Dec (Ref.: Jan-Apr)	0.0292 (0.0343)	0.0186 (0.0342)	0.0189 (0.0342)	0.0788 (0.0368)*	0.0780 (0.0366)*	0.0779 (0.0366)*
AIC	133496.1662	132727.5330	132725.9681	134505.0416	134182.8964	134182.2099
Log Likelihood	−66736.0831	−66351.7665	−66348.9841	−67240.5208	−67079.4482	−67077.1049
Num. obs.	140016	140016	140016	140016	140016	140016
Num. groups: id	33204	33204	33204	33204	33204	33204
Var: id (Intercept)	0.7461	0.6902	0.6910	0.7890	0.7477	0.7468

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$.

Table A50: Explaining norm violations (main negative binomial).

	Experience norm violation	Experience norm violation	Experience norm violation	Violate norms	Violate norms	Violate norms
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Intercept	−2.8349 (0.0425)***	−3.1102 (0.0448)***	−3.1125 (0.0448)***	−2.7388 (0.0426)***	−2.8775 (0.0455)***	−2.8785 (0.0455)***
Egocentric offline network density	−0.2982 (0.5392)		−0.4928 (0.5349)	0.3896 (0.4690)		0.2866 (0.4652)
Alter offline network density	−4.3994 (3.2875)		−5.7037 (3.2724)+	0.8156 (2.7324)		0.0938 (2.7130)
Ego offline density * Alter offline density	4.7971 (3.3013)		6.0873 (3.2872)+	−0.3099 (2.7408)		0.4500 (2.7216)
Offline network size	−0.0058 (0.0032)+		−0.0036 (0.0031)	0.0003 (0.0028)		0.0012 (0.0028)
Meetup attendee	−0.0686 (0.5581)	−0.4262 (0.0510)***	0.1237 (0.5532)	−0.6442 (0.4836)	−0.1969 (0.0488)***	−0.5546 (0.4796)
Egocentric online network density		0.2089 (0.0282)***	0.2083 (0.0282)***		−0.0103 (0.0303)	−0.0113 (0.0303)
Alter online network density		1.6585 (0.2760)***	1.6567 (0.2760)***		0.0184 (0.2623)	0.0168 (0.2623)
Ego online density * Alter online density		−2.1998 (0.2911)***	−2.1976 (0.2911)***		−0.1394 (0.2611)	−0.1375 (0.2610)
Online network size		−0.0042 (0.0002)***	−0.0042 (0.0002)***		−0.0022 (0.0001)***	−0.0022 (0.0001)***
Edits this month (log)	0.3776 (0.0071)***	0.4417 (0.0075)***	0.4420 (0.0075)***	0.7058 (0.0077)***	0.7431 (0.0081)***	0.7432 (0.0081)***
Total edits (log)	0.0123 (0.0074)+	0.0438 (0.0077)***	0.0439 (0.0077)***	−0.1233 (0.0078)***	−0.0973 (0.0080)***	−0.0970 (0.0080)***
Years since first edit	−0.0165 (0.0048)***	−0.0186 (0.0048)***	−0.0185 (0.0048)***	−0.0329 (0.0050)***	−0.0362 (0.0050)***	−0.0361 (0.0050)***
Was administrator	−1.5183 (0.1190)***	−1.1954 (0.1182)***	−1.1797 (0.1188)***	−0.9200 (0.1026)***	−0.7487 (0.1009)***	−0.7346 (0.1016)***
Month of year: May-Aug (Ref.: Jan-Apr)	−0.0987 (0.0198)***	−0.1078 (0.0199)***	−0.1079 (0.0199)***	−0.0045 (0.0206)	−0.0061 (0.0206)	−0.0069 (0.0206)
Month of year: Sep-Dec (Ref.: Jan-Apr)	0.0293 (0.0343)	0.0140 (0.0342)	0.0145 (0.0342)	0.0777 (0.0368)*	0.0767 (0.0367)*	0.0754 (0.0366)*
AIC	133496.9784	132648.3163	132646.6329	134506.2853	134185.0834	134185.2575
Log Likelihood	−66734.4892	−66310.1581	−66305.3165	−67239.1427	−67078.5417	−67074.6287
Num. obs.	140016	140016	140016	140016	140016	140016
Num. groups: id	33204	33204	33204	33204	33204	33204
Var: id (Intercept)	0.7456	0.6827	0.6829	0.7885	0.7479	0.7464

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$.

Table A51: Explaining norm punishments (main negative binomial).

	Experience norm pun.	Experience norm pun.	Experience norm pun.	Punishing norm violators	Punishing norm violators	Punishing norm violators
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Intercept	-3.2725 (0.0458)***	-3.5984 (0.0478)***	-3.5985 (0.0478)***	-6.8145 (0.0642)***	-6.8278 (0.0665)***	-6.8248 (0.0666)***
Egocentric offline network density	0.4596 (0.3748)		0.2815 (0.3739)	-0.0223 (0.1451)		-0.0251 (0.1450)
Offline network size	-0.0014 (0.0034)		0.0013 (0.0035)	0.0012 (0.0013)		0.0012 (0.0013)
Meetup attendee	-0.4090 (0.3773)	0.0333 (0.0562)	-0.2275 (0.3781)	0.0420 (0.1536)	0.0447 (0.0338)	0.0450 (0.1535)
Egocentric online network density		0.1397 (0.0278)***	0.1395 (0.0278)***		-0.0135 (0.0279)	-0.0130 (0.0279)
Online network size		-0.0123 (0.0005)***	-0.0123 (0.0005)***		-0.0001 (0.0001)*	-0.0001 (0.0001)*
Experienced norm violations	2.0510 (0.0205)***	1.9914 (0.0201)***	1.9913 (0.0201)***			
Edits this month (log)	-0.1309 (0.0091)***	-0.0211 (0.0098)*	-0.0209 (0.0098)*	0.4877 (0.0055)***	0.4895 (0.0055)***	0.4894 (0.0055)***
Total edits (log)	0.0214 (0.0078)**	0.0771 (0.0081)***	0.0771 (0.0081)***	0.5172 (0.0098)***	0.5208 (0.0099)***	0.5202 (0.0099)***
Years since first edit	-0.0017 (0.0051)	-0.0109 (0.0051)*	-0.0108 (0.0051)*	-0.0847 (0.0062)***	-0.0853 (0.0063)***	-0.0853 (0.0063)***
Was administrator	-0.2694 (0.1317)*	0.1405 (0.1337)	0.1381 (0.1339)	1.3867 (0.1344)***	1.4090 (0.1343)***	1.3964 (0.1346)***
Month of year: May-Aug (Ref.: Jan-Apr)	-0.0142 (0.0261)	-0.0264 (0.0257)	-0.0264 (0.0257)	-0.0393 (0.0127)**	-0.0399 (0.0127)**	-0.0396 (0.0127)**
Month of year: Sep-Dec (Ref.: Jan-Apr)	0.0011 (0.0381)	-0.0076 (0.0377)	-0.0077 (0.0377)	0.0116 (0.0287)	0.0110 (0.0287)	0.0115 (0.0287)
AIC	80909.5615	80081.0832	80084.4216	162510.1849	162506.4617	162508.6219
Log Likelihood	-40441.7807	-40027.5416	-40027.2108	-81243.0924	-81241.2309	-81240.3110
Num. obs.	140016	140016	140016	140016	140016	140016
Num. groups: id	33204	33204	33204	33204	33204	33204
Var: id (Intercept)	0.0000	0.0000	0.0000	2.6714	2.6779	2.6766

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$.

Table A52: Explaining rewards (main negative binomial).

	Receiving rewards	Receiving rewards	Receiving rewards	Rewarding others	Rewarding others	Rewarding others
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Intercept	−5.2531 (0.0447)***	−5.1944 (0.0477)***	−5.1770 (0.0476)***	−6.4969 (0.0806)***	−6.5327 (0.0831)***	−6.5081 (0.0831)***
Egocentric offline network density	−0.3229 (0.1241)**		−0.3132 (0.1241)*	−0.5125 (0.1717)**		−0.5126 (0.1717)**
Previous norm punishments conducted	0.0032 (0.0067)	−0.0052 (0.0160)	−0.0038 (0.0160)			
Offline density * Norm punishments	−0.0373 (0.0286)		−0.0369 (0.0286)			
Offline network size	0.0027 (0.0011)*		0.0026 (0.0011)*	0.0012 (0.0015)		0.0012 (0.0015)
Meetup attendee	0.5369 (0.1289)***	0.3089 (0.0292)***	0.5266 (0.1289)***	0.7057 (0.1815)***	0.2589 (0.0427)***	0.7060 (0.1815)***
Egocentric online network density		−0.0766 (0.0271)**	−0.0743 (0.0270)**		0.0219 (0.0343)	0.0240 (0.0343)
Online density * Norm punishments		0.0192 (0.0416)	0.0222 (0.0415)			
Online network size		0.0002 (0.0000)***	0.0002 (0.0000)***		0.0000 (0.0001)	0.0000 (0.0001)
Edits this month (log)	0.7914 (0.0058)***	0.7862 (0.0059)***	0.7854 (0.0059)***	0.8509 (0.0078)***	0.8517 (0.0078)***	0.8510 (0.0078)***
Total edits (log)	0.2093 (0.0074)***	0.2073 (0.0074)***	0.2048 (0.0074)***	0.2300 (0.0123)***	0.2332 (0.0124)***	0.2295 (0.0124)***
Years since first edit	−0.0458 (0.0047)***	−0.0455 (0.0047)***	−0.0455 (0.0047)***	−0.1197 (0.0080)***	−0.1196 (0.0080)***	−0.1194 (0.0080)***
Was administrator	0.5925 (0.0789)***	0.6091 (0.0789)***	0.5688 (0.0788)***	0.9086 (0.1746)***	0.9591 (0.1749)***	0.9095 (0.1747)***
Month of year: May-Aug (Ref.: Jan-Apr)	−0.0460 (0.0123)***	−0.0441 (0.0123)***	−0.0434 (0.0123)***	−0.0446 (0.0160)**	−0.0464 (0.0160)**	−0.0451 (0.0160)**
Month of year: Sep-Dec (Ref.: Jan-Apr)	0.0043 (0.0263)	0.0040 (0.0263)	0.0058 (0.0263)	0.0845 (0.0390)*	0.0807 (0.0391)*	0.0838 (0.0391)*
AIC	150966.4395	150977.5348	150942.9228	124930.4036	124950.6350	124933.8840
Log Likelihood	−75469.2198	−75474.7674	−75454.4614	−62453.2018	−62463.3175	−62452.9420
Num. obs.	140016	140016	140016	140016	140016	140016
Num. groups: id	33204	33204	33204	33204	33204	33204
Var: id (Intercept)	0.8491	0.8531	0.8437	4.2721	4.3053	4.2719

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$.

Table A53: Explaining rewards (restricted; main negative binomial).

	Receiving rewards	Receiving rewards	Receiving rewards	Rewarding others	Rewarding others	Rewarding others
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Intercept	-6.8308 (0.1939)***	-8.2385 (0.1945)***	-8.2309 (0.1946)***	-9.2795 (0.1902)***	-9.1032 (0.2048)***	-9.0590 (0.2038)***
Egocentric offline network density	0.3734 (0.6150)		0.1236 (0.6197)	-1.5690 (0.4289)***		-1.5635 (0.4288)***
Offline network size	0.0009 (0.0050)		0.0034 (0.0051)	-0.0012 (0.0034)		-0.0012 (0.0034)
Meetup attendee	0.0375 (0.6024)	0.3948 (0.1093)***	0.1983 (0.6115)	2.0620 (0.4321)***	0.7380 (0.1003)***	2.0510 (0.4320)***
Egocentric online network density		-0.0529 (0.1022)	-0.0520 (0.1021)		-0.3578 (0.1225)**	-0.3486 (0.1223)**
Online network size		-0.0130 (0.0007)***	-0.0130 (0.0007)***		-0.0001 (0.0002)	-0.0001 (0.0002)
Edits this month (log)	0.7074 (0.0225)***	0.9277 (0.0254)***	0.9275 (0.0254)***	0.7602 (0.0231)***	0.7559 (0.0237)***	0.7532 (0.0237)***
Total edits (log)	0.1669 (0.0229)***	0.3135 (0.0252)***	0.3134 (0.0252)***	0.2413 (0.0287)***	0.2444 (0.0288)***	0.2397 (0.0288)***
Years since first edit	-0.0725 (0.0145)***	-0.0934 (0.0152)***	-0.0935 (0.0152)***	-0.1027 (0.0176)***	-0.1036 (0.0176)***	-0.1040 (0.0175)***
Was administrator	-0.8142 (0.2186)***	-0.3280 (0.2216)	-0.3393 (0.2218)	0.2469 (0.2139)	0.2978 (0.2137)	0.2353 (0.2141)
Month of year: May-Aug (Ref.: Jan-Apr)	-0.1734 (0.0677)*	-0.2134 (0.0658)**	-0.2134 (0.0658)**	-0.0850 (0.0502)$^{+}$	-0.0777 (0.0503)	-0.0787 (0.0502)
Month of year: Sep-Dec (Ref.: Jan-Apr)	0.0586 (0.1050)	0.0020 (0.1069)	0.0010 (0.1068)	0.0997 (0.1062)	0.1180 (0.1062)	0.1071 (0.1062)
AIC	26749.0094	26085.1527	26088.4776	23132.8537	23147.0291	23128.4642
Log Likelihood	-13362.5047	-13030.5764	-13030.2388	-11554.4268	-11561.5145	-11550.2321
Num. obs.	140016	140016	140016	140016	140016	140016
Num. groups: id	33204	33204	33204	33204	33204	33204
Var: id (Intercept)	1.0123	1.8824	1.8687	4.2727	4.2994	4.2615

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$.

A.3.4 Logit Models

Table A54: Explaining norm violations (binary).

	Exp. norm violation	Exp. norm violation	Exp. norm violation	Violate norms	Violate norms	Violate norms
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Intercept	-2.7528 (0.0445)***	-3.0969 (0.0451)***	-3.0987 (0.0452)***	-2.6678 (0.0452)***	-2.8621 (0.0465)***	-2.8638 (0.0466)***
Egocentric offline network density	0.4688 (0.3379)		0.3785 (0.3290)	0.4683 (0.3043)		0.4637 (0.2964)
Offline network size	-0.0065 (0.0030)*		-0.0022 (0.0029)	-0.0005 (0.0025)		0.0015 (0.0025)
Meetup attendee	-0.6909 (0.3410)*	-0.3714 (0.0548)***	-0.6183 (0.3309)$^{+}$	-0.5868 (0.3044)$^{+}$	-0.1823 (0.0526)***	-0.5930 (0.2958)*
Egocentric online network density		0.1184 (0.0241)***	0.1178 (0.0241)***		-0.0415 (0.0270)	-0.0420 (0.0270)
Online network size		-0.0082 (0.0003)***	-0.0082 (0.0003)***		-0.0038 (0.0002)***	-0.0038 (0.0002)***
Edits this month (log)	0.2716 (0.0075)***	0.3679 (0.0078)***	0.3681 (0.0078)***	0.6059 (0.0083)***	0.6595 (0.0085)***	0.6597 (0.0085)***
Total edits (log)	0.0128 (0.0077)$^{+}$	0.0752 (0.0078)***	0.0752 (0.0078)***	-0.1180 (0.0083)***	-0.0731 (0.0084)***	-0.0730 (0.0084)***
Years since first edit	-0.0148 (0.0050)**	-0.0220 (0.0049)***	-0.0218 (0.0049)***	-0.0397 (0.0053)***	-0.0450 (0.0052)***	-0.0449 (0.0052)***
Was administrator	-1.4779 (0.1349)***	-0.9336 (0.1327)***	-0.9170 (0.1332)***	-1.0262 (0.1163)***	-0.7252 (0.1117)***	-0.7180 (0.1124)***
Month of year: May-Aug (Ref.: Jan-Apr)	-0.0989 (0.0209)***	-0.1083 (0.0208)***	-0.1086 (0.0208)***	-0.0072 (0.0218)	-0.0120 (0.0217)	-0.0121 (0.0217)
Month of year: Sep-Dec (Ref.: Jan-Apr)	0.0129 (0.0360)	-0.0014 (0.0351)	-0.0008 (0.0352)	0.1067 (0.0390)**	0.1014 (0.0383)**	0.1018 (0.0383)**
AIC	101422.2248	100157.8663	100154.5282	93398.9573	92799.1702	92799.9938
Log Likelihood	-50700.1124	-50067.9331	-50064.2641	-46688.4787	-46388.5851	-46386.9969
Num. obs.	140016	140016	140016	140016	140016	140016
Num. groups: id	33204	33204	33204	33204	33204	33204
Var: id (Intercept)	0.9018	0.7122	0.7133	0.9820	0.8400	0.8400

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$.

Table A55: Explaining norm violations (binary).

	Experience norm violation	Experience norm violation	Experience norm violation	Violate norms	Violate norms	Violate norms
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Intercept	−2.7529 (0.0445)***	−3.0896 (0.0454)***	−3.0916 (0.0455)***	−2.6672 (0.0452)***	−2.8514 (0.0470)***	−2.8526 (0.0470)***
Egocentric offline network density	−0.0795 (0.6006)		−0.3083 (0.5853)	0.4628 (0.5268)		0.3243 (0.5148)
Alter offline network density	−3.5622 (3.5753)		−4.5737 (3.4879)	0.8113 (3.1317)		−0.1636 (3.0658)
Ego offline density * Alter offline density	3.7895 (3.5958)		4.7869 (3.5102)	−0.4286 (3.1526)		0.5634 (3.0878)
Offline network size	−0.0083 (0.0038)*		−0.0046 (0.0036)	0.0003 (0.0031)		0.0018 (0.0030)
Meetup attendee	−0.1638 (0.6246)	−0.3682 (0.0546)***	0.0629 (0.6077)	−0.6890 (0.5435)	−0.1817 (0.0526)***	−0.5550 (0.5307)
Egocentric online network density		0.2440 (0.0279)***	0.2434 (0.0279)***		−0.0132 (0.0306)	−0.0138 (0.0306)
Alter online network density		1.8611 (0.2780)***	1.8598 (0.2780)***		−0.0917 (0.2669)	−0.0929 (0.2669)
Ego online density * Alter online density		−2.4373 (0.2955)***	−2.4351 (0.2954)***		−0.1093 (0.2652)	−0.1081 (0.2652)
Online network size		−0.0080 (0.0003)***	−0.0079 (0.0003)***		−0.0038 (0.0002)***	−0.0038 (0.0002)***
Edits this month (log)	0.2716 (0.0075)***	0.3650 (0.0078)***	0.3653 (0.0078)***	0.6058 (0.0083)***	0.6582 (0.0086)***	0.6584 (0.0086)***
Total edits (log)	0.0128 (0.0077)+	0.0637 (0.0079)***	0.0638 (0.0079)***	−0.1180 (0.0083)***	−0.0755 (0.0084)***	−0.0753 (0.0084)***
Years since first edit	−0.0148 (0.0050)**	−0.0188 (0.0049)***	−0.0187 (0.0049)***	−0.0397 (0.0053)***	−0.0442 (0.0052)***	−0.0442 (0.0052)***
Was administrator	−1.4777 (0.1349)***	−0.9144 (0.1320)***	−0.8983 (0.1325)***	−1.0259 (0.1162)***	−0.7226 (0.1117)***	−0.7150 (0.1123)***
Month of year: May-Aug (Ref.: Jan-Apr)	−0.0989 (0.0209)***	−0.1103 (0.0208)***	−0.1105 (0.0208)***	−0.0075 (0.0218)	−0.0133 (0.0217)	−0.0136 (0.0217)
Month of year: Sep-Dec (Ref.: Jan-Apr)	0.0131 (0.0360)	−0.0064 (0.0351)	−0.0057 (0.0351)	0.1063 (0.0390)**	0.0992 (0.0383)**	0.0993 (0.0383)**
AIC	101424.8689	100063.1142	100061.9849	93401.6713	92798.5883	92802.0355
Log Likelihood	−50699.4344	−50018.5571	−50013.9925	−46687.8357	−46386.2942	−46384.0177
Num. obs.	140016	140016	140016	140016	140016	140016
Num. groups: id	33204	33204	33204	33204	33204	33204
Var: id (Intercept)	0.9018	0.6981	0.6990	0.9811	0.8387	0.8379

***$p < 0.001$; **$p < 0.01$; *$p < 0.05$; +$p < 0.1$.

Table A56: Explaining norm punishments (binary).

	Experience norm pun.	Experience norm pun.	Experience norm pun.	Punishing norm violators	Punishing norm violators	Punishing norm violators
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Intercept	-3.3633 (0.0492)***	-3.8909 (0.0528)***	-3.8909 (0.0528)***	-8.0653 (0.0922)***	-7.7995 (0.0945)***	-7.7981 (0.0946)***
Egocentric offline network density	0.3820 (0.4280)		0.0377 (0.4452)	0.0586 (0.4077)		0.0898 (0.4084)
Offline network size	-0.0042 (0.0041)		0.0002 (0.0044)	0.0098 (0.0038)**		0.0086 (0.0038)*
Meetup attendee	-0.2446 (0.4339)	0.1561 (0.0652)*	0.1203 (0.4549)	0.1515 (0.4202)	0.4019 (0.0789)***	0.1260 (0.4208)
Egocentric online network density		0.1750 (0.0295)***	0.1749 (0.0295)***		-0.0473 (0.0390)	-0.0459 (0.0390)
Online network size		-0.0249 (0.0007)***	-0.0249 (0.0007)***		0.0030 (0.0003)***	0.0030 (0.0003)***
Experienced norm violations	3.2103 (0.0225)***	3.2408 (0.0230)***	3.2407 (0.0230)***			
Edits this month (log)	-0.1971 (0.0100)***	-0.0293 (0.0109)**	-0.0293 (0.0109)**	0.6873 (0.0104)***	0.6549 (0.0107)***	0.6545 (0.0107)***
Total edits (log)	0.0440 (0.0085)***	0.1322 (0.0090)***	0.1322 (0.0090)***	0.6092 (0.0141)***	0.5651 (0.0144)***	0.5646 (0.0144)***
Years since first edit	0.0039 (0.0055)	-0.0108 (0.0057)$^{+}$	-0.0108 (0.0057)$^{+}$	-0.0782 (0.0088)***	-0.0693 (0.0088)***	-0.0694 (0.0088)***
Was administrator	-0.2581 (0.1511)$^{+}$	0.3428 (0.1589)*	0.3426 (0.1589)*	2.0805 (0.2136)***	1.9860 (0.2142)***	1.9343 (0.2152)***
Month of year: May-Aug (Ref.: Jan-Apr)	-0.0041 (0.0286)	-0.0182 (0.0289)	-0.0182 (0.0289)	-0.0231 (0.0274)	-0.0167 (0.0274)	-0.0155 (0.0274)
Month of year: Sep-Dec (Ref.: Jan-Apr)	-0.0066 (0.0414)	-0.0161 (0.0419)	-0.0161 (0.0419)	0.0100 (0.0551)	0.0142 (0.0549)	0.0138 (0.0549)
AIC	53841.7196	52370.8787	52374.8644	72112.2883	71984.8201	71979.7856
Log Likelihood	-26908.8598	-26173.4393	-26173.4322	-36045.1442	-35981.4101	-35976.8928
Num. obs.	140016	140016	140016	140016	140016	140016
Num. groups: id	33204	33204	33204	33204	33204	33204
Var: id (Intercept)	0.0000	0.0000	0.0000	4.0426	3.9402	3.9491

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$.

Table A57: Explaining rewards (binary).

	Receiving rewards Model 1	Receiving rewards Model 2	Receiving rewards Model 3	Rewarding others Model 4	Rewarding others Model 5	Rewarding others Model 6
Intercept	−5.8829 (0.0619)***	−5.6331 (0.0656)***	−5.6222 (0.0655)***	−7.6521 (0.1152)***	−7.5878 (0.1190)***	−7.5530 (0.1186)***
Egocentric offline network density	−0.1917 (0.3344)		−0.1803 (0.3367)	−1.2897 (0.4541)**		−1.2795 (0.4560)**
Previous norm punishments conducted	−0.0132 (0.0144)	−0.0640 (0.0363)+	−0.0626 (0.0365)+			
Offline density * Norm punishments	−0.0109 (0.0721)		−0.0052 (0.0720)			
Offline network size	0.0140 (0.0033)***		0.0131 (0.0033)***	0.0118 (0.0044)**		0.0113 (0.0044)**
Meetup attendee	0.7148 (0.3430)*	0.8880 (0.0579)***	0.7199 (0.3453)*	1.7959 (0.4718)***	0.9311 (0.0918)***	1.7915 (0.4738)***
Egocentric online network density		−0.0704 (0.0359)*	−0.0673 (0.0359)+		−0.0297 (0.0507)	−0.0244 (0.0506)
Online density * Norm punishments		0.1190 (0.0783)	0.1169 (0.0783)			
Online network size		0.0031 (0.0002)***	0.0031 (0.0002)***		0.0013 (0.0003)***	0.0013 (0.0003)***
Edits this month (log)	0.9796 (0.0100)***	0.9393 (0.0104)***	0.9383 (0.0104)***	1.1537 (0.0148)***	1.1409 (0.0150)***	1.1392 (0.0150)***
Total edits (log)	0.2265 (0.0100)***	0.1896 (0.0104)***	0.1883 (0.0104)***	0.2296 (0.0174)***	0.2153 (0.0180)***	0.2097 (0.0179)***
Years since first edit	−0.0422 (0.0066)***	−0.0357 (0.0066)***	−0.0356 (0.0066)***	−0.1151 (0.0111)***	−0.1113 (0.0112)***	−0.1111 (0.0112)***
Was administrator	1.1886 (0.1368)***	1.1325 (0.1395)***	1.0890 (0.1400)***	1.2657 (0.2446)***	1.3183 (0.2470)***	1.1854 (0.2474)***
Month of year: May-Aug (Ref.: Jan-Apr)	−0.0530 (0.0255)*	−0.0499 (0.0256)+	−0.0478 (0.0256)+	−0.0741 (0.0329)*	−0.0731 (0.0329)*	−0.0702 (0.0329)*
Month of year: Sep-Dec (Ref.: Jan-Apr)	0.0368 (0.0461)	0.0438 (0.0462)	0.0427 (0.0461)	0.0344 (0.0715)	0.0325 (0.0717)	0.0325 (0.0717)
AIC	72482.0839	72318.8616	72282.6392	54289.4912	54309.6706	54266.1665
Log Likelihood	−36228.0419	−36146.4308	−36125.3196	−27133.7456	−27143.8353	−27120.0833
Num. obs.	140016	140016	140016	140016	140016	140016
Num. groups: id	33204	33204	33204	33204	33204	33204
Var: id (Intercept)	1.2483	1.2574	1.2488	6.6801	6.8209	6.7832

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$.

Table A58: Explaining rewards (restricted; binary).

	Receiving rewards	Receiving rewards	Receiving rewards	Rewarding others	Rewarding others	Rewarding others
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Intercept	−7.2048 (0.1453)***	−7.7727 (0.1505)***	−7.7725 (0.1505)***	−9.3746 (0.1979)***	−9.2255 (0.2150)***	−9.1818 (0.2139)***
Egocentric offline network density	−0.0632 (0.5793)		−0.0858 (0.5464)	−1.4914 (0.4890)**		−1.4865 (0.4887)**
Offline network size	−0.0053 (0.0049)		−0.0004 (0.0046)	0.0016 (0.0040)		0.0015 (0.0040)
Meetup attendee	0.2805 (0.5791)	0.1764 (0.0990)+	0.2562 (0.5418)	2.0306 (0.4911)***	0.8616 (0.1069)***	2.0215 (0.4907)***
Egocentric online network density		−0.1138 (0.0865)	−0.1138 (0.0865)		−0.3330 (0.1317)*	−0.3208 (0.1315)*
Online network size		−0.0117 (0.0006)***	−0.0117 (0.0006)***		−0.0002 (0.0002)	−0.0002 (0.0002)
Edits this month (log)	0.5288 (0.0200)***	0.7056 (0.0208)***	0.7056 (0.0208)***	0.8134 (0.0254)***	0.8114 (0.0262)***	0.8087 (0.0262)***
Total edits (log)	0.1312 (0.0221)***	0.2703 (0.0223)***	0.2703 (0.0223)***	0.2076 (0.0299)***	0.2129 (0.0303)***	0.2082 (0.0303)***
Years since first edit	−0.0509 (0.0141)***	−0.0765 (0.0137)***	−0.0765 (0.0137)***	−0.0922 (0.0185)***	−0.0937 (0.0186)***	−0.0941 (0.0185)***
Was administrator	−0.9532 (0.2263)***	−0.3351 (0.2098)	−0.3349 (0.2104)	0.2668 (0.2198)	0.3382 (0.2195)	0.2623 (0.2200)
Month of year: May-Aug (Ref.: Jan-Apr)	−0.1466 (0.0540)**	−0.1557 (0.0539)**	−0.1557 (0.0539)**	−0.0625 (0.0577)	−0.0568 (0.0578)	−0.0562 (0.0577)
Month of year: Sep-Dec (Ref.: Jan-Apr)	0.0164 (0.0970)	0.0287 (0.0931)	0.0286 (0.0931)	0.1352 (0.1173)	0.1535 (0.1173)	0.1434 (0.1173)
AIC	20533.2556	19932.0223	19935.9966	17595.7087	17611.8624	17593.4960
Log Likelihood	−10255.6278	−9955.0112	−9954.9983	−8786.8543	−8794.9312	−8783.7480
Num. obs.	140016	140016	140016	140016	140016	140016
Num. groups: id	33204	33204	33204	33204	33204	33204
Var: id (Intercept)	2.9091	1.9609	1.9610	4.4261	4.4446	4.4024

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$.

A.3.5 Meetup Attendees Only

Table A59: Explaining norm violations (meetup attendees only).

	Exp. norm violation	Exp. norm violation	Exp. norm violation	Violate norms	Violate norms	Violate norms
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Intercept	-1.1497 (0.5011)*	-1.8606 (0.3625)***	-1.9022 (0.5248)***	-2.6530 (0.4340)***	-2.7908 (0.3420)***	-3.0877 (0.4638)***
Egocentric offline network density	-0.0657 (0.3739)		0.0290 (0.3666)	0.2127 (0.3161)		0.3114 (0.3118)
Offline network size	-0.0016 (0.0032)		0.0010 (0.0031)	-0.0003 (0.0026)		0.0008 (0.0026)
Egocentric online network density		-0.3196 (0.2340)	-0.3161 (0.2343)		-0.3246 (0.2237)	-0.3451 (0.2244)
Online network size		-0.0057 (0.0008)***	-0.0057 (0.0008)***		-0.0025 (0.0004)***	-0.0025 (0.0004)***
Edits this month (log)	0.0566 (0.0388)	0.1808 (0.0419)***	0.1803 (0.0420)***	0.4598 (0.0354)***	0.5283 (0.0377)***	0.5306 (0.0377)***
Total edits (log)	-0.1596 (0.0526)**	-0.0381 (0.0533)	-0.0387 (0.0533)	-0.0813 (0.0471)$^{+}$	-0.0160 (0.0480)	-0.0128 (0.0480)
Years since first edit	0.0457 (0.0322)	0.0137 (0.0317)	0.0137 (0.0317)	-0.0033 (0.0283)	-0.0217 (0.0281)	-0.0208 (0.0280)
Was administrator	-1.0242 (0.2415)***	-0.8003 (0.2386)***	-0.8088 (0.2400)***	-0.5908 (0.1832)**	-0.4720 (0.1776)**	-0.4685 (0.1782)**
Month of year: May-Aug (Ref.: Jan-Apr)	-0.1311 (0.1151)	-0.1419 (0.1157)	-0.1404 (0.1157)	-0.1234 (0.0939)	-0.1088 (0.0942)	-0.1111 (0.0943)
Month of year: Sep-Dec (Ref.: Jan-Apr)	0.0051 (0.1785)	0.0250 (0.1769)	0.0238 (0.1769)	-0.1330 (0.1499)	-0.1368 (0.1484)	-0.1389 (0.1481)
AIC	6766.2288	6699.3166	6703.1729	9977.4561	9931.5733	9934.1885
Log Likelihood	-3372.1144	-3338.6583	-3338.5865	-4977.7281	-4954.7866	-4954.0942
Num. obs.	7109	7109	7109	7109	7109	7109
Num. groups: id	897	897	897	897	897	897
Var: id (Intercept)	1.2505	1.0804	1.0770	1.0961	0.9884	0.9758

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$.

Table A60: Explaining norm violations (meetup attendees only).

	Experience norm violation	Experience norm violation	Experience norm violation	Violate norms	Violate norms	Violate norms
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Intercept	−0.6468 (0.7585)	−1.7554 (0.3790)***	−1.1505 (0.7666)	−2.8196 (0.6278)***	−2.7418 (0.3594)***	−3.0899 (0.6526)***
Egocentric offline network density	−0.6714 (0.6638)		−0.7235 (0.6522)	0.2593 (0.5382)		0.2410 (0.5314)
Alter offline network density	−3.2805 (3.9883)		−4.6307 (3.9367)	1.4541 (3.1052)		0.7004 (3.0792)
Ego offline density * Alter offline density	3.8243 (4.0052)		5.1877 (3.9554)	−0.9905 (3.1153)		−0.1938 (3.0903)
Offline network size	−0.0029 (0.0040)		−0.0008 (0.0039)	0.0010 (0.0032)		0.0016 (0.0032)
Egocentric online network density		−0.0010 (0.2732)	0.0197 (0.2735)		−0.4502 (0.2512)$^{+}$	−0.4697 (0.2514)$^{+}$
Alter online network density		0.1252 (2.5428)	0.2140 (2.5486)		−1.4026 (2.1266)	−1.3823 (2.1235)
Ego online density * Alter online density		−3.3607 (3.0401)	−3.5213 (3.0505)		2.0092 (2.1883)	1.9687 (2.1848)
Online network size		−0.0054 (0.0008)***	−0.0054 (0.0008)***		−0.0025 (0.0004)***	−0.0025 (0.0004)***
Edits this month (log)	0.0556 (0.0388)	0.1694 (0.0423)***	0.1689 (0.0423)***	0.4591 (0.0354)***	0.5260 (0.0380)***	0.5276 (0.0380)***
Total edits (log)	−0.1593 (0.0525)**	−0.0629 (0.0539)	−0.0630 (0.0538)	−0.0822 (0.0470)$^{+}$	−0.0133 (0.0489)	−0.0110 (0.0488)
Years since first edit	0.0464 (0.0322)	0.0188 (0.0318)	0.0197 (0.0317)	−0.0025 (0.0283)	−0.0221 (0.0281)	−0.0204 (0.0280)
Was administrator	−1.0256 (0.2409)***	−0.7871 (0.2376)***	−0.8005 (0.2384)***	−0.5892 (0.1827)**	−0.4766 (0.1775)**	−0.4699 (0.1776)**
Month of year: May-Aug (Ref.: Jan-Apr)	−0.1342 (0.1155)	−0.1447 (0.1158)	−0.1442 (0.1161)	−0.1313 (0.0941)	−0.1057 (0.0942)	−0.1151 (0.0945)
Month of year: Sep-Dec (Ref.: Jan-Apr)	0.0015 (0.1787)	0.0220 (0.1767)	0.0185 (0.1768)	−0.1484 (0.1500)	−0.1373 (0.1483)	−0.1545 (0.1481)
AIC	6767.9070	6693.1563	6697.8019	9979.6773	9934.3951	9939.0054
Log Likelihood	−3370.9535	−3333.5781	−3331.9010	−4976.8386	−4954.1976	−4952.5027
Num. obs.	7109	7109	7109	7109	7109	7109
Num. groups: id	897	897	897	897	897	897
Var: id (Intercept)	1.2343	1.0624	1.0408	1.0862	0.9851	0.9607

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$.

Table A61: Explaining norm punishments (meetup attendees only).

	Experience norm pun.	Experience norm pun.	Experience norm pun.	Punishing norm violators	Punishing norm violators	Punishing norm violators
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Intercept	-2.2281 (0.4478)***	-2.7318 (0.3149)***	-2.8922 (0.4747)***	-7.0227 (0.3331)***	-6.6014 (0.3199)***	-6.7584 (0.3479)***
Egocentric offline network density	0.1664 (0.3500)		0.1532 (0.3464)	0.1531 (0.1398)		0.1598 (0.1399)
Offline network size	-0.0000 (0.0032)		0.0013 (0.0032)	0.0006 (0.0012)		0.0006 (0.0012)
Egocentric online network density		-0.0096 (0.2205)	-0.0098 (0.2209)		-0.3582 (0.1285)**	-0.3631 (0.1285)**
Online network size		-0.0097 (0.0014)***	-0.0097 (0.0014)***		-0.0002 (0.0001)	-0.0002 (0.0001)
Experienced norm violations	1.6919 (0.0684)***	1.6277 (0.0652)***	1.6281 (0.0652)***			
Edits this month (log)	-0.2430 (0.0386)***	-0.0758 (0.0433)$^{+}$	-0.0746 (0.0436)$^{+}$	0.4253 (0.0150)***	0.4206 (0.0153)***	0.4212 (0.0153)***
Total edits (log)	-0.0965 (0.0434)*	-0.0050 (0.0445)	-0.0052 (0.0445)	0.6373 (0.0408)***	0.6246 (0.0411)***	0.6261 (0.0412)***
Years since first edit	0.0584 (0.0274)*	0.0431 (0.0272)	0.0434 (0.0272)	-0.0875 (0.0212)***	-0.0842 (0.0212)***	-0.0839 (0.0212)***
Was administrator	-0.2606 (0.2304)	-0.0514 (0.2346)	-0.0583 (0.2353)	0.4828 (0.1690)**	0.4740 (0.1674)**	0.4725 (0.1673)**
Month of year: May-Aug (Ref.: Jan-Apr)	-0.0615 (0.1301)	-0.0883 (0.1282)	-0.0874 (0.1281)	-0.0414 (0.0305)	-0.0349 (0.0306)	-0.0363 (0.0306)
Month of year: Sep-Dec (Ref.: Jan-Apr)	-0.1717 (0.1747)	-0.1879 (0.1724)	-0.1903 (0.1725)	-0.0479 (0.0597)	-0.0409 (0.0597)	-0.0440 (0.0597)
AIC	3821.7345	3759.9786	3763.7698	23775.7837	23768.6851	23771.2395
Log Likelihood	-1898.8673	-1867.9893	-1867.8849	-11876.8918	-11873.3425	-11872.6198
Num. obs.	7109	7109	7109	7109	7109	7109
Num. groups: id	897	897	897	897	897	897
Var: id (Intercept)	0.0000	0.0000	0.0000	1.7589	1.7258	1.7211

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$.

Table A62: Explaining rewards (meetup attendees only).

	Receiving rewards	Receiving rewards	Receiving rewards	Rewarding others	Rewarding others	Rewarding others
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Intercept	-3.6130 (0.2041)***	-3.1757 (0.1894)***	-3.0900 (0.2165)***	-4.3516 (0.3412)***	-4.2611 (0.3156)***	-3.8854 (0.3521)***
Egocentric offline network density	-0.0765 (0.1139)		-0.0569 (0.1131)	-0.3457 (0.1553)*		-0.3312 (0.1548)*
Offline density * Norm punishments	-0.0239 (0.0704)		-0.0217 (0.0706)			
Offline network size	0.0034 (0.0009)***		0.0034 (0.0009)***	0.0010 (0.0013)		0.0008 (0.0013)
Egocentric online network density		-0.5028 (0.1026)***	-0.4877 (0.1024)***		-0.5266 (0.1251)***	-0.5120 (0.1251)***
Online density * Norm punishments		-0.0730 (0.1728)	-0.0578 (0.1750)			
Online network size		0.0003 (0.0001)**	0.0003 (0.0001)**		0.0002 (0.0001)	0.0002 (0.0001)
Previous norm punishments conducted	-0.0171 (0.0520)	-0.0027 (0.0667)	0.0059 (0.0776)			
Edits this month (log)	0.6894 (0.0138)***	0.6690 (0.0141)***	0.6677 (0.0140)***	0.6925 (0.0177)***	0.6795 (0.0179)***	0.6781 (0.0179)***
Total edits (log)	0.1535 (0.0248)***	0.1333 (0.0254)***	0.1167 (0.0250)***	0.2289 (0.0420)***	0.2142 (0.0423)***	0.1975 (0.0423)***
Years since first edit	-0.0435 (0.0136)**	-0.0374 (0.0137)**	-0.0355 (0.0134)**	-0.0831 (0.0233)***	-0.0764 (0.0234)**	-0.0741 (0.0232)**
Was administrator	0.3180 (0.0965)***	0.3144 (0.0981)**	0.2861 (0.0950)**	0.1701 (0.1906)	0.1448 (0.1917)	0.1346 (0.1899)
Month of year: May-Aug (Ref.: Jan-Apr)	-0.0697 (0.0260)**	-0.0637 (0.0259)*	-0.0612 (0.0259)*	-0.0366 (0.0340)	-0.0315 (0.0340)	-0.0280 (0.0340)
Month of year: Sep-Dec (Ref.: Jan-Apr)	-0.0091 (0.0491)	-0.0067 (0.0490)	0.0009 (0.0488)	0.0029 (0.0688)	0.0077 (0.0686)	0.0148 (0.0686)
AIC	24283.5833	24265.9879	24242.8261	22664.4831	22653.0839	22645.7065
Log Likelihood	-12128.7917	-12119.9940	-12105.4131	-11321.2415	-11315.5420	-11309.8532
Num. obs.	7109	7109	7109	7109	7109	7109
Num. groups: id	897	897	897	897	897	897
Var: id (Intercept)	0.5385	0.5610	0.5180	2.2148	2.2454	2.1919

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$.

Table A63: Explaining rewards (restricted; meetup attendees only).

	Receiving rewards	Receiving rewards	Receiving rewards	Rewarding others	Rewarding others	Rewarding others
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Intercept	-2.5997 (0.8896)**	-4.6737 (0.7155)***	-4.8730 (0.9273)***	-4.8938 (0.5634)***	-5.1534 (0.5287)***	-4.0285 (0.6219)***
Egocentric offline network density	0.1990 (0.6085)		0.0460 (0.6010)	-1.1497 (0.3508)**		-1.1391 (0.3499)**
Offline network size	0.0069 (0.0047)		0.0097 (0.0047)*	0.0002 (0.0027)		-0.0000 (0.0027)
Egocentric online network density		-1.0206 (0.5522)$^{+}$	-0.9576 (0.5449)$^{+}$		-1.1251 (0.3742)**	-1.0644 (0.3750)**
Online network size		-0.0208 (0.0023)***	-0.0210 (0.0023)***		-0.0000 (0.0003)	-0.0000 (0.0003)
Edits this month (log)	0.4156 (0.0763)***	0.8632 (0.0892)***	0.8388 (0.0878)***	0.5862 (0.0463)***	0.5657 (0.0480)***	0.5574 (0.0478)***
Total edits (log)	-0.1851 (0.1021)$^{+}$	0.1407 (0.0996)	0.1499 (0.0974)	0.1054 (0.0678)	0.0894 (0.0696)	0.0672 (0.0693)
Years since first edit	0.0011 (0.0570)	-0.0650 (0.0559)	-0.0738 (0.0547)	-0.0816 (0.0363)*	-0.0759 (0.0368)*	-0.0763 (0.0364)*
Was administrator	-0.5487 (0.3398)	-0.2408 (0.3554)	-0.2674 (0.3441)	-0.0002 (0.2085)	-0.0085 (0.2107)	-0.0302 (0.2073)
Month of year: May-Aug (Ref.: Jan-Apr)	-0.4821 (0.2396)*	-0.4829 (0.2366)*	-0.4719 (0.2330)*	-0.1280 (0.0972)	-0.1053 (0.0978)	-0.1077 (0.0975)
Month of year: Sep-Dec (Ref.: Jan-Apr)	-0.0613 (0.3289)	-0.0248 (0.3322)	-0.0535 (0.3250)	0.1565 (0.1704)	0.2046 (0.1712)	0.1776 (0.1700)
AIC	3365.8748	3219.0725	3214.4478	5724.3020	5736.7498	5719.5104
Log Likelihood	-1671.9374	-1598.5362	-1594.2239	-2851.1510	-2857.3749	-2846.7552
Num. obs.	7109	7109	7109	7109	7109	7109
Num. groups: id	897	897	897	897	897	897
Var: id (Intercept)	0.3288	0.8310	0.6530	1.6197	1.6968	1.5866

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$.

A.3.6 Models Including Outliers

Table A64: Explaining norm violations (with outliers).

	Exp. norm violation	Exp. norm violation	Exp. norm violation	Violate norms	Violate norms	Violate norms
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Intercept	$-2.8334\ (0.0426)^{***}$	$-3.1141\ (0.0444)^{***}$	$-3.1163\ (0.0444)^{***}$	$-2.7394\ (0.0428)^{***}$	$-2.8911\ (0.0450)^{***}$	$-2.8927\ (0.0450)^{***}$
Egocentric offline network density	$0.3509\ (0.3004)$		$0.3752\ (0.2979)$	$0.3687\ (0.2737)$		$0.4080\ (0.2710)$
Offline network size	$-0.0043\ (0.0025)^{+}$		$-0.0009\ (0.0025)$	$-0.0015\ (0.0023)$		$0.0003\ (0.0022)$
Meetup attendee	$-0.6560\ (0.3002)^{*}$	$-0.4281\ (0.0511)^{***}$	$-0.7039\ (0.2971)^{*}$	$-0.4760\ (0.2734)^{+}$	$-0.1959\ (0.0489)^{***}$	$-0.5313\ (0.2705)^{*}$
Egocentric online network density		$0.0931\ (0.0246)^{***}$	$0.0925\ (0.0246)^{***}$		$-0.0307\ (0.0267)$	$-0.0316\ (0.0267)$
Online network size		$-0.0044\ (0.0002)^{***}$	$-0.0044\ (0.0002)^{***}$		$-0.0023\ (0.0001)^{***}$	$-0.0023\ (0.0001)^{***}$
Edits this month (log)	$0.3755\ (0.0071)^{***}$	$0.4438\ (0.0075)^{***}$	$0.4440\ (0.0075)^{***}$	$0.7032\ (0.0077)^{***}$	$0.7444\ (0.0080)^{***}$	$0.7446\ (0.0080)^{***}$
Total edits (log)	$0.0118\ (0.0074)$	$0.0540\ (0.0076)^{***}$	$0.0542\ (0.0076)^{***}$	$-0.1237\ (0.0078)^{***}$	$-0.0943\ (0.0080)^{***}$	$-0.0941\ (0.0080)^{***}$
Years since first edit	$-0.0164\ (0.0048)^{***}$	$-0.0214\ (0.0048)^{***}$	$-0.0213\ (0.0048)^{***}$	$-0.0330\ (0.0050)^{***}$	$-0.0369\ (0.0050)^{***}$	$-0.0368\ (0.0050)^{***}$
Was administrator	$-1.5409\ (0.1190)^{***}$	$-1.2150\ (0.1185)^{***}$	$-1.1987\ (0.1191)^{***}$	$-0.9492\ (0.1029)^{***}$	$-0.7596\ (0.1009)^{***}$	$-0.7443\ (0.1016)^{***}$
Month of year: May-Aug (Ref.: Jan-Apr)	$-0.0985\ (0.0198)^{***}$	$-0.1063\ (0.0199)^{***}$	$-0.1066\ (0.0199)^{***}$	$-0.0035\ (0.0206)$	$-0.0055\ (0.0206)$	$-0.0058\ (0.0206)$
Month of year: Sep-Dec (Ref.: Jan-Apr)	$0.0311\ (0.0344)$	$0.0189\ (0.0342)$	$0.0192\ (0.0342)$	$0.0818\ (0.0369)^{*}$	$0.0797\ (0.0367)^{*}$	$0.0796\ (0.0367)^{*}$
AIC	133564.0302	132743.2930	132741.8473	134625.4934	134244.1051	134243.7438
Log Likelihood	−66770.0151	−66359.6465	−66356.9236	−67300.7467	−67110.0525	−67107.8719
Num. obs.	140151	140151	140151	140151	140151	140151
Num. groups: id	33210	33210	33210	33210	33210	33210
Var: id (Intercept)	0.7542	0.6918	0.6926	0.8072	0.7556	0.7549

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$.

Table A65: Explaining norm violations (with outliers).

	Experience norm violation	Experience norm violation	Experience norm violation	Violate norms	Violate norms	Violate norms
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Intercept	-2.8333 (0.0426)***	-3.1127 (0.0448)***	-3.1150 (0.0448)***	-2.7387 (0.0428)***	-2.8862 (0.0455)***	-2.8872 (0.0455)***
Egocentric offline network density	-0.3966 (0.5391)		-0.5151 (0.5348)	0.2695 (0.4692)		0.2099 (0.4650)
Alter offline network density	-4.6597 (3.2929)		-5.7764 (3.2740)$^{+}$	0.5482 (2.7364)		-0.1154 (2.7143)
Ego offline density * Alter offline density	5.0862 (3.3061)		6.1670 (3.2886)$^{+}$	-0.0101 (2.7442)		0.6831 (2.7226)
Offline network size	-0.0065 (0.0032)*		-0.0037 (0.0031)	-0.0006 (0.0028)		0.0008 (0.0028)
Meetup attendee	0.0293 (0.5583)	-0.4251 (0.0510)***	0.1454 (0.5532)	-0.5222 (0.4841)	-0.1952 (0.0489)***	-0.4789 (0.4796)
Egocentric online network density		0.2082 (0.0282)***	0.2077 (0.0282)***		-0.0118 (0.0303)	-0.0128 (0.0303)
Alter online network density		1.6539 (0.2760)***	1.6522 (0.2760)***		0.0094 (0.2624)	0.0080 (0.2624)
Ego online density * Alter online density		-2.1954 (0.2911)***	-2.1934 (0.2911)***		-0.1314 (0.2612)	-0.1297 (0.2611)
Online network size		-0.0043 (0.0002)***	-0.0043 (0.0002)***		-0.0023 (0.0001)***	-0.0023 (0.0001)***
Edits this month (log)	0.3755 (0.0071)***	0.4419 (0.0075)***	0.4421 (0.0075)***	0.7032 (0.0077)***	0.7437 (0.0081)***	0.7438 (0.0081)***
Total edits (log)	0.0118 (0.0074)	0.0443 (0.0077)***	0.0445 (0.0077)***	-0.1238 (0.0078)***	-0.0958 (0.0080)***	-0.0956 (0.0080)***
Years since first edit	-0.0164 (0.0048)***	-0.0187 (0.0048)***	-0.0185 (0.0048)***	-0.0329 (0.0050)***	-0.0364 (0.0050)***	-0.0363 (0.0050)***
Was administrator	-1.5410 (0.1190)***	-1.1987 (0.1181)***	-1.1830 (0.1187)***	-0.9494 (0.1029)***	-0.7578 (0.1009)***	-0.7425 (0.1016)***
Month of year: May-Aug (Ref.: Jan-Apr)	-0.0985 (0.0198)***	-0.1079 (0.0199)***	-0.1081 (0.0199)***	-0.0040 (0.0206)	-0.0060 (0.0206)	-0.0068 (0.0206)
Month of year: Sep-Dec (Ref.: Jan-Apr)	0.0311 (0.0344)	0.0143 (0.0342)	0.0147 (0.0342)	0.0806 (0.0369)*	0.0783 (0.0367)*	0.0771 (0.0367)*
AIC	133564.4190	132664.2759	132662.5853	134626.4389	134246.2884	134246.5035
Log Likelihood	-66768.2095	-66318.1379	-66313.2926	-67299.2194	-67109.1442	-67105.2518
Num. obs.	140151	140151	140151	140151	140151	140151
Num. groups: id	33210	33210	33210	33210	33210	33210
Var: id (Intercept)	0.7536	0.6844	0.6845	0.8066	0.7559	0.7544

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$.

Table A66: Explaining norm punishments (with outliers).

	Experience norm pun.	Experience norm pun.	Experience norm pun.	Punishing norm violators	Punishing norm violators	Punishing norm violators
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Intercept	$-3.2721\ (0.0458)^{***}$	$-3.5984\ (0.0478)^{***}$	$-3.5986\ (0.0478)^{***}$	$-6.8303\ (0.0641)^{***}$	$-6.8436\ (0.0665)^{***}$	$-6.8408\ (0.0665)^{***}$
Egocentric offline network density	0.4467 (0.3746)		0.2815 (0.3739)	−0.0132 (0.1445)		−0.0152 (0.1444)
Offline network size	−0.0016 (0.0034)		0.0013 (0.0035)	0.0012 (0.0013)		0.0012 (0.0013)
Meetup attendee	−0.3947 (0.3771)	0.0333 (0.0562)	−0.2274 (0.3781)	0.0393 (0.1530)	0.0506 (0.0336)	0.0412 (0.1529)
Egocentric online network density		$0.1397\ (0.0278)^{***}$	$0.1395\ (0.0278)^{***}$		−0.0126 (0.0279)	−0.0122 (0.0279)
Online network size		$-0.0123\ (0.0005)^{***}$	$-0.0123\ (0.0005)^{***}$		$-0.0001\ (0.0001)^{*}$	$-0.0001\ (0.0001)^{*}$
Experienced norm violations	$2.0521\ (0.0205)^{***}$	$1.9915\ (0.0201)^{***}$	$1.9913\ (0.0201)^{***}$			
Edits this month (log)	$-0.1316\ (0.0091)^{***}$	$-0.0211\ (0.0098)^{*}$	$-0.0209\ (0.0098)^{*}$	$0.4882\ (0.0054)^{***}$	$0.4900\ (0.0055)^{***}$	$0.4899\ (0.0055)^{***}$
Total edits (log)	$0.0213\ (0.0078)^{**}$	$0.0772\ (0.0081)^{***}$	$0.0771\ (0.0081)^{***}$	$0.5193\ (0.0098)^{***}$	$0.5227\ (0.0099)^{***}$	$0.5221\ (0.0099)^{***}$
Years since first edit	−0.0017 (0.0051)	$-0.0109\ (0.0051)^{*}$	$-0.0108\ (0.0051)^{*}$	$-0.0848\ (0.0063)^{***}$	$-0.0854\ (0.0063)^{***}$	$-0.0853\ (0.0063)^{***}$
Was administrator	$-0.2747\ (0.1315)^{*}$	0.1405 (0.1337)	0.1381 (0.1339)	$1.4207\ (0.1343)^{***}$	$1.4433\ (0.1342)^{***}$	$1.4306\ (0.1345)^{***}$
Month of year: May-Aug (Ref.: Jan-Apr)	−0.0142 (0.0261)	−0.0264 (0.0257)	−0.0264 (0.0257)	$-0.0421\ (0.0126)^{***}$	$-0.0427\ (0.0126)^{***}$	$-0.0424\ (0.0126)^{***}$
Month of year: Sep-Dec (Ref.: Jan-Apr)	0.0015 (0.0381)	−0.0076 (0.0377)	−0.0077 (0.0377)	0.0062 (0.0285)	0.0057 (0.0285)	0.0061 (0.0285)
AIC	80913.8559	80081.2206	80084.5594	164481.4330	164478.5026	164480.7059
Log Likelihood	−40443.9280	−40027.6103	−40027.2797	−82228.7165	−82227.2513	−82226.3529
Num. obs.	140151	140151	140151	140151	140151	140151
Num. groups: id	33210	33210	33210	33210	33210	33210
Var: id (Intercept)	0.0000	0.0000	0.0000	2.6978	2.7058	2.7044

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$.

Table A67: Explaining rewards (with outliers).

	Receiving rewards	Receiving rewards	Receiving rewards	Rewarding others	Rewarding others	Rewarding others
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Intercept	−5.2593 (0.0445)***	−5.1999 (0.0476)***	−5.1829 (0.0475)***	−6.5105 (0.0804)***	−6.5483 (0.0830)***	−6.5244 (0.0830)***
Egocentric offline network density	−0.3118 (0.1233)*		−0.3042 (0.1233)*	−0.4912 (0.1708)**		−0.4924 (0.1708)**
Previous norm punishments conducted	0.0032 (0.0067)	−0.0052 (0.0160)	−0.0038 (0.0160)			
Offline density * Norm punishments	−0.0375 (0.0285)		−0.0371 (0.0286)			
Offline network size	0.0026 (0.0010)*		0.0026 (0.0010)*	0.0012 (0.0015)		0.0012 (0.0015)
Meetup attendee	0.5298 (0.1281)***	0.3108 (0.0291)***	0.5219 (0.1281)***	0.6847 (0.1806)***	0.2580 (0.0426)***	0.6861 (0.1806)***
Egocentric online network density		−0.0787 (0.0270)**	−0.0763 (0.0270)**		0.0199 (0.0343)	0.0220 (0.0343)
Online density * Norm punishments		0.0189 (0.0416)	0.0220 (0.0414)			
Online network size		0.0002 (0.0000)***	0.0002 (0.0000)***		−0.0000 (0.0001)	−0.0000 (0.0001)
Edits this month (log)	0.7915 (0.0057)***	0.7864 (0.0058)***	0.7857 (0.0058)***	0.8508 (0.0077)***	0.8519 (0.0078)***	0.8513 (0.0078)***
Total edits (log)	0.2095 (0.0074)***	0.2077 (0.0074)***	0.2052 (0.0074)***	0.2319 (0.0123)***	0.2358 (0.0124)***	0.2321 (0.0124)***
Years since first edit	−0.0451 (0.0046)***	−0.0449 (0.0047)***	−0.0448 (0.0046)***	−0.1196 (0.0080)***	−0.1198 (0.0080)***	−0.1195 (0.0080)***
Was administrator	0.5924 (0.0784)***	0.6098 (0.0784)***	0.5690 (0.0783)***	0.9015 (0.1736)***	0.9547 (0.1739)***	0.9049 (0.1737)***
Month of year: May-Aug (Ref.: Jan-Apr)	−0.0416 (0.0122)***	−0.0400 (0.0122)**	−0.0391 (0.0122)**	−0.0391 (0.0159)*	−0.0411 (0.0159)**	−0.0397 (0.0159)*
Month of year: Sep-Dec (Ref.: Jan-Apr)	0.0010 (0.0261)	0.0011 (0.0261)	0.0028 (0.0261)	0.0842 (0.0388)*	0.0803 (0.0388)*	0.0833 (0.0388)*
AIC	152031.3001	152042.7809	152009.2528	126007.7327	126027.1832	126011.2551
Log Likelihood	−76001.6501	−76007.3904	−75987.6264	−62991.8663	−63001.5916	−62991.6276
Num. obs.	140151	140151	140151	140151	140151	140151
Num. groups: id	33210	33210	33210	33210	33210	33210
Var: id (Intercept)	0.8479	0.8515	0.8421	4.2733	4.3058	4.2729

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$.

Table A68: Explaining rewards (restricted; with outliers).

	Receiving rewards	Receiving rewards	Receiving rewards	Rewarding others	Rewarding others	Rewarding others
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Intercept	-8.1263 $(0.2128)^{***}$	-8.2418 $(0.1945)^{***}$	-8.2342 $(0.1946)^{***}$	-9.2837 $(0.1893)^{***}$	-9.1006 $(0.2039)^{***}$	-9.0593 $(0.2029)^{***}$
Egocentric offline network density	-0.1739 (0.7159)		0.1193 (0.6199)	-1.4436 $(0.4248)^{***}$		-1.4376 $(0.4247)^{***}$
Offline network size	-0.0055 (0.0061)		0.0034 (0.0051)	-0.0008 (0.0034)		-0.0008 (0.0034)
Meetup attendee	0.5685 (0.7181)	0.3960 $(0.1094)^{***}$	0.2032 (0.6118)	1.9536 $(0.4285)^{***}$	0.7428 $(0.0997)^{***}$	1.9423 $(0.4285)^{***}$
Egocentric online network density		-0.0537 (0.1022)	-0.0529 (0.1021)		-0.3599 $(0.1222)^{**}$	-0.3509 $(0.1221)^{**}$
Online network size		-0.0131 $(0.0007)^{***}$	-0.0131 $(0.0007)^{***}$		-0.0001 (0.0001)	-0.0001 (0.0001)
Edits this month (log)	0.7045 $(0.0244)^{***}$	0.9277 $(0.0254)^{***}$	0.9275 $(0.0254)^{***}$	0.7597 $(0.0229)^{***}$	0.7546 $(0.0236)^{***}$	0.7522 $(0.0236)^{***}$
Total edits (log)	0.1732 $(0.0262)^{***}$	0.3139 $(0.0252)^{***}$	0.3138 $(0.0252)^{***}$	0.2434 $(0.0286)^{***}$	0.2461 $(0.0287)^{***}$	0.2415 $(0.0287)^{***}$
Years since first edit	-0.0614 $(0.0170)^{***}$	-0.0934 $(0.0152)^{***}$	-0.0935 $(0.0152)^{***}$	-0.1033 $(0.0175)^{***}$	-0.1044 $(0.0175)^{***}$	-0.1045 $(0.0175)^{***}$
Was administrator	-1.1846 $(0.2752)^{***}$	-0.3297 (0.2216)	-0.3411 (0.2217)	0.2292 (0.2114)	0.2799 (0.2111)	0.2164 (0.2117)
Month of year: May-Aug (Ref.: Jan-Apr)	-0.2030 $(0.0668)^{**}$	-0.2139 $(0.0658)^{**}$	-0.2139 $(0.0658)^{**}$	-0.0746 (0.0497)	-0.0686 (0.0498)	-0.0681 (0.0498)
Month of year: Sep-Dec (Ref.: Jan-Apr)	-0.0219 (0.1179)	0.0016 (0.1069)	0.0006 (0.1069)	0.1029 (0.1056)	0.1211 (0.1057)	0.1106 (0.1056)
AIC	26746.7506	26087.1671	26090.4903	23408.4970	23420.2744	23404.0324
Log Likelihood	-13361.3753	-13031.5835	-13031.2451	-11692.2485	-11698.1372	-11688.0162
Num. obs.	140151	140151	140151	140151	140151	140151
Num. groups: id	33210	33210	33210	33210	33210	33210
Var: id (Intercept)	4.7903	1.8883	1.8746	4.2254	4.2549	4.2170

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$.

A.3.7 Models Excluding Reverted Reverts

Table A69: Explaining norm violations (excluding reverts of reverts).

	Exp. norm violation	Exp. norm violation	Exp. norm violation	Violate norms	Violate norms	Violate norms
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Intercept	$-2.9495\ (0.0436)^{***}$	$-3.2216\ (0.0456)^{***}$	$-3.2240\ (0.0456)^{***}$	$-2.7728\ (0.0435)^{***}$	$-2.9141\ (0.0459)^{***}$	$-2.9156\ (0.0460)^{***}$
Egocentric offline network density	0.4259 (0.3069)		0.4059 (0.3045)	0.4486 (0.2784)		$0.4608\ (0.2762)^{+}$
Offline network size	−0.0039 (0.0026)		−0.0012 (0.0026)	0.0000 (0.0023)		0.0013 (0.0023)
Meetup attendee	$-0.7320\ (0.3067)^{*}$	$-0.4380\ (0.0523)^{***}$	$-0.7318\ (0.3038)^{*}$	$-0.5752\ (0.2780)^{*}$	$-0.1963\ (0.0499)^{***}$	$-0.5997\ (0.2756)^{*}$
Egocentric online network density		$0.0956\ (0.0251)^{***}$	$0.0949\ (0.0251)^{***}$		−0.0154 (0.0273)	−0.0162 (0.0273)
Online network size		$-0.0043\ (0.0002)^{***}$	$-0.0042\ (0.0002)^{***}$		$-0.0020\ (0.0001)^{***}$	$-0.0020\ (0.0001)^{***}$
Edits this month (log)	$0.3716\ (0.0072)^{***}$	$0.4360\ (0.0076)^{***}$	$0.4362\ (0.0076)^{***}$	$0.6939\ (0.0079)^{***}$	$0.7295\ (0.0082)^{***}$	$0.7297\ (0.0082)^{***}$
Total edits (log)	$0.0203\ (0.0075)^{**}$	$0.0607\ (0.0078)^{***}$	$0.0609\ (0.0078)^{***}$	$-0.1355\ (0.0080)^{***}$	$-0.1097\ (0.0082)^{***}$	$-0.1095\ (0.0082)^{***}$
Years since first edit	$-0.0165\ (0.0049)^{***}$	$-0.0214\ (0.0049)^{***}$	$-0.0212\ (0.0049)^{***}$	$-0.0350\ (0.0051)^{***}$	$-0.0384\ (0.0051)^{***}$	$-0.0383\ (0.0051)^{***}$
Was administrator	$-1.5447\ (0.1222)^{***}$	$-1.2433\ (0.1217)^{***}$	$-1.2241\ (0.1223)^{***}$	$-0.9173\ (0.1052)^{***}$	$-0.7516\ (0.1035)^{***}$	$-0.7418\ (0.1042)^{***}$
Month of year: May-Aug (Ref.: Jan-Apr)	$-0.1021\ (0.0202)^{***}$	$-0.1094\ (0.0202)^{***}$	$-0.1098\ (0.0202)^{***}$	0.0018 (0.0210)	0.0008 (0.0210)	0.0005 (0.0210)
Month of year: Sep-Dec (Ref.: Jan-Apr)	0.0310 (0.0351)	0.0207 (0.0349)	0.0211 (0.0349)	$0.0921\ (0.0377)^{*}$	$0.0919\ (0.0376)^{*}$	$0.0918\ (0.0376)^{*}$
AIC	128380.8417	127671.5997	127669.0775	123330.6112	123056.1173	123056.3163
Log Likelihood	−64178.4209	−63823.7999	−63820.5387	−61653.3056	−61516.0587	−61514.1581
Num. obs.	140022	140022	140022	140022	140022	140022
Num. groups: id	33204	33204	33204	33204	33204	33204
Var: id (Intercept)	0.7785	0.7235	0.7243	0.7952	0.7559	0.7549

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$.

Table A70: Explaining norm violations (excluding reverts of reverts).

	Exp. norm violation	Exp. norm violation	Exp. norm violation	Violate norms	Violate norms	Violate norms
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Intercept	−2.9494 (0.0436)***	−3.2199 (0.0460)***	−3.2224 (0.0460)***	−2.7722 (0.0435)***	−2.9067 (0.0465)***	−2.9076 (0.0465)***
Egocentric offline network density	−0.2993 (0.5521)		−0.4867 (0.5478)	0.3932 (0.4798)		0.3063 (0.4765)
Alter offline network density	−4.6271 (3.3779)		−5.8887 (3.3635)$^{+}$	0.6849 (2.8161)		0.0227 (2.8011)
Ego offline density * Alter offline density	4.9937 (3.3922)		6.2412 (3.3787)$^{+}$	−0.2306 (2.8269)		0.4651 (2.8121)
Offline network size	−0.0061 (0.0032)$^{+}$		−0.0040 (0.0032)	0.0008 (0.0028)		0.0018 (0.0028)
Meetup attendee	−0.0545 (0.5714)	−0.4350 (0.0521)***	0.1304 (0.5666)	−0.6451 (0.4947)	−0.1958 (0.0499)***	−0.5718 (0.4912)
Egocentric online network density		0.2112 (0.0288)***	0.2106 (0.0288)***		0.0019 (0.0310)	0.0011 (0.0310)
Alter online network density		1.6730 (0.2832)***	1.6707 (0.2831)***		−0.1000 (0.2671)	−0.1015 (0.2671)
Ego online density * Alter online density		−2.2182 (0.2991)***	−2.2155 (0.2991)***		−0.0321 (0.2643)	−0.0304 (0.2642)
Online network size		−0.0041 (0.0002)***	−0.0041 (0.0002)***		−0.0020 (0.0001)***	−0.0020 (0.0001)***
Edits this month (log)	0.3716 (0.0072)***	0.4340 (0.0077)***	0.4343 (0.0077)***	0.6938 (0.0079)***	0.7287 (0.0082)***	0.7288 (0.0082)***
Total edits (log)	0.0204 (0.0075)**	0.0510 (0.0079)***	0.0511 (0.0079)***	−0.1355 (0.0080)***	−0.1112 (0.0082)***	−0.1109 (0.0082)***
Years since first edit	−0.0165 (0.0049)***	−0.0186 (0.0049)***	−0.0185 (0.0049)***	−0.0350 (0.0051)***	−0.0380 (0.0051)***	−0.0378 (0.0051)***
Was administrator	−1.5445 (0.1222)***	−1.2265 (0.1213)***	−1.2078 (0.1219)***	−0.9173 (0.1052)***	−0.7501 (0.1035)***	−0.7401 (0.1042)***
Month of year: May-Aug (Ref.: Jan-Apr)	−0.1021 (0.0202)***	−0.1111 (0.0202)***	−0.1113 (0.0202)***	0.0014 (0.0210)	0.0000 (0.0211)	−0.0006 (0.0211)
Month of year: Sep-Dec (Ref.: Jan-Apr)	0.0311 (0.0351)	0.0161 (0.0349)	0.0166 (0.0349)	0.0910 (0.0377)*	0.0904 (0.0376)*	0.0893 (0.0376)*
AIC	128381.8151	127595.3880	127592.9661	123332.4595	123058.1884	123059.9299
Log Likelihood	−64176.9076	−63783.6940	−63778.4831	−61652.2297	−61515.0942	−61511.9650
Num. obs.	140022	140022	140022	140022	140022	140022
Num. groups: id	33204	33204	33204	33204	33204	33204
Var: id (Intercept)	0.7779	0.7153	0.7154	0.7948	0.7559	0.7544

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$.

Table A71: Explaining norm punishments (excluding reverts of reverts).

	Experience norm pun.	Experience norm pun.	Experience norm pun.	Punishing norm violators	Punishing norm violators	Punishing norm violators
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Intercept	$-3.3504\ (0.0471)^{***}$	$-3.6763\ (0.0492)^{***}$	$-3.6764\ (0.0492)^{***}$	$-6.9995\ (0.0667)^{***}$	$-7.0094\ (0.0692)^{***}$	$-7.0070\ (0.0692)^{***}$
Egocentric offline network density	0.4052 (0.3860)		0.2062 (0.3842)	0.0064 (0.1460)		0.0031 (0.1459)
Offline network size	−0.0018 (0.0035)		0.0009 (0.0036)	0.0012 (0.0013)		0.0011 (0.0013)
Meetup attendee	−0.3659 (0.3884)	0.0249 (0.0578)	−0.1648 (0.3884)	0.0174 (0.1545)	0.0459 (0.0341)	0.0207 (0.1544)
Egocentric online network density		$0.1370\ (0.0286)^{***}$	$0.1368\ (0.0286)^{***}$		−0.0177 (0.0291)	−0.0173 (0.0291)
Online network size		$-0.0127\ (0.0005)^{***}$	$-0.0127\ (0.0005)^{***}$		$-0.0001\ (0.0001)^{*}$	$-0.0001\ (0.0001)^{*}$
Experienced norm violations	$2.1457\ (0.0215)^{***}$	$2.0844\ (0.0211)^{***}$	$2.0842\ (0.0211)^{***}$			
Edits this month (log)	$-0.1331\ (0.0094)^{***}$	$-0.0217\ (0.0100)^{*}$	$-0.0215\ (0.0100)^{*}$	$0.4633\ (0.0056)^{***}$	$0.4650\ (0.0056)^{***}$	$0.4649\ (0.0056)^{***}$
Total edits (log)	$0.0227\ (0.0081)^{**}$	$0.0797\ (0.0083)^{***}$	$0.0797\ (0.0083)^{***}$	$0.5336\ (0.0101)^{***}$	$0.5370\ (0.0102)^{***}$	$0.5365\ (0.0102)^{***}$
Years since first edit	−0.0016 (0.0052)	$-0.0113\ (0.0052)^{*}$	$-0.0113\ (0.0052)^{*}$	$-0.0870\ (0.0065)^{***}$	$-0.0876\ (0.0065)^{***}$	$-0.0876\ (0.0065)^{***}$
Was administrator	$-0.2466\ (0.1354)^{+}$	0.1658 (0.1378)	0.1642 (0.1379)	$1.4642\ (0.1368)^{***}$	$1.4832\ (0.1367)^{***}$	$1.4730\ (0.1370)^{***}$
Month of year: May-Aug (Ref.: Jan-Apr)	−0.0133 (0.0268)	−0.0259 (0.0264)	−0.0259 (0.0264)	$-0.0418\ (0.0129)^{**}$	$-0.0422\ (0.0129)^{**}$	$-0.0420\ (0.0129)^{**}$
Month of year: Sep-Dec (Ref.: Jan-Apr)	0.0030 (0.0391)	−0.0046 (0.0386)	−0.0046 (0.0386)	0.0044 (0.0291)	0.0038 (0.0291)	0.0041 (0.0291)
AIC	77644.6066	76834.0327	76837.6876	153010.6440	153006.6638	153009.3251
Log Likelihood	−38809.3033	−38404.0163	−38403.8438	−76493.3220	−76491.3319	−76490.6625
Num. obs.	140022	140022	140022	140022	140022	140022
Num. groups: id	33204	33204	33204	33204	33204	33204
Var: id (Intercept)	0.0000	0.0000	0.0000	2.7653	2.7711	2.7699

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$.

Table A72: Explaining rewards (excluding reverts of reverts).

	Receiving rewards	Receiving rewards	Receiving rewards	Rewarding others	Rewarding others	Rewarding others
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Intercept	−5.2531 (0.0447)***	−5.1948 (0.0477)***	−5.1774 (0.0476)***	−6.4983 (0.0806)***	−6.5340 (0.0832)***	−6.5099 (0.0831)***
Egocentric offline network density	−0.3226 (0.1241)**		−0.3127 (0.1241)*	−0.5031 (0.1717)**		−0.5034 (0.1717)**
Previous norm punishments conducted	0.0026 (0.0068)	0.0002 (0.0163)	0.0014 (0.0163)			
Offline density * Norm punishments	−0.0345 (0.0294)		−0.0335 (0.0294)			
Offline network size	0.0027 (0.0011)*		0.0026 (0.0011)*	0.0011 (0.0015)		0.0012 (0.0015)
Meetup attendee	0.5362 (0.1289)***	0.3087 (0.0292)***	0.5256 (0.1289)***	0.6977 (0.1814)***	0.2590 (0.0427)***	0.6982 (0.1815)***
Egocentric online network density		−0.0754 (0.0270)**	−0.0730 (0.0270)**		0.0221 (0.0343)	0.0241 (0.0343)
Online density * Norm punishments		0.0026 (0.0429)	0.0057 (0.0428)			
Online network size		0.0002 (0.0000)***	0.0002 (0.0000)***		0.0000 (0.0001)	0.0000 (0.0001)
Edits this month (log)	0.7917 (0.0058)***	0.7864 (0.0059)***	0.7857 (0.0059)***	0.8513 (0.0078)***	0.8521 (0.0078)***	0.8515 (0.0078)***
Total edits (log)	0.2091 (0.0074)***	0.2072 (0.0074)***	0.2046 (0.0074)***	0.2300 (0.0123)***	0.2332 (0.0124)***	0.2296 (0.0124)***
Years since first edit	−0.0458 (0.0047)***	−0.0455 (0.0047)***	−0.0455 (0.0047)***	−0.1197 (0.0080)***	−0.1197 (0.0080)***	−0.1195 (0.0080)***
Was administrator	0.5923 (0.0789)***	0.6088 (0.0789)***	0.5686 (0.0788)***	0.9089 (0.1746)***	0.9586 (0.1749)***	0.9101 (0.1747)***
Month of year: May-Aug (Ref.: Jan-Apr)	−0.0458 (0.0123)***	−0.0439 (0.0123)***	−0.0431 (0.0123)***	−0.0448 (0.0160)**	−0.0465 (0.0160)**	−0.0453 (0.0160)**
Month of year: Sep-Dec (Ref.: Jan-Apr)	0.0043 (0.0263)	0.0042 (0.0263)	0.0060 (0.0263)	0.0849 (0.0390)*	0.0811 (0.0391)*	0.0841 (0.0391)*
AIC	151015.0623	151026.2715	150992.0415	124981.7345	125001.1962	124985.2232
Log Likelihood	−75493.5311	−75499.1357	−75479.0208	−62478.8673	−62488.5981	−62478.6116
Num. obs.	140022	140022	140022	140022	140022	140022
Num. groups: id	33204	33204	33204	33204	33204	33204
Var: id (Intercept)	0.8495	0.8534	0.8439	4.2735	4.3061	4.2733

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$.

Table A73: Explaining rewards (restricted; excluding reverts of reverts).

	Receiving rewards	Receiving rewards	Receiving rewards	Rewarding others	Rewarding others	Rewarding others
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Intercept	-8.3544 (0.0802)***	-7.5680 (0.0824)***	-7.5426 (0.0822)***	-6.6130 (0.0842)***	-6.6408 (0.0871)***	-6.6139 (0.0870)***
Egocentric offline network density	-0.4482 (0.1599)**		-0.4081 (0.1578)**	-0.4909 (0.1800)**		-0.4898 (0.1801)**
Offline network size	0.0019 (0.0014)		0.0017 (0.0013)	0.0019 (0.0015)		0.0019 (0.0015)
Meetup attendee	0.5847 (0.1658)***	0.2260 (0.0369)***	0.5388 (0.1635)***	0.6770 (0.1902)***	0.2651 (0.0449)***	0.6760 (0.1902)***
Egocentric online network density		-1.0737 (0.0518)***	-1.0692 (0.0518)***		0.0059 (0.0371)	0.0083 (0.0370)
Online network size		0.0003 (0.0001)***	0.0003 (0.0001)***		0.0000 (0.0001)	0.0000 (0.0001)
Edits this month (log)	0.9439 (0.0086)***	0.9104 (0.0086)***	0.9096 (0.0086)***	0.8702 (0.0083)***	0.8706 (0.0084)***	0.8699 (0.0084)***
Total edits (log)	0.4737 (0.0123)***	0.4487 (0.0121)***	0.4452 (0.0120)***	0.2100 (0.0129)***	0.2133 (0.0130)***	0.2093 (0.0130)***
Years since first edit	-0.1188 (0.0071)***	-0.1152 (0.0069)***	-0.1153 (0.0069)***	-0.1219 (0.0083)***	-0.1220 (0.0083)***	-0.1217 (0.0083)***
Was administrator	0.5796 (0.0949)***	0.5282 (0.0927)***	0.4934 (0.0926)***	0.9486 (0.1754)***	1.0017 (0.1758)***	0.9468 (0.1756)***
Month of year: May-Aug (Ref.: Jan-Apr)	-0.0841 (0.0164)***	-0.0619 (0.0163)***	-0.0609 (0.0163)***	-0.0479 (0.0170)**	-0.0494 (0.0170)**	-0.0479 (0.0170)**
Month of year: Sep-Dec (Ref.: Jan-Apr)	0.0508 (0.0358)	0.0695 (0.0354)*	0.0717 (0.0354)*	0.0944 (0.0412)*	0.0909 (0.0412)*	0.0942 (0.0412)*
AIC	106298.0231	105781.9589	105761.9119	112138.3707	112160.4043	112142.1635
Log Likelihood	-53137.0116	-52878.9794	-52866.9559	-56057.1854	-56068.2021	-56057.0818
Num. obs.	140022	140022	140022	140022	140022	140022
Num. groups: id	33204	33204	33204	33204	33204	33204
Var: id (Intercept)	1.1803	1.1233	1.1125	4.2631	4.2995	4.2634

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$.

A.3.8 Models Using Normrevert

Using “normrv” instead of “rv” in line with Panciera et al. (2009).

Table A74: Explaining norm violations (using norm reverts only).

	Exp. norm violation	Exp. norm violation	Exp. norm violation	Violate norms	Violate norms	Violate norms
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Intercept	-5.1932 (0.0617)***	-4.9599 (0.0669)***	-4.9608 (0.0670)***	-5.7973 (0.1035)***	-5.5475 (0.1100)***	-5.5472 (0.1101)***
Egocentric offline network density	0.1190 (0.2683)		0.1332 (0.2671)	-0.0188 (0.4318)		0.0041 (0.4328)
Offline network size	0.0001 (0.0022)		-0.0001 (0.0022)	0.0017 (0.0035)		0.0014 (0.0035)
Meetup attendee	-0.3424 (0.2676)	-0.2569 (0.0514)***	-0.3598 (0.2663)	0.0217 (0.4310)	0.0444 (0.0845)	0.0017 (0.4318)
Egocentric online network density		-0.3135 (0.0440)***	-0.3141 (0.0440)***		-0.2708 (0.0668)***	-0.2702 (0.0668)***
Online network size		0.0002 (0.0001)*	0.0002 (0.0001)*		0.0005 (0.0001)***	0.0005 (0.0001)***
Edits this month (log)	0.7448 (0.0098)***	0.7294 (0.0101)***	0.7295 (0.0101)***	0.8090 (0.0166)***	0.7890 (0.0170)***	0.7889 (0.0170)***
Total edits (log)	0.0489 (0.0105)***	0.0457 (0.0106)***	0.0458 (0.0106)***	-0.1389 (0.0170)***	-0.1482 (0.0172)***	-0.1484 (0.0172)***
Years since first edit	0.0040 (0.0067)	0.0011 (0.0066)	0.0012 (0.0066)	0.0073 (0.0107)	0.0052 (0.0107)	0.0052 (0.0107)
Was administrator	-0.0516 (0.0937)	-0.0972 (0.0925)	-0.0923 (0.0930)	0.1554 (0.1576)	0.0845 (0.1569)	0.0753 (0.1578)
Month of year: May-Aug (Ref.: Jan-Apr)	-0.3519 (0.0247)***	-0.3443 (0.0247)***	-0.3445 (0.0247)***	-0.0688 (0.0416)$^{+}$	-0.0632 (0.0417)	-0.0629 (0.0417)
Month of year: Sep-Dec (Ref.: Jan-Apr)	-0.2716 (0.0441)***	-0.2590 (0.0440)***	-0.2588 (0.0440)***	-0.0137 (0.0748)	-0.0055 (0.0747)	-0.0058 (0.0747)
AIC	71350.2898	71286.6779	71290.0839	33303.3846	33264.9880	33268.6641
Log Likelihood	-35663.1449	-35631.3389	-35631.0420	-16639.6923	-16620.4940	-16620.3320
Num. obs.	140016	140016	140016	140016	140016	140016
Num. groups: id	33204	33204	33204	33204	33204	33204
Var: id (Intercept)	0.7894	0.7610	0.7607	1.9715	1.9274	1.9293

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$.

Table A75: Explaining norm violations (using norm reverts only).

	Experience norm violation	Experience norm violation	Experience norm violation	Violate norms	Violate norms	Violate norms
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Intercept	$-5.1938\ (0.0617)^{***}$	$-5.0030\ (0.0682)^{***}$	$-5.0179\ (0.0685)^{***}$	$-5.7978\ (0.1036)^{***}$	$-5.5210\ (0.1110)^{***}$	$-5.5211\ (0.1110)^{***}$
Egocentric offline network density	0.1130 (0.4658)		0.1170 (0.4674)	0.2293 (0.7246)		0.2365 (0.7268)
Alter offline network density	−1.2860 (2.9516)		−1.1050 (2.9632)	1.7992 (4.2613)		1.6659 (4.2755)
Ego offline density * Alter offline density	0.7293 (2.9758)		0.5866 (2.9876)	−1.8295 (4.2741)		−1.6985 (4.2885)
Offline network size	−0.0011 (0.0027)		−0.0009 (0.0027)	0.0027 (0.0043)		0.0023 (0.0043)
Meetup attendee	−0.1825 (0.4813)	$-0.2550\ (0.0514)^{***}$	−0.2064 (0.4829)	−0.2377 (0.7479)	0.0425 (0.0845)	−0.2410 (0.7500)
Egocentric online network density		$-0.2981\ (0.0494)^{***}$	$-0.2965\ (0.0496)^{***}$		$-0.3053\ (0.0736)^{***}$	$-0.3045\ (0.0736)^{***}$
Alter online network density		$1.8865\ (0.5021)^{***}$	$1.8735\ (0.5036)^{***}$		$-1.2629\ (0.5851)^{*}$	$-1.2629\ (0.5852)^{*}$
Ego online density * Alter online density		$-1.7941\ (0.5365)^{***}$	$-1.7839\ (0.5379)^{***}$		$1.2804\ (0.5321)^{*}$	$1.2793\ (0.5323)^{*}$
Online network size		$0.0002\ (0.0001)^{*}$	$0.0002\ (0.0001)^{*}$		$0.0005\ (0.0001)^{***}$	$0.0005\ (0.0001)^{***}$
Edits this month (log)	$0.7448\ (0.0098)^{***}$	$0.7326\ (0.0102)^{***}$	$0.7332\ (0.0102)^{***}$	$0.8090\ (0.0166)^{***}$	$0.7873\ (0.0170)^{***}$	$0.7872\ (0.0171)^{***}$
Total edits (log)	$0.0489\ (0.0105)^{***}$	$0.0468\ (0.0107)^{***}$	$0.0480\ (0.0108)^{***}$	$-0.1389\ (0.0170)^{***}$	$-0.1472\ (0.0173)^{***}$	$-0.1474\ (0.0173)^{***}$
Years since first edit	0.0040 (0.0067)	0.0006 (0.0067)	0.0004 (0.0067)	0.0073 (0.0107)	0.0048 (0.0107)	0.0048 (0.0108)
Was administrator	−0.0522 (0.0937)	−0.0938 (0.0924)	−0.1174 (0.0936)	0.1547 (0.1576)	0.0801 (0.1569)	0.0703 (0.1579)
Month of year: May-Aug (Ref.: Jan-Apr)	$-0.3513\ (0.0247)^{***}$	$-0.3429\ (0.0247)^{***}$	$-0.3463\ (0.0248)^{***}$	$-0.0688\ (0.0416)^{+}$	−0.0638 (0.0417)	−0.0635 (0.0418)
Month of year: Sep-Dec (Ref.: Jan-Apr)	$-0.2708\ (0.0441)^{***}$	$-0.2568\ (0.0440)^{***}$	$-0.2576\ (0.0443)^{***}$	−0.0139 (0.0748)	−0.0053 (0.0747)	−0.0058 (0.0748)
AIC	71351.1228	71275.4545	71853.8328	33307.2011	33264.1125	33271.6427
Log Likelihood	−35661.5614	−35623.7273	−35908.9164	−16639.6005	−16618.0563	−16617.8213
Num. obs.	140016	140016	140151	140016	140016	140016
Num. groups: id	33204	33204	33210	33204	33204	33204
Var: id (Intercept)	0.7894	0.7567	0.7789	1.9732	1.9281	1.9313

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$.

Table A76: Explaining norm punishments (using norm reverts only).

	Experience norm pun.	Experience norm pun.	Experience norm pun.	Punishing norm violators	Punishing norm violators	Punishing norm violators
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Intercept	$-4.5189\ (0.0595)^{***}$	$-4.8748\ (0.0672)^{***}$	$-4.8757\ (0.0672)^{***}$	$-10.3936\ (0.1972)^{***}$	$-10.2895\ (0.2051)^{***}$	$-10.2777\ (0.2051)^{***}$
Egocentric offline network density	$0.1979\ (0.3001)$		$0.3741\ (0.2904)$	$-0.5312\ (0.3459)$		$-0.5353\ (0.3458)$
Offline network size	$0.0009\ (0.0022)$		$0.0042\ (0.0021)^{+}$	$-0.0017\ (0.0028)$		$-0.0018\ (0.0028)$
Meetup attendee	$-0.3578\ (0.2910)$	$-0.1235\ (0.0499)^{*}$	$-0.5438\ (0.2822)^{+}$	$0.5902\ (0.3655)$	$0.0668\ (0.0814)$	$0.5941\ (0.3654)$
Egocentric online network density		$-0.1326\ (0.0484)^{**}$	$-0.1326\ (0.0484)^{**}$		$-0.2050\ (0.0832)^{*}$	$-0.2050\ (0.0832)^{*}$
Online network size		$-0.0035\ (0.0001)^{***}$	$-0.0036\ (0.0001)^{***}$		$-0.0002\ (0.0001)$	$-0.0002\ (0.0001)$
Experienced norm violations	$1.8317\ (0.0315)^{***}$	$1.8224\ (0.0307)^{***}$	$1.8224\ (0.0307)^{***}$			
Edits this month (log)	$0.2533\ (0.0114)^{***}$	$0.3416\ (0.0118)^{***}$	$0.3420\ (0.0118)^{***}$	$0.4960\ (0.0145)^{***}$	$0.4961\ (0.0147)^{***}$	$0.4957\ (0.0147)^{***}$
Total edits (log)	$0.0472\ (0.0111)^{***}$	$0.1013\ (0.0112)^{***}$	$0.1014\ (0.0112)^{***}$	$0.3632\ (0.0277)^{***}$	$0.3683\ (0.0277)^{***}$	$0.3666\ (0.0277)^{***}$
Years since first edit	$-0.0135\ (0.0068)^{*}$	$-0.0197\ (0.0068)^{**}$	$-0.0195\ (0.0068)^{**}$	$-0.0442\ (0.0176)^{*}$	$-0.0450\ (0.0176)^{*}$	$-0.0452\ (0.0176)^{*}$
Was administrator	$-0.3508\ (0.0853)^{***}$	$-0.1872\ (0.0815)^{*}$	$-0.2041\ (0.0821)^{*}$	$3.2191\ (0.3415)^{***}$	$3.2215\ (0.3393)^{***}$	$3.1958\ (0.3398)^{***}$
Month of year: May-Aug (Ref.: Jan-Apr)	$-0.1370\ (0.0335)^{***}$	$-0.1238\ (0.0332)^{***}$	$-0.1237\ (0.0332)^{***}$	$-0.2747\ (0.0322)^{***}$	$-0.2726\ (0.0323)^{***}$	$-0.2724\ (0.0323)^{***}$
Month of year: Sep-Dec (Ref.: Jan-Apr)	$-0.0544\ (0.0488)$	$-0.0506\ (0.0480)$	$-0.0524\ (0.0481)$	$-0.2991\ (0.0731)^{***}$	$-0.2981\ (0.0730)^{***}$	$-0.2968\ (0.0731)^{***}$
AIC	52157.9508	51536.7598	51536.9069	39647.5916	39643.2973	39644.7059
Log Likelihood	−26065.9754	−25755.3799	−25753.4535	−19811.7958	−19809.6486	−19808.3529
Num. obs.	140016	140016	140016	140016	140016	140016
Num. groups: id	33204	33204	33204	33204	33204	33204
Var: id (Intercept)	0.0000	0.0000	0.0000	14.8747	14.6952	14.6733

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$.

Table A77: Explaining rewards (using norm reverts only).

	Receiving rewards	Receiving rewards	Receiving rewards	Rewarding others	Rewarding others	Rewarding others
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Intercept	−5.2516 (0.0447)***	−5.1926 (0.0477)***	−5.1745 (0.0476)***	−6.4969 (0.0806)***	−6.5327 (0.0831)***	−6.5081 (0.0831)***
Egocentric offline network density	−0.3117 (0.1244)*		−0.3033 (0.1244)*	−0.5125 (0.1717)**		−0.5126 (0.1717)**
Previous norm punishments conducted	0.0048 (0.0039)	−0.0120 (0.0065)+	−0.0095 (0.0067)			
Offline density * Norm punishments	−0.0143 (0.0094)		−0.0136 (0.0093)			
Offline network size	0.0027 (0.0011)*		0.0027 (0.0011)*	0.0012 (0.0015)		0.0012 (0.0015)
Meetup attendee	0.5290 (0.1289)***	0.3093 (0.0292)***	0.5200 (0.1289)***	0.7057 (0.1815)***	0.2589 (0.0427)***	0.7060 (0.1815)***
Egocentric online network density		−0.0756 (0.0269)**	−0.0729 (0.0269)**		0.0219 (0.0343)	0.0240 (0.0343)
Online density * Norm punishments		0.0681 (0.0327)*	0.0688 (0.0328)*			
Online network size		0.0002 (0.0000)***	0.0002 (0.0000)***		0.0000 (0.0001)	0.0000 (0.0001)
Edits this month (log)	0.7913 (0.0058)***	0.7857 (0.0059)***	0.7849 (0.0059)***	0.8509 (0.0078)***	0.8517 (0.0078)***	0.8510 (0.0078)***
Total edits (log)	0.2089 (0.0074)***	0.2068 (0.0074)***	0.2040 (0.0074)***	0.2300 (0.0123)***	0.2332 (0.0124)***	0.2295 (0.0124)***
Years since first edit	−0.0457 (0.0047)***	−0.0453 (0.0047)***	−0.0452 (0.0047)***	−0.1197 (0.0080)***	−0.1196 (0.0080)***	−0.1194 (0.0080)***
Was administrator	0.5929 (0.0788)***	0.6082 (0.0788)***	0.5687 (0.0787)***	0.9086 (0.1746)***	0.9591 (0.1749)***	0.9095 (0.1747)***
Month of year: May-Aug (Ref.: Jan-Apr)	−0.0455 (0.0123)***	−0.0433 (0.0123)***	−0.0425 (0.0123)***	−0.0446 (0.0160)**	−0.0464 (0.0160)**	−0.0451 (0.0160)**
Month of year: Sep-Dec (Ref.: Jan-Apr)	0.0037 (0.0263)	0.0042 (0.0263)	0.0048 (0.0263)	0.0845 (0.0390)*	0.0807 (0.0391)*	0.0838 (0.0391)*
AIC	150965.4532	150973.5005	150938.3113	124930.4036	124950.6350	124933.8840
Log Likelihood	−75468.7266	−75472.7503	−75452.1556	−62453.2018	−62463.3175	−62452.9420
Num. obs.	140016	140016	140016	140016	140016	140016
Num. groups: id	33204	33204	33204	33204	33204	33204
Var: id (Intercept)	0.8485	0.8521	0.8422	4.2721	4.3053	4.2719

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$.

Table A78: Explaining rewards (restricted; using norm reverts only).

	Receiving rewards	Receiving rewards	Receiving rewards	Rewarding others	Rewarding others	Rewarding others
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Intercept	−10.0375 (0.1598)***	−8.7180 (0.1656)***	−8.7043 (0.1652)***	−7.2663 (0.1067)***	−7.2746 (0.1130)***	−7.2357 (0.1127)***
Egocentric offline network density	0.2214 (0.4352)		0.2564 (0.4286)	−0.7318 (0.2407)**		−0.7310 (0.2407)**
Offline network size	0.0079 (0.0034)*		0.0070 (0.0034)*	0.0025 (0.0020)		0.0025 (0.0020)
Meetup attendee	−0.1869 (0.4298)	0.2036 (0.0801)*	−0.2185 (0.4226)	0.9222 (0.2516)***	0.3287 (0.0604)***	0.9206 (0.2517)***
Egocentric online network density		−1.6936 (0.1303)***	−1.6864 (0.1301)***		−0.0605 (0.0572)	−0.0559 (0.0571)
Online network size		0.0006 (0.0002)**	0.0006 (0.0002)**		−0.0000 (0.0001)	−0.0000 (0.0001)
Edits this month (log)	1.1841 (0.0218)***	1.0975 (0.0229)***	1.0970 (0.0229)***	0.8636 (0.0123)***	0.8648 (0.0124)***	0.8633 (0.0124)***
Total edits (log)	0.3942 (0.0239)***	0.3577 (0.0238)***	0.3565 (0.0237)***	0.1631 (0.0164)***	0.1686 (0.0165)***	0.1635 (0.0165)***
Years since first edit	−0.0919 (0.0137)***	−0.0905 (0.0135)***	−0.0901 (0.0135)***	−0.0998 (0.0104)***	−0.1001 (0.0105)***	−0.1002 (0.0104)***
Was administrator	0.0935 (0.1386)	0.0451 (0.1352)	0.0092 (0.1356)	0.7569 (0.1749)***	0.8268 (0.1753)***	0.7557 (0.1751)***
Month of year: May-Aug (Ref.: Jan-Apr)	−0.3400 (0.0517)***	−0.3043 (0.0515)***	−0.3046 (0.0514)***	−0.1916 (0.0246)***	−0.1919 (0.0246)***	−0.1905 (0.0246)***
Month of year: Sep-Dec (Ref.: Jan-Apr)	−0.1613 (0.0880)+	−0.1292 (0.0867)	−0.1351 (0.0866)	−0.0581 (0.0577)	−0.0595 (0.0577)	−0.0566 (0.0577)
AIC	47813.3379	47587.5924	47584.9580	61682.0996	61708.1726	61685.0631
Log Likelihood	−23894.6690	−23781.7962	−23778.4790	−30829.0498	−30842.0863	−30828.5315
Num. obs.	140016	140016	140016	140016	140016	140016
Num. groups: id	33204	33204	33204	33204	33204	33204
Var: id (Intercept)	1.3379	1.2377	1.2250	3.7796	3.8221	3.7804

***$p < 0.001$; **$p < 0.01$; *$p < 0.05$; +$p < 0.1$.

A.3.9 Models Using Talk Interaction

Table A79: Explaining norm violations (talk relation).

	Experience norm violation	Experience norm violation	Violate norms	Violate norms
	Model 1	Model 2	Model 3	Model 4
Intercept	$-2.9132\ (0.0416)^{***}$	$-2.9135\ (0.0416)^{***}$	$-2.7445\ (0.0427)^{***}$	$-2.7474\ (0.0427)^{***}$
Egocentric offline network density		$0.3348\ (0.2950)$		$0.4566\ (0.2723)^{+}$
Offline network size		$0.0033\ (0.0025)$		$0.0004\ (0.0023)$
Meetup attendee	$-0.2813\ (0.0509)^{***}$	$-0.6366\ (0.2942)^{*}$	$-0.2049\ (0.0493)^{***}$	$-0.5823\ (0.2719)^{*}$
Egocentric online (talk) network density	$0.1465\ (0.0249)^{***}$	$0.1475\ (0.0249)^{***}$	$0.0617\ (0.0247)^{*}$	$0.0610\ (0.0248)^{*}$
Online (talk) network size	$-0.0897\ (0.0041)^{***}$	$-0.0901\ (0.0042)^{***}$	$-0.0073\ (0.0009)^{***}$	$-0.0072\ (0.0009)^{***}$
Edits this month (log)	$0.4122\ (0.0072)^{***}$	$0.4124\ (0.0072)^{***}$	$0.7091\ (0.0078)^{***}$	$0.7094\ (0.0078)^{***}$
Total edits (log)	$0.0356\ (0.0073)^{***}$	$0.0357\ (0.0073)^{***}$	$-0.1231\ (0.0079)^{***}$	$-0.1228\ (0.0079)^{***}$
Years since first edit	$-0.0222\ (0.0047)^{***}$	$-0.0222\ (0.0047)^{***}$	$-0.0332\ (0.0050)^{***}$	$-0.0330\ (0.0050)^{***}$
Was administrator	$-0.9672\ (0.1190)^{***}$	$-0.9760\ (0.1192)^{***}$	$-0.8685\ (0.1018)^{***}$	$-0.8527\ (0.1024)^{***}$
Month of year: May-Aug (Ref.: Jan-Apr)	$-0.1030\ (0.0198)^{***}$	$-0.1029\ (0.0198)^{***}$	$-0.0043\ (0.0206)$	$-0.0047\ (0.0206)$
Month of year: Sep-Dec (Ref.: Jan-Apr)	$0.0290\ (0.0338)$	$0.0288\ (0.0337)$	$0.0774\ (0.0367)^{*}$	$0.0772\ (0.0367)^{*}$
AIC	132736.7068	132738.9299	134431.5130	134430.2409
Log Likelihood	−66356.3534	−66355.4649	−67203.7565	−67201.1205
Num. obs.	140016	140016	140016	140016
Num. groups: id	33204	33204	33204	33204
Var: id (Intercept)	0.6230	0.6221	0.7752	0.7744

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$.

Table A80: Explaining norm violations (talk relation).

	Exp. norm violation	Exp. norm violation	Violate norms	Violate norms
	Model 1	Model 2	Model 3	Model 4
Intercept	-2.9134 (0.0416)***	-2.9136 (0.0416)***	-2.7428 (0.0427)***	-2.7450 (0.0427)***
Egocentric offline network density		-0.4591 (0.5347)		0.3868 (0.4676)
Alter offline network density		-4.9698 (3.2650)		0.6754 (2.7255)
Ego offline density * Alter offline density		5.3958 (3.2786)$^{+}$		-0.1708 (2.7339)
Offline network size		0.0009 (0.0031)		0.0013 (0.0028)
Meetup attendee	-0.2814 (0.0509)***	0.0983 (0.5534)	-0.2072 (0.0493)***	-0.6530 (0.4822)
Egocentric online (talk) network density	0.1472 (0.0290)***	0.1486 (0.0290)***	0.0793 (0.0287)**	0.0788 (0.0287)**
Alter online (talk) network density	-0.0720 (0.2585)	-0.0695 (0.2586)	0.0890 (0.2723)	0.0862 (0.2723)
Ego online (talk) density * Alter online (talk) density	0.0623 (0.2437)	0.0585 (0.2437)	-0.1671 (0.2612)	-0.1655 (0.2612)
Online (talk) network size	-0.0896 (0.0042)***	-0.0901 (0.0042)***	-0.0073 (0.0009)***	-0.0072 (0.0009)***
Edits this month (log)	0.4123 (0.0072)***	0.4124 (0.0072)***	0.7089 (0.0078)***	0.7091 (0.0078)***
Total edits (log)	0.0356 (0.0074)***	0.0357 (0.0073)***	-0.1235 (0.0079)***	-0.1232 (0.0079)***
Years since first edit	-0.0222 (0.0047)***	-0.0222 (0.0047)***	-0.0330 (0.0050)***	-0.0329 (0.0050)***
Was administrator	-0.9674 (0.1190)***	-0.9749 (0.1193)***	-0.8688 (0.1018)***	-0.8532 (0.1024)***
Month of year: May-Aug (Ref.: Jan-Apr)	-0.1030 (0.0198)***	-0.1028 (0.0198)***	-0.0044 (0.0206)	-0.0052 (0.0206)
Month of year: Sep-Dec (Ref.: Jan-Apr)	0.0291 (0.0338)	0.0288 (0.0337)	0.0769 (0.0367)*	0.0756 (0.0367)*
AIC	132740.6271	132742.8673	134433.9294	134433.8953
Log Likelihood	-66356.3136	-66353.4337	-67202.9647	-67198.9476
Num. obs.	140016	140016	140016	140016
Num. groups: id	33204	33204	33204	33204
Var: id (Intercept)	0.6230	0.6214	0.7748	0.7736

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$.

Table A81: Explaining norm punishments (talk relation).

	Experience norm pun.	Experience norm pun.	Punishing norm violators	Punishing norm violators
	Model 1	Model 2	Model 3	Model 4
Intercept	-3.3216 (0.0459)***	-3.3220 (0.0459)***	-6.8041 (0.0642)***	-6.8011 (0.0642)***
Egocentric offline network density		0.4327 (0.3775)		-0.0127 (0.1451)
Offline) network size		0.0030 (0.0035)		0.0012 (0.0013)
Meetup attendee	0.0635 (0.0582)	-0.3633 (0.3816)	0.0429 (0.0338)	0.0310 (0.1536)
Egocentric online (talk) network density	0.0892 (0.0361)*	0.0890 (0.0362)*	0.0728 (0.0157)***	0.0729 (0.0157)***
Online (talk) network size	-0.0793 (0.0078)***	-0.0791 (0.0079)***	0.0007 (0.0005)	0.0007 (0.0005)
Experienced norm violations	2.0158 (0.0205)***	2.0157 (0.0205)***		
Edits this month (log)	-0.1041 (0.0095)***	-0.1039 (0.0095)***	0.4865 (0.0055)***	0.4865 (0.0055)***
Total edits (log)	0.0338 (0.0080)***	0.0338 (0.0080)***	0.5128 (0.0098)***	0.5122 (0.0099)***
Years since first edit	-0.0042 (0.0051)	-0.0041 (0.0051)	-0.0831 (0.0063)***	-0.0831 (0.0063)***
Was administrator	0.0392 (0.1365)	0.0348 (0.1367)	1.3969 (0.1339)***	1.3850 (0.1342)***
Month of year: May-Aug (Ref.: Jan-Apr)	-0.0191 (0.0260)	-0.0191 (0.0260)	-0.0399 (0.0127)**	-0.0397 (0.0127)**
Month of year: Sep-Dec (Ref.: Jan-Apr)	-0.0025 (0.0380)	-0.0028 (0.0380)	0.0089 (0.0287)	0.0094 (0.0287)
AIC	80768.2874	80770.9682	162489.1636	162491.4132
Log Likelihood	-40371.1437	-40370.4841	-81232.5818	-81231.7066
Num. obs.	140016	140016	140016	140016
Num. groups: id	33204	33204	33204	33204
Var: id (Intercept)	0.0000	0.0000	2.6639	2.6626

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$.

Table A82: Explaining rewards (talk relation).

	Receiving rewards	Receiving rewards	Rewarding others	Rewarding others
	Model 1	Model 2	Model 3	Model 4
Intercept	−5.2537 (0.0448)***	−5.2349 (0.0447)***	−6.4784 (0.0804)***	−6.4532 (0.0804)***
Egocentric offline network density		−0.3174 (0.1240)*		−0.4993 (0.1716)**
Previous norm punishments conducted	0.0041 (0.0092)	0.0056 (0.0093)		
Offline density * Norm punishments		−0.0370 (0.0288)		
Offline network size		0.0026 (0.0011)*		0.0012 (0.0015)
Meetup attendee	0.3056 (0.0292)***	0.5285 (0.1288)***	0.2570 (0.0427)***	0.6914 (0.1812)***
Egocentric online (talk) network density	0.0806 (0.0159)***	0.0815 (0.0159)***	0.1779 (0.0197)***	0.1784 (0.0197)***
Online (talk) density * Norm punishments	−0.0073 (0.0149)	−0.0052 (0.0150)		
Online (talk) network size	0.0017 (0.0004)***	0.0016 (0.0004)***	0.0024 (0.0007)***	0.0023 (0.0007)***
Edits this month (log)	0.7893 (0.0058)***	0.7885 (0.0058)***	0.8486 (0.0078)***	0.8479 (0.0078)***
Total edits (log)	0.2057 (0.0074)***	0.2031 (0.0074)***	0.2193 (0.0124)***	0.2157 (0.0124)***
Years since first edit	−0.0439 (0.0047)***	−0.0439 (0.0047)***	−0.1154 (0.0080)***	−0.1152 (0.0080)***
Was administrator	0.6278 (0.0789)***	0.5887 (0.0787)***	0.9488 (0.1737)***	0.9007 (0.1735)***
Month of year: May-Aug (Ref.: Jan-Apr)	−0.0464 (0.0123)***	−0.0456 (0.0123)***	−0.0438 (0.0160)**	−0.0425 (0.0160)**
Month of year: Sep-Dec (Ref.: Jan-Apr)	−0.0000 (0.0263)	0.0017 (0.0263)	0.0766 (0.0390)*	0.0796 (0.0390)*
AIC	150968.5665	150934.4056	124859.4422	124843.4961
Log Likelihood	−75470.2833	−75450.2028	−62417.7211	−62407.7481
Num. obs.	140016	140016	140016	140016
Num. groups: id	33204	33204	33204	33204
Var: id (Intercept)	0.8537	0.8440	4.2443	4.2126

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$.

Table A83: Explaining rewards (restricted; talk relation).

	Receiving rewards	Receiving rewards	Rewarding others	Rewarding others
	Model 1	Model 2	Model 3	Model 4
Intercept	-7.7163 (0.1968)***	-7.6325 (0.1962)***	-9.3220 (0.1916)***	-9.2717 (0.1905)***
Egocentric offline network density		0.2293 (0.6395)		-1.5636 (0.4288)***
Offline network size		0.0134 (0.0054)*		-0.0011 (0.0034)
Meetup attendee	0.7217 (0.1160)***	0.1759 (0.6336)	0.7431 (0.1003)***	2.0541 (0.4321)***
Egocentric online (talk) network density	0.5651 (0.0720)***	0.5812 (0.0720)***	0.0444 (0.0657)	0.0460 (0.0657)
Online (talk) network size	-0.1680 (0.0108)***	-0.1736 (0.0110)***	0.0007 (0.0014)	0.0004 (0.0014)
Edits this month (log)	0.7777 (0.0238)***	0.7778 (0.0237)***	0.7618 (0.0232)***	0.7591 (0.0232)***
Total edits (log)	0.2109 (0.0248)***	0.2100 (0.0245)***	0.2431 (0.0290)***	0.2384 (0.0289)***
Years since first edit	-0.0745 (0.0154)***	-0.0752 (0.0152)***	-0.1013 (0.0176)***	-0.1018 (0.0176)***
Was administrator	0.0007 (0.2364)	-0.0037 (0.2326)	0.3121 (0.2137)	0.2501 (0.2140)
Month of year: May-Aug (Ref.: Jan-Apr)	-0.2188 (0.0664)***	-0.2182 (0.0664)**	-0.0846 (0.0502)$^{+}$	-0.0854 (0.0502)$^{+}$
Month of year: Sep-Dec (Ref.: Jan-Apr)	-0.0137 (0.1089)	-0.0158 (0.1081)	0.1085 (0.1063)	0.0976 (0.1062)
AIC	26311.8697	26304.8977	23155.1327	23136.3193
Log Likelihood	-13143.9348	-13138.4488	-11565.5663	-11554.1597
Num. obs.	140016	140016	140016	140016
Num. groups: id	33204	33204	33204	33204
Var: id (Intercept)	2.2037	2.0053	4.3049	4.2633

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$.

A.3.10 FE Models

Table A84: Explaining norm violations (FE).

	Exp. norm violation	Exp. norm violation	Exp. norm violation	Violate norms	Violate norms	Violate norms
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Intercept	1.5840 (0.1086)***	0.8276 (0.1112)***	0.8184 (0.1113)***	0.7679 (0.0853)***	0.1603 (0.0904)$^{+}$	0.1588 (0.0904)$^{+}$
Egocentric offline network density	0.5925 (0.3497)$^{+}$		0.5924 (0.3565)$^{+}$	0.0797 (0.2781)		0.2233 (0.2776)
Offline network size	−0.0041 (0.0030)		−0.0019 (0.0031)	0.0004 (0.0023)		0.0014 (0.0023)
Meetup attendee	−0.6336 (0.3528)$^{+}$	−0.2582 (0.0709)***	−0.7025 (0.3623)$^{+}$	−0.1304 (0.2808)	−0.0711 (0.0553)	−0.2919 (0.2802)
Egocentric online network density		0.0044 (0.0270)	0.0040 (0.0270)		0.0435 (0.0291)	0.0435 (0.0292)
Online network size		−0.0066 (0.0003)***	−0.0066 (0.0003)***		−0.0028 (0.0002)***	−0.0028 (0.0002)***
Edits this month (log)	0.2265 (0.0076)***	0.2730 (0.0079)***	0.2735 (0.0079)***	0.4294 (0.0077)***	0.4716 (0.0080)***	0.4717 (0.0080)***
Total edits (log)	−0.5178 (0.0170)***	−0.3646 (0.0176)***	−0.3640 (0.0177)***	−0.4957 (0.0136)***	−0.3994 (0.0142)***	−0.3991 (0.0142)***
Years since first edit	0.1469 (0.0086)***	0.1066 (0.0086)***	0.1076 (0.0086)***	0.1066 (0.0073)***	0.0898 (0.0074)***	0.0898 (0.0074)***
Was administrator	0.1850 (0.2179)	0.1337 (0.2202)	0.1611 (0.2244)	−0.3425 (0.1347)*	−0.3519 (0.1319)**	−0.3551 (0.1341)**
DF	8	8	10	8	8	10
Log Likelihood	−36636.1977	−36367.0106	−36362.1828	−37773.3953	−37557.6265	−37557.3009
AIC	73288.3955	72750.0211	72744.3657	75562.7906	75131.2530	75134.6018
nobs	140016	140016	140016	140016	140016	140016

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$.

Table A85: Explaining norm violations (FE).

	Experience norm violation	Experience norm violation	Experience norm violation	Violate norms	Violate norms	Violate norms
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Intercept	1.5829 (0.1086)***	0.8106 (0.1118)***	0.8003 (0.1118)***	0.7693 (0.0853)***	0.1395 (0.0910)	0.1402 (0.0911)
Egocentric offline network density	0.3234 (0.6022)		0.2820 (0.6102)	0.2542 (0.4595)		0.2564 (0.4604)
Alter offline network density	−2.8177 (3.5953)		−3.1220 (3.6228)	2.7678 (2.6673)		1.6442 (2.6840)
Ego offline density * Alter offline density	2.5119 (3.6323)		2.8026 (3.6543)	−2.1662 (2.6790)		−1.0868 (2.6936)
Meetup attendee	−0.2616 (0.6122)	−0.2581 (0.0709)***	−0.2822 (0.6243)	−0.4895 (0.4735)	−0.0707 (0.0554)	−0.4859 (0.4740)
Offline network size	−0.0058 (0.0035)$^{+}$		−0.0039 (0.0037)	0.0025 (0.0028)		0.0028 (0.0027)
Egocentric online network density		0.0299 (0.0305)	0.0295 (0.0305)		0.0566 (0.0333)$^{+}$	0.0566 (0.0333)$^{+}$
Alter online network density		0.4320 (0.2592)$^{+}$	0.4301 (0.2592)$^{+}$		0.5602 (0.2776)*	0.5601 (0.2776)*
Ego online density * Alter online density		−0.5104 (0.2675)$^{+}$	−0.5089 (0.2675)$^{+}$		−0.5043 (0.2795)$^{+}$	−0.5045 (0.2795)$^{+}$
Online network size		−0.0065 (0.0003)***	−0.0065 (0.0003)***		−0.0028 (0.0002)***	−0.0028 (0.0002)***
Edits this month (log)	0.2266 (0.0076)***	0.2734 (0.0079)***	0.2739 (0.0079)***	0.4293 (0.0077)***	0.4722 (0.0080)***	0.4721 (0.0080)***
Total edits (log)	−0.5175 (0.0170)***	−0.3649 (0.0177)***	−0.3640 (0.0177)***	−0.4959 (0.0136)***	−0.3984 (0.0143)***	−0.3985 (0.0143)***
Years since first edit	0.1468 (0.0086)***	0.1067 (0.0086)***	0.1076 (0.0086)***	0.1066 (0.0073)***	0.0896 (0.0074)***	0.0896 (0.0074)***
Was administrator	0.1896 (0.2184)	0.1349 (0.2202)	0.1647 (0.2249)	−0.3378 (0.1349)*	−0.3521 (0.1319)**	−0.3525 (0.1343)**
DF	10	10	14	10	10	14
Log Likelihood	−36635.5917	−36365.0043	−36359.4970	−37770.8314	−37555.5255	−37553.2677
AIC	73291.1835	72750.0087	72746.9939	75561.6628	75131.0509	75134.5354
nobs	140016	140016	140016	140016	140016	140016

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$.

Table A86: Explaining norm punishments (FE).

	Experience norm pun.	Experience norm pun.	Experience norm pun.	Punishing norm violators	Punishing norm violators	Punishing norm violators
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Intercept	2.2698 (0.4193)***	106.9903 ()	512.1801 ()	0.0426 (0.1009)	−3.2520 (0.0905)***	−3.2517 (0.0905)***
Egocentric offline network density	−0.1501 (0.5143)		0.4208 ()	0.1592 (0.1226)		0.2634 (0.1059)*
Offline network size	−0.0067 (0.0057)		−0.0047 ()	−0.0005 (0.0010)		0.0022 (0.0009)**
Meetup attendee	0.2099 (0.5585)	−0.1777 ()	−0.6886 ()	−0.1345 (0.1302)	0.0796 (0.0249)**	−0.1985 (0.1138)$^{+}$
Egocentric online network density		−0.3690 ()	0.0929 ()		−1.5320 (0.0353)***	−1.5273 (0.0353)***
Online network size		−0.0036 ()	0.0038 ()		−0.0005	−0.0005
Experienced norm violations	0.8785 (0.0080)***	1.2434 ()	1.1017 ()			
Edits this month (log)	0.0204 (0.0097)*	−0.2088 ()	0.0620 ()	0.3686 (0.0054)***	0.5703 (0.0057)***	0.5702 (0.0057)***
Total edits (log)	0.2477 (0.0532)***	0.0696 ()	3.3815 ()	−0.0959 (0.0131)***	0.2919 (0.0126)***	0.2918 (0.0127)***
Years since first edit	−0.0856 (0.0324)**	0.9141 ()	−0.7649 ()	0.0674 (0.0073)***	−0.0505 (0.0061)***	−0.0504 (0.0061)***
Was administrator	−2.0451 (1.5709)	−112.4124 ()	−196.3028 ()	0.0958 (0.0656)	0.7134 (0.0695)***	0.7060 (0.0694)***
DF	9	9	11	8	8	10
Log Likelihood	−17712.6657	−7047.7470	−6974.2531	−54600.3738	−57956.0650	−57948.9524
AIC	35443.3314	14113.4939	13970.5062	109216.7476	115928.1300	115917.9049
nobs	140016	140016	140016	140016	140016	140016

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$.

Table A87: Explaining rewards (FE).

	Receiving rewards	Receiving rewards	Receiving rewards	Rewarding others	Rewarding others	Rewarding others
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Intercept	-1.6075 (0.1024)***	-1.5786 (0.1063)***	-1.5674 (0.1064)***	-1.7546 (0.0936)***	-1.7555 (0.0983)***	-1.7542 (0.0984)***
Egocentric offline network density	-0.2198 (0.1112)*		-0.2166 (0.1110)$^{+}$	-0.3993 (0.1259)**		-0.3990 (0.1259)**
Previous norm punishments conducted	0.0046 (0.0065)	-0.0067 (0.0164)	-0.0059 (0.0163)			
Offline density * Norm punishments	-0.0247 (0.0272)		-0.0259 (0.0274)			
Offline network size	0.0009 (0.0009)		0.0008 (0.0009)	-0.0024 (0.0010)*		-0.0025 (0.0010)*
Meetup attendee	0.2910 (0.1175)*	0.1083 (0.0287)***	0.2845 (0.1174)*	0.5020 (0.1320)***	0.0919 (0.0323)**	0.4996 (0.1320)***
Egocentric online network density		-0.1183 (0.0331)***	-0.1176 (0.0331)***		-0.0334 (0.0374)	-0.0330 (0.0374)
Online density * Norm punishments		0.0270 (0.0440)	0.0303 (0.0438)			
Online network size		-0.0001 (0.0000)***	-0.0001 (0.0000)**		-0.0001 (0.0000)**	-0.0001 (0.0000)**
Edits this month (log)	0.6569 (0.0061)***	0.6590 (0.0063)***	0.6581 (0.0063)***	0.6416 (0.0070)***	0.6437 (0.0071)***	0.6436 (0.0071)***
Total edits (log)	-0.0605 (0.0141)***	-0.0587 (0.0143)***	-0.0607 (0.0143)***	-0.0877 (0.0138)***	-0.0854 (0.0139)***	-0.0856 (0.0139)***
Years since first edit	0.0397 (0.0081)***	0.0426 (0.0082)***	0.0423 (0.0082)***	0.0530 (0.0076)***	0.0535 (0.0076)***	0.0529 (0.0076)***
Was administrator	-0.1832 (0.0771)*	-0.1492 (0.0779)$^{+}$	-0.1636 (0.0778)*	0.0718 (0.0883)	0.0901 (0.0883)	0.0797 (0.0882)
DF	10	10	13	8	8	10
Log Likelihood	-49933.4887	-49929.0824	-49922.0808	-40132.5012	-40133.4029	-40128.3790
AIC	99886.9773	99878.1649	99870.1616	80281.0024	80282.8059	80276.7579
nobs	140016	140016	140016	140016	140016	140016

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$.

Table A88: Explaining rewards (restricted; FE).

	Receiving rewards	Receiving rewards	Receiving rewards	Rewarding others	Rewarding others	Rewarding others
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Intercept	−1.8784 (0.2758)***	−2.8979 (0.3050)***	−2.8997 (0.3051)***	−2.1023 (0.3443)***	−1.8802 (0.3633)***	−1.8608 (0.3641)***
Egocentric offline network density	−0.0446 (0.5588)		0.0557 (0.5793)	−0.8676 (0.3801)*		−0.8728 (0.3805)*
Offline network size	−0.0030 (0.0042)		−0.0010 (0.0045)	−0.0011 (0.0030)		−0.0013 (0.0030)
Meetup attendee	−0.2096 (0.5544)	−0.3610 (0.1181)**	−0.3744 (0.5772)	1.0509 (0.3904)**	0.3070 (0.0991)**	1.0566 (0.3907)**
Egocentric online network density		−0.4344 (0.1155)***	−0.4353 (0.1156)***		−0.2666 (0.1456)+	−0.2557 (0.1456)+
Online network size		−0.0101 (0.0008)***	−0.0101 (0.0008)***		0.0001 (0.0001)	0.0001 (0.0001)
Edits this month (log)	0.4098 (0.0222)***	0.5178 (0.0238)***	0.5180 (0.0238)***	0.5175 (0.0242)***	0.5087 (0.0246)***	0.5082 (0.0246)***
Total edits (log)	−0.3976 (0.0408)***	−0.1809 (0.0441)***	−0.1813 (0.0441)***	−0.1433 (0.0454)**	−0.1559 (0.0460)***	−0.1576 (0.0460)***
Years since first edit	0.1227 (0.0196)***	0.0761 (0.0201)***	0.0770 (0.0202)***	0.0355 (0.0226)	0.0439 (0.0226)+	0.0384 (0.0227)+
Was administrator	−0.0823 (0.2693)	−0.2071 (0.2736)	−0.2108 (0.2737)	0.4249 (0.2540)+	0.4740 (0.2577)+	0.4140 (0.2552)
DF	8	8	10	8	8	10
Log Likelihood	−6140.9849	−6010.8738	−6010.7735	−6391.4264	−6393.3968	−6389.3164
AIC	12297.9698	12037.7476	12041.5470	12798.8528	12802.7937	12798.6329
nobs	140016	140016	140016	140016	140016	140016

***$p < 0.001$; **$p < 0.01$; *$p < 0.05$; +$p < 0.1$.

A.3.11 Models Using Categorical Density

Table A89: Explaining norm violations (categories of density).

	Exp. norm violation	Exp. norm violation	Exp. norm violation	Violate norms	Violate norms	Violate norms
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Intercept	$-2.8362\ (0.0425)^{***}$	$-3.1947\ (0.0441)^{***}$	$-3.1978\ (0.0441)^{***}$	$-2.7397\ (0.0426)^{***}$	$-2.9273\ (0.0445)^{***}$	$-2.9294\ (0.0445)^{***}$
Egocentric offline network density: Middle (Ref.: Low)	$-0.5145\ (0.1025)^{***}$		$-0.5301\ (0.1003)^{***}$	$-0.2467\ (0.0940)^{**}$		$-0.2600\ (0.0930)^{**}$
Egocentric offline network density: High (Ref.: Low)	$-0.2562\ (0.0727)^{***}$		$-0.2908\ (0.0716)^{***}$	$-0.0869\ (0.0687)$		$-0.0978\ (0.0681)$
Offline network size	$-0.0039\ (0.0019)^{*}$		$-0.0008\ (0.0019)$	$-0.0019\ (0.0017)$		$-0.0006\ (0.0017)$
Meetup attendee		$-0.4337\ (0.0507)^{***}$			$-0.1954\ (0.0488)^{***}$	
Egocentric online network density: Middle (Ref.: Low)		$0.4525\ (0.0277)^{***}$	$0.4518\ (0.0277)^{***}$		$0.1093\ (0.0295)^{***}$	$0.1088\ (0.0295)^{***}$
Egocentric online network density: High (Ref.: Low)		$-0.3281\ (0.1516)^{*}$	$-0.3287\ (0.1516)^{*}$		$0.0080\ (0.1286)$	$0.0074\ (0.1286)$
Online network size		$-0.0043\ (0.0002)^{***}$	$-0.0043\ (0.0002)^{***}$		$-0.0022\ (0.0001)^{***}$	$-0.0021\ (0.0001)^{***}$
Edits this month (log)	$0.3778\ (0.0071)^{***}$	$0.4299\ (0.0075)^{***}$	$0.4303\ (0.0075)^{***}$	$0.7059\ (0.0077)^{***}$	$0.7406\ (0.0081)^{***}$	$0.7409\ (0.0081)^{***}$
Total edits (log)	$0.0124\ (0.0074)^{+}$	$0.0139\ (0.0079)^{+}$	$0.0142\ (0.0079)^{+}$	$-0.1233\ (0.0078)^{***}$	$-0.1068\ (0.0084)^{***}$	$-0.1065\ (0.0084)^{***}$
Years since first edit	$-0.0164\ (0.0048)^{***}$	$-0.0095\ (0.0048)^{*}$	$-0.0093\ (0.0048)^{+}$	$-0.0329\ (0.0050)^{***}$	$-0.0328\ (0.0050)^{***}$	$-0.0326\ (0.0050)^{***}$
Was administrator	$-1.5196\ (0.1190)^{***}$	$-1.1595\ (0.1174)^{***}$	$-1.1454\ (0.1180)^{***}$	$-0.9167\ (0.1026)^{***}$	$-0.7372\ (0.1010)^{***}$	$-0.7206\ (0.1016)^{***}$
Month of year: May-Aug (Ref.: Jan-Apr)	$-0.0987\ (0.0198)^{***}$	$-0.1036\ (0.0198)^{***}$	$-0.1039\ (0.0198)^{***}$	$-0.0041\ (0.0206)$	$-0.0062\ (0.0206)$	$-0.0066\ (0.0206)$
Month of year: Sep-Dec (Ref.: Jan-Apr)	$0.0287\ (0.0343)$	$0.0076\ (0.0341)$	$0.0073\ (0.0341)$	$0.0781\ (0.0368)^{*}$	$0.0718\ (0.0367)^{+}$	$0.0709\ (0.0367)^{+}$
AIC	133491.4288	132449.5205	132444.4049	134504.6392	134172.0654	134171.1038
Log Likelihood	−66733.7144	−66211.7603	−66207.2025	−67240.3196	−67073.0327	−67070.5519
Num. obs.	140016	140016	140016	140016	140016	140016
Num. groups: id	33204	33204	33204	33204	33204	33204
Var: id (Intercept)	0.7459	0.6643	0.6649	0.7890	0.7501	0.7492

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$.

Table A90: Explaining norm violations (categories of density).

	Experience norm violation	Experience norm violation	Experience norm violation	Violate norms	Violate norms	Violate norms
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Intercept	−2.8361	−3.1918	−3.1948	−2.7392	−2.9257	−2.9273
Egocentric offline network density: Middle (Ref.: Low)	−0.1567		−0.1605	−0.0679		−0.0720
Egocentric offline network density: High (Ref.: Low)	−0.0151		−0.0366	0.0580		0.0540
Alter offline network density: Middle (Ref.: Low)	−0.2028		−0.2111	−0.1115		−0.1170
Alter offline network density: High (Ref.: Low)	0.0310		0.0140	0.1016		0.0990
Ego offline density middle * Alter offline density middle	−0.1567		−0.1605	−0.0679		−0.0720
Ego offline density middle * Alter offline density high	0.0000		0.0000	0.0000		0.0000
Ego offline density high * Alter offline density middle	−0.0461		−0.0505	−0.0435		−0.0450
Ego offline density high * Alter offline density high	0.0310		0.0140	0.1016		0.0990
Offline network size	−0.0038		−0.0008	−0.0019		−0.0005
Meetup attendee		−0.4338			−0.1955	
Egocentric online network density: Middle (Ref.: Low)		0.1351	0.1341		−0.1021	−0.1030
Egocentric online network density: High (Ref.: Low)		−13.1137	−13.2270		−13.4728	−13.3946
Alter online network density: Middle (Ref.: Low)		4.3813	4.4189		4.5774	4.5510
Alter online network density: High (Ref.: Low)		−1.0171	−1.0552		−0.4906	−0.4627
Ego online density middle * Alter online density middle		−4.0599	−4.0971		−4.3638	−4.3371
Ego online density middle * Alter online density high		−0.0843	−0.0453		0.6822	0.6551
Ego online density high * Alter online density middle		8.4412	8.5160		8.9412	8.8882
Ego online density high * Alter online density high		−0.9328	−1.0099		−1.1729	−1.1179
Online network size		−0.0043	−0.0043		−0.0022	−0.0021
Edits this month (log)	0.3778	0.4295	0.4299	0.7059	0.7405	0.7407
Total edits (log)	0.0124	0.0132	0.0134	−0.1233	−0.1073	−0.1070
Years since first edit	−0.0164	−0.0092	−0.0090	−0.0329	−0.0327	−0.0325
Was administrator	−1.5198	−1.1585	−1.1448	−0.9167	−0.7368	−0.7201
Month of year: May-Aug (Ref.: Jan-Apr)	−0.0988	−0.1038	−0.1042	−0.0043	−0.0060	−0.0066
Month of year: Sep-Dec (Ref.: Jan-Apr)	0.0286	0.0074	0.0071	0.0778	0.0717	0.0706
AIC						
Log Likelihood						
Num. obs.	140016	140016	140016	140016	140016	140016
Num. groups: id	33204	33204	33204	33204	33204	33204
Var: id (Intercept)	0.7460	0.6636	0.6643	0.7886	0.7494	0.7482

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$.

Table A91: Explaining norm punishments (categories of density).

	Exp. norm pun.	Exp. norm pun.	Exp. norm pun.	Pun. norm violators	Pun. norm violators	Pun. norm violators
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Intercept	$-3.2726\ (0.0458)^{***}$	$-3.6430\ (0.0478)^{***}$	$-3.6432\ (0.0478)^{***}$	$-6.8142\ (0.0641)^{***}$	$-6.9846\ (0.0670)^{***}$	$-6.9811\ (0.0670)^{***}$
Egocentric offline network density: Middle (Ref.: Low)	$-0.0688\ (0.1263)$		$-0.0086\ (0.1260)$	$0.0352\ (0.0569)$		$0.0344\ (0.0568)$
Egocentric offline network density: High (Ref.: Low)	$0.0767\ (0.0848)$		$0.0545\ (0.0842)$	$0.0181\ (0.0389)$		$0.0157\ (0.0388)$
Offline network size	$-0.0030\ (0.0026)$		$0.0001\ (0.0027)$	$0.0011\ (0.0011)$		$0.0012\ (0.0011)$
Meetup attendee		$0.0263\ (0.0560)$			$0.0439\ (0.0337)$	
Egocentric online network density: Middle (Ref.: Low)		$0.3200\ (0.0304)^{***}$	$0.3198\ (0.0304)^{***}$		$0.4032\ (0.0380)^{***}$	$0.4035\ (0.0380)^{***}$
Egocentric online network density: High (Ref.: Low)		$-0.1398\ (0.1670)$	$-0.1399\ (0.1670)$		$0.0425\ (0.1648)$	$0.0429\ (0.1647)$
Online network size		$-0.0127\ (0.0005)^{***}$	$-0.0127\ (0.0005)^{***}$		$-0.0001\ (0.0001)^{*}$	$-0.0001\ (0.0001)^{*}$
Experienced norm violations	$2.0510\ (0.0205)^{***}$	$1.9771\ (0.0201)^{***}$	$1.9769\ (0.0201)^{***}$			
Edits this month (log)	$-0.1309\ (0.0091)^{***}$	$-0.0317\ (0.0098)^{**}$	$-0.0315\ (0.0098)^{**}$	$0.4877\ (0.0055)^{***}$	$0.4856\ (0.0055)^{***}$	$0.4854\ (0.0055)^{***}$
Total edits (log)	$0.0213\ (0.0078)^{**}$	$0.0562\ (0.0084)^{***}$	$0.0562\ (0.0084)^{***}$	$0.5172\ (0.0098)^{***}$	$0.4877\ (0.0103)^{***}$	$0.4870\ (0.0103)^{***}$
Years since first edit	$-0.0017\ (0.0051)$	$-0.0051\ (0.0051)$	$-0.0050\ (0.0051)$	$-0.0847\ (0.0062)^{***}$	$-0.0745\ (0.0063)^{***}$	$-0.0745\ (0.0063)^{***}$
Was administrator	$-0.2675\ (0.1316)^{*}$	$0.1694\ (0.1332)$	$0.1682\ (0.1333)$	$1.3861\ (0.1344)^{***}$	$1.4304\ (0.1336)^{***}$	$1.4167\ (0.1338)^{***}$
Month of year: May-Aug (Ref.: Jan-Apr)	$-0.0142\ (0.0261)$	$-0.0229\ (0.0257)$	$-0.0229\ (0.0257)$	$-0.0393\ (0.0127)^{**}$	$-0.0398\ (0.0127)^{**}$	$-0.0394\ (0.0127)^{**}$
Month of year: Sep-Dec (Ref.: Jan-Apr)	$0.0009\ (0.0381)$	$-0.0117\ (0.0376)$	$-0.0118\ (0.0376)$	$0.0117\ (0.0287)$	$0.0052\ (0.0286)$	$0.0058\ (0.0286)$
AIC	80909.7520	79990.5100	79994.1941	162510.0623	162387.8981	162389.6964
Log Likelihood	−40441.8760	−39981.2550	−39981.0971	−81243.0312	−81180.9490	−81179.8482
Num. obs.	140016	140016	140016	140016	140016	140016
Num. groups: id	33204	33204	33204	33204	33204	33204
Var: id (Intercept)	0.0000	0.0000	0.0000	2.6714	2.6475	2.6460

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$.

Table A92: Explaining rewards (categories of density).

	Receiving rewards	Receiving rewards	Receiving rewards	Rewarding others	Rewarding others	Rewarding others
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Intercept	−5.2532 (0.0446)***	−5.3357 (0.0483)***	−5.3175 (0.0482)***	−6.5001 (0.0806)***	−6.7080 (0.0844)***	−6.6857 (0.0844)***
Egocentric offline network density: Middle (Ref.: Low)	0.3254 (0.0482)***		0.3207 (0.0482)***	0.3195 (0.0681)***		0.3194 (0.0680)***
Egocentric offline network density: High (Ref.: Low)	0.1934 (0.0347)***		0.1920 (0.0347)***	0.1700 (0.0482)***		0.1695 (0.0481)***
Previous norm punishments conducted	0.0036 (0.0067)	−10.7549 (360.2998)	−10.7019 (350.9917)			
Offline density middle * Norm punishments	−0.0304 (0.0252)		−0.0290 (0.0252)			
Offline density high * Norm punishments	−0.0254 (0.0373)		−0.0231 (0.0372)			
Offline network size	0.0034 (0.0009)***		0.0034 (0.0009)***	0.0027 (0.0012)*		0.0028 (0.0012)*
Meetup attendee		0.3098 (0.0292)***			0.2595 (0.0426)***	
Egocentric online network density: Middle (Ref.: Low)		0.2144 (0.0351)***	0.2159 (0.0350)***		0.4678 (0.0485)***	0.4688 (0.0484)***
Egocentric online network density: High (Ref.: Low)		0.2810 (0.1375)*	0.2825 (0.1374)*		0.5579 (0.1614)***	0.5592 (0.1613)***
Online density middle * Norm punishments		10.7555 (360.2998)	10.7052 (350.9917)			
Online density high * Norm punishments		10.6027 (360.3007)	10.5485 (350.9926)			
Online network size		0.0002 (0.0000)***	0.0002 (0.0000)***		0.0000 (0.0001)	0.0000 (0.0001)
Edits this month (log)	0.7914 (0.0058)***	0.7843 (0.0059)***	0.7834 (0.0059)***	0.8510 (0.0078)***	0.8462 (0.0078)***	0.8456 (0.0078)***
Total edits (log)	0.2092 (0.0074)***	0.1918 (0.0078)***	0.1891 (0.0078)***	0.2303 (0.0123)***	0.1965 (0.0130)***	0.1930 (0.0129)***
Years since first edit	−0.0458 (0.0047)***	−0.0399 (0.0047)***	−0.0398 (0.0047)***	−0.1195 (0.0080)***	−0.1082 (0.0081)***	−0.1078 (0.0081)***
Was administrator	0.5907 (0.0789)***	0.6283 (0.0788)***	0.5856 (0.0786)***	0.9098 (0.1746)***	0.9887 (0.1744)***	0.9398 (0.1742)***
Month of year: May-Aug (Ref.: Jan-Apr)	−0.0456 (0.0123)***	−0.0453 (0.0123)***	−0.0441 (0.0123)***	−0.0444 (0.0160)**	−0.0444 (0.0160)**	−0.0429 (0.0160)**
Month of year: Sep-Dec (Ref.: Jan-Apr)	0.0046 (0.0263)	−0.0027 (0.0263)	−0.0006 (0.0263)	0.0838 (0.0390)*	0.0754 (0.0390)+	0.0778 (0.0390)*
AIC	150964.1926	150949.5653	150911.8355	124931.4049	124853.9646	124837.7138
Log Likelihood	−75467.0963	−75458.7827	−75435.9177	−62453.7024	−62413.9823	−62403.8569
Num. obs.	140016	140016	140016	140016	140016	140016
Num. groups: id	33204	33204	33204	33204	33204	33204
Var: id (Intercept)	0.8491	0.8497	0.8399	4.2756	4.2795	4.2494

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$.

Table A93: Explaining rewards (restricted; categories of density).

	Receiving rewards	Receiving rewards	Receiving rewards	Rewarding others	Rewarding others	Rewarding others
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Intercept	-6.8419 (0.2038)***	-26.6560 (1079.0333)	-25.3819 (804.8149)	-9.2928 (0.1906)***	-9.6381 (0.2304)***	-9.6028 (0.2297)***
Egocentric offline network density: Middle (Ref.: Low)	0.3767 (0.2009)$^{+}$		0.1273 (0.1497)	0.8640 (0.1628)***		0.8577 (0.1620)***
Egocentric offline network density: High (Ref.: Low)	0.4020 (0.1613)*		0.2136 (0.1359)	0.4300 (0.1268)***		0.4264 (0.1263)***
Offline network size	-0.0012 (0.0036)		0.0061 (0.0023)**	0.0044 (0.0027)		0.0045 (0.0027)$^{+}$
Meetup attendee		0.3774 (0.1024)***			0.7452 (0.0997)***	
Egocentric online network density: Middle (Ref.: Low)		19.4730 (1079.0333)	19.0103 (804.8149)		0.5291 (0.1854)**	0.5341 (0.1852)**
Egocentric online network density: High (Ref.: Low)		17.5236 (1079.0336)	17.0573 (804.8153)		-0.7423 (1.0553)	-0.7381 (1.0550)
Online network size		-0.0121 (0.0006)***	-0.0094 (0.0005)***		-0.0000 (0.0001)	-0.0000 (0.0001)
Edits this month (log)	0.7071 (0.0225)***	0.8924 (0.0251)***	0.8596 (0.0231)***	0.7602 (0.0231)***	0.7591 (0.0236)***	0.7561 (0.0236)***
Total edits (log)	0.1667 (0.0229)***	0.2011 (0.0249)***	0.1723 (0.0218)***	0.2423 (0.0287)***	0.2210 (0.0300)***	0.2168 (0.0299)***
Years since first edit	-0.0725 (0.0145)***	-0.0614 (0.0148)***	-0.0644 (0.0130)***	-0.1027 (0.0176)***	-0.0947 (0.0177)***	-0.0951 (0.0177)***
Was administrator	-0.8174 (0.2210)***	-0.2042 (0.2040)	-0.1676 (0.1591)	0.2388 (0.2144)	0.3325 (0.2122)	0.2602 (0.2131)
Month of year: May-Aug (Ref.: Jan-Apr)	-0.1743 (0.0678)*	-0.2113 (0.0656)**	-0.1437 (0.0632)*	-0.0822 (0.0502)	-0.0835 (0.0502)$^{+}$	-0.0814 (0.0501)
Month of year: Sep-Dec (Ref.: Jan-Apr)	0.0575 (0.1053)	-0.0336 (0.1041)	0.0204 (0.0934)	0.1053 (0.1062)	0.1028 (0.1060)	0.0974 (0.1059)
AIC	26749.3626	25763.9282	25969.0398	23137.5758	23146.8107	23132.3658
Log Likelihood	-13362.6813	-12868.9641	-12969.5199	-11556.7879	-11560.4053	-11551.1829
Num. obs.	140016	140016	140016	140016	140016	140016
Num. groups: id	33204	33204	33204	33204	33204	33204
Var: id (Intercept)	1.0430	1.2781	0.0000	4.2942	4.2345	4.2162

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$.

A.4 Models on Elections

A.4.1 Running for Administrator

A.4.1.1 Bivariate LPMs

Table A94: Running for administrator, bivariate LPM.

	Model 1	Model 2	Model 3
Intercept	$0.0290\ (0.0024)^{***}$	$0.0234\ (0.0024)^{***}$	$0.0278\ (0.0024)^{***}$
Been at meetings (cm)	$0.0030\ (0.0011)^{**}$		
Been at meetings (cwc)	$0.0042\ (0.0011)^{***}$		
Number of users met (log, cm)		$0.0089\ (0.0023)^{***}$	
Number of users met (log, cwc)		$0.0089\ (0.0021)^{***}$	
Meetup centrality (cm)			$0.1784\ (0.0428)^{***}$
Meetup centrality (cwc)			$0.0636\ (0.0234)^{**}$
AIC	−7306.6411	−7320.0866	−7331.1728
BIC	−7271.1084	−7284.5539	−7295.6401
Log Likelihood	3658.3206	3665.0433	3670.5864
Num. obs.	9014	9014	9014
Num. groups: id	3973	3973	3973
Var: id (Intercept)	0.0098	0.0098	0.0097
Var: Residual	0.0192	0.0192	0.0192

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$.

A.4.1.2 REWB LPM

Table A95: Running for administrator, main LPM.

	Empty model	Model 1	Model 2	Model 3	Full model
Intercept	0.0341 (0.0023)***	0.1388 (0.0100)***	0.1376 (0.0101)***	0.1393 (0.0101)***	0.1364 (0.0100)***
Been at meetings (cm)		−0.0010 (0.0007)			−0.0003 (0.0013)
Been at meetings (cwc)		0.0007 (0.0010)			−0.0002 (0.0013)
Number of users met (log, cm)			−0.0020 (0.0015)		0.0000 (0.0030)
Number of users met (log, cwc)			0.0040 (0.0018)*		0.0060 (0.0024)*
Meetup centrality (cm)				−0.0312 (0.0257)	−0.0274 (0.0424)
Meetup centrality (cwc)				0.0015 (0.0221)	−0.0311 (0.0265)
Number of users collaborated with (log, cm)		0.0321 (0.0048)***	0.0322 (0.0048)***	0.0323 (0.0048)***	0.0327 (0.0048)***
Number of users collaborated with (log, cwc)		0.0010 (0.0041)	0.0006 (0.0040)	0.0015 (0.0040)	0.0012 (0.0041)
Collaboration centrality (cm)		0.2111 (0.0930)*	0.2071 (0.0928)*	0.2110 (0.0930)*	0.2068 (0.0929)*
Collaboration centrality (cwc)		0.3200 (0.0953)***	0.3204 (0.0954)***	0.3171 (0.0953)***	0.3170 (0.0953)***
Number of users talked to (log, cm)		0.0316 (0.0061)***	0.0317 (0.0060)***	0.0313 (0.0060)***	0.0315 (0.0060)***
Number of users talked to (log, cwc)		0.0082 (0.0041)*	0.0085 (0.0041)*	0.0084 (0.0041)*	0.0089 (0.0041)*
Talk centrality (cm)		0.4556 (0.2027)*	0.4528 (0.2032)*	0.4696 (0.2017)*	0.4700 (0.2007)*
Talk centrality (cwc)		0.7258 (0.1942)***	0.7169 (0.1955)***	0.7307 (0.1947)***	0.7187 (0.1943)***
Mainspace edits 2 months before (log, cm)		−0.0017 (0.0033)	−0.0017 (0.0033)	−0.0020 (0.0033)	−0.0021 (0.0033)
Mainspace edits 2 months before (log, cwc)		−0.0114 (0.0033)***	−0.0112 (0.0033)***	−0.0116 (0.0033)***	−0.0116 (0.0033)***
Total edits up to election (log, cm)		−0.0383 (0.0025)***	−0.0383 (0.0024)***	−0.0383 (0.0025)***	−0.0382 (0.0024)***
Total edits up to election (log, cwc)		0.0105 (0.0015)***	0.0103 (0.0014)***	0.0107 (0.0014)***	0.0106 (0.0015)***
Number of times reverted others (log, cm)		−0.0193 (0.0074)**	−0.0189 (0.0074)*	−0.0193 (0.0073)**	−0.0193 (0.0074)**
Number of times reverted others (log, cwc)		0.0017 (0.0033)	0.0016 (0.0033)	0.0017 (0.0033)	0.0017 (0.0033)
Number of times got reverted (log, cm)		−0.0017 (0.0058)	−0.0018 (0.0058)	−0.0016 (0.0058)	−0.0016 (0.0057)
Number of times got reverted (log, cwc)		0.0011 (0.0028)	0.0010 (0.0028)	0.0011 (0.0028)	0.0010 (0.0028)
Years since first edit (cm)		−0.0006 (0.0008)	−0.0007 (0.0009)	−0.0006 (0.0009)	−0.0007 (0.0009)
Years since first edit (cwc)		0.0025 (0.0008)***	0.0026 (0.0008)***	0.0025 (0.0008)**	0.0026 (0.0008)***
Number of previous elections ran		0.1281 (0.0196)***	0.1277 (0.0195)***	0.1283 (0.0195)***	0.1279 (0.0195)***
Year of election: 09-14 (Ref.: 03-08)		−0.0394 (0.0065)***	−0.0391 (0.0065)***	−0.0395 (0.0065)***	−0.0400 (0.0065)***
Year of election: 15-20 (Ref.: 03-08)		−0.0677 (0.0082)***	−0.0671 (0.0082)***	−0.0677 (0.0082)***	−0.0676 (0.0082)***
AIC	−7295.1333	−9888.1289	−9896.4509	−9900.8605	−9858.7617
BIC	−7273.8137	−9703.3590	−9711.6810	−9716.0906	−9645.5657
Log Likelihood	3650.5667	4970.0645	4974.2254	4976.4303	4959.3809
Num. obs.	9014	9014	9014	9014	9014
Num. groups: id	3973	3973	3973	3973	3973
Var: id (Intercept)	0.0097	0.0017	0.0017	0.0017	0.0017
Var: Residual	0.0194	0.0175	0.0175	0.0175	0.0175

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$.

A.4.1.3 REWB GLM

Table A96: Running for administrator, GLM.

	Empty model	Model 1	Model 2	Model 3	Full model
Intercept	−10.4815 (0.3607)***	−8.8222 (1.2227)***	−8.8366 (1.2179)***	−8.8538 (1.2189)***	−8.8339 (1.2283)***
Been at meetings (cm)		−0.0504 (0.0482)			−0.1564 (0.0871)+
Been at meetings (cwc)		0.0796 (0.0438)+			0.1081 (0.0567)+
Number of users met (log, cm)			−0.0064 (0.0894)		0.0508 (0.1695)
Number of users met (log, cwc)			0.1109 (0.0895)		0.1235 (0.1251)
Meetup centrality (cm)				1.1479 (0.9777)	2.8389 (1.4366)*
Meetup centrality (cwc)				−0.4075 (0.7603)	−2.2360 (1.0418)*
Number of users collaborated with (log, cm)		2.1141 (0.4036)***	2.0846 (0.4010)***	2.0879 (0.4005)***	2.1179 (0.4046)***
Number of users collaborated with (log, cwc)		1.6278 (0.5232)**	1.6316 (0.5216)**	1.6770 (0.5226)**	1.6121 (0.5238)**
Collaboration centrality (cm)		−10.9465 (2.4021)***	−10.8634 (2.3979)***	−10.9010 (2.4012)***	−11.1452 (2.4338)***
Collaboration centrality (cwc)		2.3266 (2.5998)	2.1137 (2.5978)	2.2417 (2.5885)	2.7412 (2.6179)
Number of users talked to (log, cm)		0.5699 (0.1776)**	0.5684 (0.1776)**	0.5483 (0.1758)**	0.5896 (0.1784)***
Number of users talked to (log, cwc)		0.8320 (0.1898)***	0.8440 (0.1900)***	0.8652 (0.1900)***	0.8522 (0.1913)***
Talk centrality (cm)		3.7183 (2.8290)	3.3027 (2.7956)	2.6317 (2.8261)	3.3587 (2.8822)
Talk centrality (cwc)		−2.2392 (2.9730)	−1.9068 (2.9546)	−1.8161 (2.9578)	−2.7272 (3.0028)
Mainspace edits 2 months before (log, cm)		−0.0845 (0.2187)	−0.0743 (0.2175)	−0.0678 (0.2174)	−0.0870 (0.2202)
Mainspace edits 2 months before (log, cwc)		−1.0269 (0.3595)**	−1.0218 (0.3584)**	−1.0487 (0.3597)**	−1.0506 (0.3645)**
Total edits up to election (log, cm)		−0.4966 (0.0845)***	−0.4923 (0.0844)***	−0.4946 (0.0839)***	−0.5044 (0.0858)***
Total edits up to election (log, cwc)		0.3807 (0.1080)***	0.3915 (0.1075)***	0.4184 (0.1087)***	0.3892 (0.1103)***
Number of times reverted others (log, cm)		−0.0495 (0.2400)	−0.0306 (0.2398)	−0.0151 (0.2409)	−0.0267 (0.2434)
Number of times reverted others (log, cwc)		0.0511 (0.1610)	0.0548 (0.1613)	0.0486 (0.1610)	0.0732 (0.1612)
Number of times got reverted (log, cm)		−0.2094 (0.1611)	−0.2224 (0.1619)	−0.2261 (0.1620)	−0.2418 (0.1649)
Number of times got reverted (log, cwc)		0.0777 (0.1417)	0.0755 (0.1420)	0.0784 (0.1422)	0.0769 (0.1412)
Years since first edit (cm)		−0.2922 (0.0683)***	−0.2940 (0.0684)***	−0.2980 (0.0682)***	−0.2980 (0.0687)***
Years since first edit (cwc)		−0.0116 (0.0716)	−0.0129 (0.0715)	−0.0116 (0.0717)	−0.0213 (0.0726)
Number of previous elections ran		1.6751 (0.1529)***	1.6744 (0.1536)***	1.6949 (0.1533)***	1.6937 (0.1535)***
Year of election: 09-14 (Ref.: 03-08)		−0.1270 (0.2522)	−0.1348 (0.2519)	−0.1179 (0.2538)	−0.1512 (0.2564)
Year of election: 15-20 (Ref.: 03-08)		−1.5122 (0.3607)***	−1.5109 (0.3613)***	−1.5156 (0.3600)***	−1.5116 (0.3601)***
AIC	1620.2350	1004.2483	1005.8203	1006.1703	1005.3134
BIC	1634.4480	1181.9117	1183.4837	1183.8337	1211.4029
Log Likelihood	−808.1175	−477.1241	−477.9102	−478.0852	−473.6567
Num. obs.	9014	9014	9014	9014	9014
Num. groups: id	3973	3973	3973	3973	3973
Var: id (Intercept)	165.7562	0.0000	0.0000	0.0000	0.0000

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$.

A.4.1.4 FE LPM

Table A97: Running for administrator, FE LPM.

	Model 1	Model 2	Model 3	Full model
Been at meetings	0.0005 (0.0011)			0.0006 (0.0013)
Number of users met (log)		0.0010 (0.0024)		0.0009 (0.0033)
Meetup centrality			−0.0004 (0.0225)	−0.0112 (0.0271)
Number of users collaborated with (log)	−0.0044 (0.0049)	−0.0041 (0.0049)	−0.0039 (0.0049)	−0.0043 (0.0049)
Collaboration centrality	0.2909 (0.1161)*	0.2894 (0.1159)*	0.2895 (0.1160)*	0.2905 (0.1159)*
Number of users talked to (log)	0.0086 (0.0048)+	0.0087 (0.0047)+	0.0087 (0.0047)+	0.0087 (0.0048)+
Talk centrality	0.4939 (0.2363)*	0.4965 (0.2382)*	0.5004 (0.2369)*	0.4941 (0.2367)*
Mainspace edits 2 months before (log)	−0.0042 (0.0040)	−0.0043 (0.0040)	−0.0045 (0.0040)	−0.0043 (0.0040)
Total edits up to election (log)	0.0062 (0.0022)**	0.0063 (0.0022)**	0.0064 (0.0022)**	0.0062 (0.0022)**
Number of times reverted others (log)	0.0004 (0.0039)	0.0004 (0.0039)	0.0004 (0.0039)	0.0004 (0.0039)
Number of times got reverted (log)	−0.0021 (0.0033)	−0.0022 (0.0033)	−0.0021 (0.0033)	−0.0022 (0.0033)
Years since first edit	−0.0019 (0.0012)	−0.0019 (0.0012)	−0.0019 (0.0012)	−0.0018 (0.0012)
Number of previous elections ran	0.0661 (0.0554)	0.0661 (0.0553)	0.0668 (0.0551)	0.0663 (0.0553)
Year of election: 09-14 (Ref.: 03-08)	0.0143 (0.0107)	0.0143 (0.0107)	0.0143 (0.0107)	0.0137 (0.0106)
Year of election: 15-20 (Ref.: 03-08)	0.0269 (0.0148)+	0.0269 (0.0148)+	0.0269 (0.0148)+	0.0265 (0.0148)+
R^2	0.03	0.03	0.03	0.03
Adj. R^2	−0.73	−0.73	−0.73	−0.73
Num. obs.	9014	9014	9014	9014

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$.

A.4.1.5 FE GLM

Table A98: Running for administrator, FE GLM.

	Model 1	Model 2	Model 3	Full model
Been at meetings	0.0468 (0.0403)			0.0256 (0.0608)
Number of users met (log)		0.1291 (0.0758)$^{+}$		0.1953 (0.1160)$^{+}$
Meetup centrality			0.1270 (0.6844)	−1.3588 (0.9833)
Number of users collaborated with (log)	1.9623 (0.2928)***	1.9614 (0.2927)***	1.9665 (0.2930)***	1.9774 (0.2933)***
Collaboration centrality	0.8647 (1.4808)	0.8601 (1.4797)	0.7950 (1.4822)	0.8579 (1.4805)
Number of users talked to (log)	0.5794 (0.1267)***	0.5743 (0.1268)***	0.5871 (0.1268)***	0.5793 (0.1270)***
Talk centrality	9.9339 (2.0739)***	9.8622 (2.0693)***	10.0599 (2.0856)***	9.5771 (2.0844)***
Mainspace edits 2 months before (log)	−0.2481 (0.2087)	−0.2527 (0.2086)	−0.2419 (0.2085)	−0.2617 (0.2090)
Total edits up to election (log)	0.3881 (0.0476)***	0.3817 (0.0478)***	0.3943 (0.0476)***	0.3810 (0.0479)***
Number of times reverted others (log)	−0.2508 (0.1055)*	−0.2477 (0.1056)*	−0.2522 (0.1055)*	−0.2446 (0.1057)*
Number of times got reverted (log)	0.1701 (0.0928)$^{+}$	0.1672 (0.0927)$^{+}$	0.1694 (0.0927)$^{+}$	0.1681 (0.0928)$^{+}$
Years since first edit	−0.3046 (0.0693)***	−0.3009 (0.0692)***	−0.3000 (0.0688)***	−0.3020 (0.0695)***
Number of previous elections ran	0.6350 (0.2049)**	0.6304 (0.2050)**	0.6402 (0.2048)**	0.6290 (0.2050)**
Year of election: 09-14 (Ref.: 03-08)	0.2525 (0.2769)	0.2058 (0.2787)	0.2539 (0.2764)	0.1740 (0.2811)
Year of election: 15-20 (Ref.: 03-08)	1.9051 (0.5605)***	1.8562 (0.5613)***	1.9045 (0.5590)***	1.8470 (0.5629)**
Log Likelihood	−986.8093	−986.0222	−987.4789	−985.0738
Deviance	1973.6186	1972.0445	1974.9577	1970.1475
Num. obs.	3472	3472	3472	3472

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$.

A.4.2 Winning Elections

A.4.2.1 Bivariate LPMs

Table A99: Winning elections, bivariate linear regression model.

	Model 1	Model 2	Model 3
Intercept	0.5768 (0.0182)***	0.5579 (0.0184)***	0.5748 (0.0175)***
Been at meetings	0.0181 (0.0047)***		
Proportion of voters met		0.0202 (0.0034)***	
Meetup centrality			0.3456 (0.0590)***
R^2	0.0185	0.0406	0.0254
Adj. R^2	0.0176	0.0398	0.0246
Num. obs.	1179	1179	1179

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$.

A.4.2.2 LPM

Table A100: Winning elections, main LPM.

	Model 1	Model 2	Model 3	Full model
Intercept	−0.0670 (0.0997)	−0.0556 (0.0973)	−0.0738 (0.0972)	−0.0773 (0.0992)
Been at meetings	0.0117 (0.0047)*			−0.0077 (0.0059)
Proportion of voters met		0.0168 (0.0035)***		0.0274 (0.0085)**
Meetup centrality			0.2733 (0.0664)***	−0.1693 (0.1364)
Proportion of voters collaborated with	0.0013 (0.0015)	0.0011 (0.0015)	0.0011 (0.0015)	0.0010 (0.0015)
Collaboration centrality	0.2860 (0.1849)	0.3364 (0.1826)$^{+}$	0.3017 (0.1842)	0.3480 (0.1831)$^{+}$
Porportion of voters talked to	0.0011 (0.0019)	0.0009 (0.0018)	0.0012 (0.0019)	0.0009 (0.0018)
Talk centrality	−0.2334 (0.1356)$^{+}$	−0.2386 (0.1343)$^{+}$	−0.2538 (0.1349)$^{+}$	−0.2094 (0.1341)
Mainspace edits 2 months before (log)	0.0417 (0.0138)**	0.0424 (0.0135)**	0.0442 (0.0135)**	0.0430 (0.0135)**
Total edits up to election (log)	0.0352 (0.0154)*	0.0279 (0.0150)$^{+}$	0.0333 (0.0150)*	0.0296 (0.0151)$^{+}$
Proportion of voters reverted candidate	−0.0077 (0.0055)	−0.0072 (0.0054)	−0.0076 (0.0055)	−0.0071 (0.0054)
Proportion of voters reverted by candidate	−0.0043 (0.0046)	−0.0043 (0.0046)	−0.0043 (0.0046)	−0.0044 (0.0046)
Years since first edit	0.0463 (0.0075)***	0.0471 (0.0074)***	0.0464 (0.0073)***	0.0476 (0.0074)***
Number of previous elections ran	−0.0280 (0.0271)	−0.0292 (0.0261)	−0.0314 (0.0265)	−0.0243 (0.0272)
Year of election: 09-14 (Ref.: 03-08)	−0.1735 (0.0409)***	−0.1480 (0.0406)***	−0.1572 (0.0409)***	−0.1467 (0.0404)***
Year of election: 15-20 (Ref.: 03-08)	−0.3891 (0.0575)***	−0.3631 (0.0564)***	−0.3823 (0.0561)***	−0.3572 (0.0569)***
R^2	0.13	0.15	0.14	0.15
Adj. R^2	0.12	0.14	0.13	0.14
Num. obs.	1164	1164	1164	1164

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$.

A.4.2.3 GLM

Table A101: Winning elections, GLM.

	Model 1	Model 2	Model 3	Full model
Intercept	-2.6266 (0.4936)***	-2.6024 (0.4900)***	-2.6977 (0.4861)***	-2.7099 (0.5040)***
Been at meetings	0.0652 (0.0298)*			-0.0566 (0.0362)
Proportion of voters met		0.1010 (0.0263)***		0.1862 (0.0682)**
Meetup centrality			1.5578 (0.4460)***	-1.1819 (0.8827)
Proportion of voters collaborated with	0.0054 (0.0071)	0.0046 (0.0071)	0.0046 (0.0072)	0.0042 (0.0072)
Collaboration centrality	1.5423 (0.9072)$^{+}$	1.7846 (0.9064)*	1.6235 (0.9075)$^{+}$	1.8404 (0.9180)*
Porportion of voters talked to	0.0055 (0.0097)	0.0050 (0.0094)	0.0058 (0.0096)	0.0051 (0.0094)
Talk centrality	-1.1758 (0.6511)$^{+}$	-1.2645 (0.6615)$^{+}$	-1.2842 (0.6608)$^{+}$	-1.1507 (0.6548)$^{+}$
Mainspace edits 2 months before (log)	0.1872 (0.0670)**	0.1940 (0.0668)**	0.2008 (0.0664)**	0.1964 (0.0669)**
Total edits up to election (log)	0.1574 (0.0742)*	0.1237 (0.0726)$^{+}$	0.1528 (0.0720)*	0.1305 (0.0735)$^{+}$
Proportion of voters reverted candidate	-0.0379 (0.0378)	-0.0355 (0.0366)	-0.0377 (0.0382)	-0.0353 (0.0365)
Proportion of voters reverted by candidate	-0.0196 (0.0206)	-0.0197 (0.0207)	-0.0199 (0.0212)	-0.0202 (0.0214)
Years since first edit	0.2248 (0.0411)***	0.2338 (0.0419)***	0.2260 (0.0405)***	0.2371 (0.0417)***
Number of previous elections ran	-0.1357 (0.1329)	-0.1500 (0.1303)	-0.1549 (0.1314)	-0.1264 (0.1339)
Year of election: 09-14 (Ref.: 03-08)	-0.8170 (0.1951)***	-0.7291 (0.1969)***	-0.7545 (0.1963)***	-0.7201 (0.1968)***
Year of election: 15-20 (Ref.: 03-08)	-1.8602 (0.3083)***	-1.7899 (0.3063)***	-1.8534 (0.3016)***	-1.7492 (0.3061)***
AIC	1398.94	1428.15	1416.71	1396.37
BIC	1469.77	1498.99	1487.55	1477.33
Log Likelihood	-685.47	-700.08	-694.36	-682.19
Deviance	1370.94	1400.15	1388.71	1364.37
Num. obs.	1164	1164	1164	1164

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$.

A.4.3 Voting in Elections

A.4.3.1 Bivariate LPMs

Table A102: Voting in elections, bivariate LPM.

	Model 1	Model 2	Model 3	Model 4	Model 5
Intercept	0.0412 (0.0013)***	0.0422 (0.0013)***	0.0398 (0.0013)***	0.0423 (0.0013)***	0.0983 (0.0037)***
Met candidate (cm)	3.1028 (0.1908)***				
Met candidate (cwc)	0.2050 (0.0063)***				
Been at meetings (cm)		0.0209 (0.0017)***			
Been at meetings (cwc)		0.0070 (0.0009)***			
Proportion of voters met (log, cm)			0.0286 (0.0018)***		
Proportion of voters met (log, cwc)			0.0108 (0.0007)***		
Meetup centrality (cm)				0.5408 (0.0372)***	
Meetup centrality (cwc)				0.1007 (0.0128)***	
Difference candidate-voter meetup centrality (cm)					−0.5037 (0.0340)***
Difference candidate-voter meetup centrality (cwc)					0.0356 (0.0034)***
AIC	267216.4453	273549.4169	268004.9007	273900.8255	274994.6841
BIC	267275.5061	273608.4778	268063.9616	273959.8864	275053.7449
Log Likelihood	−133603.2226	−136769.7085	−133997.4504	−136945.4128	−137492.3420
Num. obs.	996668	996668	996668	996668	996668
Num. groups: id	13979	13979	13979	13979	13979
Var: id (Intercept)	0.0155	0.0160	0.0156	0.0157	0.0158
Var: Residual	0.0747	0.0752	0.0748	0.0752	0.0753

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$.

A.4.3.2 REWB LPM

Table A103: Voting in elections, main LPM.

	Empty model	Model 1	Model 2	Model 3	Model 4	Full model
Intercept	0.0507 (0.0013)***	0.0067 (0.0249)	0.0093 (0.0249)	0.0108 (0.0250)	0.0241 (0.0290)	0.0286 (0.0288)
Met candidate (cm)		0.7298 (0.1737)***				1.5343 (0.4252)***
Met candidate (cwc)		0.1569 (0.0057)***				0.1229 (0.0052)***
Been at meetings (cm)			0.0043 (0.1737)			−0.0002 (0.0018)
Been at meetings (cwc)			0.0033 (0.0057)			0.0010 (0.0009)
Proportion of voters met (log, cm)				0.0064 (0.0015)***		0.0104 (0.0031)**
Proportion of voters met (log, cwc)				0.0068 (0.0006)***		0.0097 (0.0006)***
Meetup centrality (cm)					−0.0226 (0.0824)	−0.4686 (0.1130)***
Meetup centrality (cwc)					0.0908 (0.0116)***	−0.0917 (0.0138)***
Difference candidate-voter meetup centrality (cm)					−0.1144 (0.0764)	−0.1226 (0.0769)
Difference candidate-voter meetup centrality (cwc)					0.0473 (0.0020)***	0.0274 (0.0017)***
Collaborated with the candidate (cm)		0.0788 (0.0252)**	0.0813 (0.0252)*	0.0801 (0.0252)**	0.0806 (0.0253)**	0.0787 (0.0252)**
Collaborated with the candidate (cwc)		0.0551 (0.0017)***	0.0580 (0.0017)***	0.0576 (0.0017)***	0.0580 (0.0017)***	0.0553 (0.0017)***
Proportion of voters collaborated with (log, cm)		0.0003 (0.0008)	0.0002 (0.0008)	0.0002 (0.0008)	0.0003 (0.0008)	0.0002 (0.0008)
Proportion of voters collaborated with (log, cwc)		−0.0007 (0.0002)**	−0.0007 (0.0002)**	−0.0009 (0.0002)***	−0.0006 (0.0002)**	−0.0008 (0.0002)***
Collaboration centrality (cm)		−0.0906 (0.1143)	−0.0965 (0.1143)	−0.0821 (0.1147)	−0.0645 (0.1142)	−0.0617 (0.1135)
Collaboration centrality (cwc)		0.3433 (0.0344)***	0.3371 (0.0344)***	0.3566 (0.0344)***	0.3342 (0.0344)***	0.3642 (0.0344)***
Difference candidate-voter collaboration centrality (cm)		−0.2805 (0.0521)***	−0.2872 (0.0521)	−0.2777 (0.0522)***	−0.2431 (0.0517)***	−0.2567 (0.0514)***
Difference candidate-voter collaboration centrality (cwc)		−0.0158 (0.0033)***	−0.0205 (0.0033)***	−0.0201 (0.0034)***	−0.0154 (0.0034)***	−0.0119 (0.0033)***
Talked to candidate (log, cm)		0.2903 (0.1166)*	0.2991 (0.1166)	0.2924 (0.1166)*	0.2920 (0.1170)*	0.2823 (0.1166)*
Talked to candidate (log, cwc)		0.1299 (0.0044)***	0.1398 (0.0044)***	0.1385 (0.0045)***	0.1386 (0.0045)***	0.1295 (0.0044)***
Proportion of voters talked to (log, cm)		0.0156 (0.0042)***	0.0157 (0.0042)	0.0152 (0.0043)***	0.0152 (0.0043)***	0.0154 (0.0042)***
Proportion of voters talked to (log, cwc)		0.0164 (0.0011)***	0.0165 (0.0011)***	0.0157 (0.0011)***	0.0164 (0.0011)***	0.0155 (0.0011)***
Talk centrality (cm)		0.5557 (0.2075)**	0.6096 (0.2075)	0.5474 (0.2070)**	0.4608 (0.2147)*	0.4364 (0.2145)*
Talk centrality (cwc)		−0.1681 (0.0249)***	−0.1715 (0.0249)***	−0.1560 (0.0247)***	−0.1803 (0.0249)***	−0.1526 (0.0249)***
Difference candidate-voter talk centrality (cm)		−0.1438 (0.0721)*	−0.1362 (0.0721)	−0.1824 (0.0719)*	−0.2886 (0.0857)***	−0.2672 (0.0859)**
Difference candidate-voter talk centrality (cwc)		0.0446 (0.0041)***	0.0514 (0.0041)***	0.0518 (0.0042)***	0.0362 (0.0041)***	0.0387 (0.0041)***
Mainspace edits 2 months before (log, cm)		−0.0005 (0.0015)	−0.0006 (0.0015)	−0.0005 (0.0015)	−0.0004 (0.0015)	−0.0006 (0.0015)
Mainspace edits 2 months before (log, cwc)		0.0093 (0.0010)***	0.0091 (0.0010)***	0.0091 (0.0010)***	0.0093 (0.0010)***	0.0090 (0.0010)***
Total edits up to election (log, cm)		0.0120 (0.0012)***	0.0120 (0.0012)	0.0119 (0.0012)***	0.0118 (0.0012)***	0.0114 (0.0012)***
Total edits up to election (log, cwc)		0.0372 (0.0031)***	0.0353 (0.0031)***	0.0329 (0.0031)***	0.0355 (0.0031)***	0.0330 (0.0030)***
Difference candidate-voter in total edits (cm)		−0.0002 (0.0006)	−0.0002 (0.0006)	−0.0002 (0.0006)	−0.0003 (0.0006)	−0.0002 (0.0006)
Difference candidate-voter in total edits (cwc)		0.0017 (0.0001)***	0.0018 (0.0001)***	0.0018 (0.0001)***	0.0016 (0.0001)***	0.0016 (0.0001)***
Years since first edit (cm)		−0.0012 (0.0007)+	−0.0012 (0.0007)	−0.0012 (0.0007)+	−0.0012 (0.0007)+	−0.0012 (0.0007)+
Years since first edit (cwc)		−0.0005 (0.0009)	−0.0002 (0.0009)	0.0008 (0.0009)	−0.0004 (0.0009)	0.0006 (0.0009)
Was reverted by the candidate (cm)		−0.5304 (0.6981)	−0.5649 (0.6981)	−0.5044 (0.6985)	−0.5542 (0.7007)	−0.5616 (0.6977)
Was reverted by the candidate (cwc)		0.0271 (0.0061)***	0.0271 (0.0061)***	0.0276 (0.0061)***	0.0270 (0.0061)***	0.0275 (0.0061)***
Reverted the candidate (cm)		1.9755 (0.7869)*	2.0923 (0.7869)	1.9978 (0.7870)*	2.0149 (0.7875)*	2.0016 (0.7866)*
Reverted the candidate (cm)		0.0403 (0.0066)***	0.0404 (0.0066)***	0.0398 (0.0066)***	0.0408 (0.0066)***	0.0395 (0.0066)***
Year of election: 09-14 (Ref.: 03-08)		0.0019 (0.0039)	0.0005 (0.0039)	0.0030 (0.0039)	0.0058 (0.0039)	0.0040 (0.0039)
Year of election: 15-20 (Ref.: 03-08)		0.0152 (0.0058)**	0.0152 (0.0058)**	0.0144 (0.0059)*	0.0173 (0.0059)**	0.0147 (0.0058)*
AIC	276580.6492	196920.6263	201747.0845	199052.9392	200409.0899	193614.6842
BIC	276616.0857	197334.0524	202160.5105	199466.3652	200846.1403	194122.6077
Log Likelihood	−138287.3246	−98425.3132	−100838.5422	−99491.4696	−100167.5449	−96764.3421
Num. obs.	996668	996668	996668	996668	996668	996668
Num. groups: id	13979	13979	13979	13979	13979	13979
Var: id (Intercept)	0.0166	0.0107	0.0107	0.0107	0.0107	0.0107
Var: Residual	0.0754	0.0698	0.0701	0.0700	0.0700	0.0696

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$.

A.4.3.3 REWB GLM

Table A104: Voting in elections, GLM.

	Empty model	Model 1	Model 2	Model 3	Model 4	Full model
Intercept	−7.0767 (0.0748)***	−14.8572 (0.8046)***	−14.5117 (0.8008)***	−14.5775 (0.8032)***	−13.6211 (1.0207)***	−15.2654 (1.0382)***
Met candidate (cm)		21.8553 (2.6949)***				16.7941 (8.5060)*
Met candidate (cwc)		1.2388 (0.0233)***				0.9083 (0.0253)***
Been at meetings (cm)			0.1762 (0.0241)***			0.0741 (0.0377)*
Been at meetings (cwc)			0.0191 (0.0017)***			0.0024 (0.0020)
Proportion of voters met (log, cm)				0.2168 (0.0265)***		0.3142 (0.0694)***
Proportion of voters met (log, cwc)				0.0548 (0.0014)***		0.0925 (0.0024)***
Meetup centrality (cm)					0.8446 (3.8761)	−5.2343 (4.3315)
Meetup centrality (cwc)					0.9436 (0.0303)***	−0.8558 (0.0488)***
Difference candidate-voter meetup centrality (cm)					−3.3499 (3.8552)	0.5610 (3.8936)
Difference candidate-voter meetup centrality (cwc)					0.6405 (0.0170)***	0.3906 (0.0180)***
Collaborated with the candidate (cm)		2.5390 (0.6374)***	2.4717 (0.6408)***	2.4319 (0.6443)***	2.5482 (0.6399)***	2.5035 (0.6473)***
Collaborated with the candidate (cwc)		0.4460 (0.0106)***	0.4685 (0.0105)***	0.4693 (0.0105)***	0.4610 (0.0105)***	0.4471 (0.0106)***
Proportion of voters collaborated with (log, cm)		0.0722 (0.0125)***	0.0708 (0.0125)***	0.0687 (0.0126)***	0.0847 (0.0125)***	0.0704 (0.0127)***
Proportion of voters collaborated with (log, cwc)		−0.0064 (0.0008)***	−0.0060 (0.0008)***	−0.0078 (0.0008)***	−0.0041 (0.0008)***	−0.0069 (0.0008)***
Collaboration centrality (cm)		−7.4189 (2.2573)**	−7.4725 (2.2550)***	−6.9864 (2.2654)**	−8.0444 (2.3363)***	−7.3743 (2.3499)**
Collaboration centrality (cwc)		1.5795 (0.1075)***	1.4334 (0.1071)***	1.6264 (0.1076)***	1.4015 (0.1074)***	1.7424 (0.1085)***
Difference candidate-voter collaboration centrality (cm)		−4.1591 (1.6619)*	−3.8924 (1.6623)*	−4.3516 (1.6675)**	−3.4174 (1.7781)$^{+}$	−3.8609 (1.7875)*
Difference candidate-voter collaboration centrality (cwc)		−0.0735 (0.0310)*	−0.1629 (0.0309)***	−0.1514 (0.0310)***	−0.0340 (0.0311)	0.0148 (0.0312)
Talked to candidate (log, cm)		−1.1430 (1.4763)	0.6203 (1.4047)	−2.1138 (1.5486)	−0.3784 (1.4579)	−0.3356 (1.4490)
Talked to candidate (log, cwc)		0.7413 (0.0212)***	0.8072 (0.0210)***	0.7971 (0.0211)***	0.7989 (0.0211)***	0.7536 (0.0213)***
Proportion of voters talked to (log, cm)		0.0598 (0.0563)	0.0586 (0.0562)	0.0720 (0.0566)	−0.0116 (0.0565)	0.0852 (0.0568)
Proportion of voters talked to (log, cwc)		0.1285 (0.0021)***	0.1279 (0.0021)***	0.1232 (0.0021)***	0.1269 (0.0021)***	0.1210 (0.0021)***
Talk centrality (cm)		11.2598 (3.8512)**	8.5093 (3.8492)*	7.9161 (3.8619)*	7.9941 (5.1126)	8.0436 (5.1396)
Talk centrality (cwc)		−1.1805 (0.0725)***	−1.1310 (0.0722)***	−1.0596 (0.0724)***	−1.2867 (0.0725)***	−1.0771 (0.0732)***
Difference candidate-voter talk centrality (cm)		−4.1964 (3.2587)	−6.2553 (3.2555)$^{+}$	−6.7348 (3.2673)*	−9.2478 (4.6496)*	−5.3455 (4.6987)
Difference candidate-voter talk centrality (cwc)		0.7549 (0.0388)***	0.8703 (0.0385)***	0.8539 (0.0386)***	0.6423 (0.0391)***	0.6736 (0.0393)***
Mainspace edits 2 months before (log, cm)		0.1217 (0.0527)*	0.1303 (0.0526)*	0.0936 (0.0526)$^{+}$	0.1408 (0.0530)**	0.1362 (0.0532)*
Mainspace edits 2 months before (log, cwc)		0.3549 (0.0056)***	0.3499 (0.0056)***	0.3525 (0.0056)***	0.3525 (0.0056)***	0.3551 (0.0056)***
Total edits up to election (log, cm)		1.2232 (0.0680)***	1.2112 (0.0677)***	1.2383 (0.0681)***	1.1454 (0.0680)***	1.2572 (0.0691)***
Total edits up to election (log, cwc)		0.4925 (0.0102)***	0.5021 (0.0105)***	0.4481 (0.0103)***	0.4785 (0.0104)***	0.4619 (0.0106)***
Difference candidate-voter in total edits (cm)		0.0829 (0.0117)***	0.0752 (0.0117)***	0.0777 (0.0117)***	0.0700 (0.0118)***	0.0852 (0.0118)***
Difference candidate-voter in total edits (cwc)		0.0193 (0.0003)***	0.0203 (0.0003)***	0.0205 (0.0003)***	0.0180 (0.0003)***	0.0184 (0.0003)***
Years since first edit (cm)		−0.0954 (0.0256)***	−0.0977 (0.0256)***	−0.0803 (0.0255)**	−0.0922 (0.0259)***	−0.0897 (0.0259)***
Years since first edit (cwc)		−0.0155 (0.0039)***	−0.0162 (0.0039)***	−0.0016 (0.0039)	−0.0160 (0.0039)***	−0.0021 (0.0039)
Was reverted by the candidate (cm)		−42.8025 (9.9219)***	−36.9079 (9.8913)***	−31.4133 (9.9161)**	−31.8035 (9.9921)**	−38.1711 (9.9768)***
Was reverted by the candidate (cwc)		0.1556 (0.0401)***	0.1283 (0.0400)**	0.1529 (0.0400)***	0.1839 (0.0400)***	0.1542 (0.0403)***
Reverted the candidate (cm)		43.9493 (10.1093)***	41.5774 (10.0820)***	30.2271 (10.1333)**	34.8049 (10.2191)***	38.9926 (10.1763)***
Reverted the candidate (cm)		0.1781 (0.0400)***	0.1809 (0.0399)***	0.1948 (0.0400)***	0.1894 (0.0399)***	0.2032 (0.0402)***
Year of election: 09-14 (Ref.: 03-08)		0.0311 (0.0159)$^{+}$	0.0031 (0.0158)	0.0546 (0.0159)***	0.0952 (0.0160)***	0.0668 (0.0161)***
Year of election: 15-20 (Ref.: 03-08)		0.3007 (0.0303)***	0.2878 (0.0302)***	0.2940 (0.0302)***	0.3404 (0.0302)***	0.2854 (0.0304)***
AIC	489910.6091	436430.3346	439151.1650	437681.0211	437720.7287	434265.8608
BIC	489934.2334	436831.9485	439552.7789	438082.6350	438145.9669	434761.9721
Log Likelihood	−244953.3045	−218181.1673	−219541.5825	−218806.5105	−218824.3643	−217090.9304
Num. obs.	996668	996668	996668	996668	996668	996668
Num. groups: id	13979	13979	13979	13979	13979	13979
Var: id (Intercept)	18.1338	6.1644	6.1491	6.1564	6.2805	6.2045

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$.

A.4.3.4 FE LPM

Table A105: Voting supportively, FE LPM.

	Model 1	Model 2	Model 3	Model 4	Full model
Met candidate	0.1567 (0.0057)***				0.1228 (0.0052)***
Been at meetings		0.0032 (0.0008)***			0.0009 (0.0009)
Proportion of voters met (log)			0.0068 (0.0006)***		0.0098 (0.0006)***
Meetup centrality				0.0905 (0.0116)***	−0.0923 (0.0138)***
Difference candidate-voter meetup centrality				0.0473 (0.0020)***	0.0273 (0.0017)***
Collaborated with the candidate	0.0550 (0.0017)***	0.0578 (0.0017)***	0.0574 (0.0017)***	0.0578 (0.0017)***	0.0551 (0.0017)***
Proportion of voters collaborated with (log)	−0.0008 (0.0002)***	−0.0008 (0.0002)***	−0.0010 (0.0002)***	−0.0008 (0.0002)***	−0.0010 (0.0002)***
Collaboration centrality	0.3538 (0.0346)***	0.3479 (0.0346)***	0.3675 (0.0347)***	0.3449 (0.0347)***	0.3753 (0.0346)***
Difference candidate-voter collaboration centrality	−0.0161 (0.0033)***	−0.0207 (0.0034)***	−0.0204 (0.0034)***	−0.0156 (0.0034)***	−0.0120 (0.0033)***
Talked to candidate (log)	0.1298 (0.0044)***	0.1397 (0.0045)***	0.1384 (0.0045)***	0.1384 (0.0045)***	0.1293 (0.0044)***
Proportion of voters talked to (log)	0.0164 (0.0011)***	0.0165 (0.0011)***	0.0158 (0.0011)***	0.0164 (0.0011)***	0.0155 (0.0011)***
Talk centrality	−0.1655 (0.0249)***	−0.1687 (0.0251)***	−0.1534 (0.0247)***	−0.1776 (0.0249)***	−0.1500 (0.0250)***
Difference candidate-voter talk centrality	0.0449 (0.0041)***	0.0517 (0.0042)***	0.0521 (0.0042)***	0.0365 (0.0041)***	0.0390 (0.0041)***
Mainspace edits 2 months before (log)	0.0098 (0.0010)***	0.0097 (0.0010)***	0.0096 (0.0010)***	0.0098 (0.0010)***	0.0095 (0.0010)***
Total edits up to election (log)	0.0376 (0.0032)***	0.0357 (0.0031)***	0.0331 (0.0031)***	0.0358 (0.0031)***	0.0333 (0.0031)***
Difference candidate-voter in total edits	0.0017 (0.0001)***	0.0018 (0.0001)***	0.0018 (0.0001)***	0.0016 (0.0001)***	0.0016 (0.0001)***
Years since first edit	−0.0006 (0.0010)	−0.0002 (0.0009)	0.0008 (0.0009)	−0.0004 (0.0009)	0.0006 (0.0009)
Was reverted by the candidate	0.0277 (0.0061)***	0.0277 (0.0061)***	0.0282 (0.0061)***	0.0276 (0.0061)***	0.0281 (0.0061)***
Reverted the candidate	0.0406 (0.0066)***	0.0407 (0.0066)***	0.0401 (0.0067)***	0.0411 (0.0066)***	0.0398 (0.0066)***
Year of election: 09-14 (Ref.: 03-08)	0.0018 (0.0040)	0.0004 (0.0040)	0.0029 (0.0040)	0.0057 (0.0040)	0.0038 (0.0040)
Year of election: 15-20 (Ref.: 03-08)	0.0164 (0.0061)**	0.0164 (0.0061)**	0.0154 (0.0061)*	0.0183 (0.0061)**	0.0155 (0.0061)*
R^2	0.07	0.07	0.07	0.07	0.08
Adj. R^2	0.06	0.06	0.06	0.06	0.06
Num. obs.	996668	996668	996668	996668	996668

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$.

A.4.3.5 FE GLM

Table A106: Voting supportively, FE GLM.

	Model 1	Model 2	Model 3	Model 4	Full model
Met candidate	1.2667 (0.0235)***				0.9364 (0.0250)***
Been at meetings		0.0212 (0.0015)***			0.0023 (0.0019)
Proportion of voters met (log)			5.1396 (0.1322)***		8.9714 (0.2428)***
Meetup centrality				0.8152 (0.0268)***	−0.8524 (0.0464)***
Difference candidate-voter meetup centrality				0.5073 (0.0126)***	0.3724 (0.0130)***
Collaborated with the candidate	0.4728 (0.0085)***	0.4891 (0.0084)***	0.4884 (0.0085)***	0.4896 (0.0085)***	0.4764 (0.0085)***
Proportion of voters collaborated with (log)	0.0377 (0.0635)	0.0124 (0.0634)	−0.0785 (0.0636)	0.1509 (0.0636)*	−0.0143 (0.0642)
Collaboration centrality	0.4494 (0.0840)***	0.4018 (0.0838)***	0.5056 (0.0840)***	0.3414 (0.0840)***	0.5687 (0.0845)***
Difference candidate-voter collaboration centrality	−0.0521 (0.0232)*	−0.0917 (0.0232)***	−0.0896 (0.0232)***	−0.0245 (0.0233)	0.0055 (0.0233)
Talked to candidate (log)	0.8940 (0.0184)***	0.9433 (0.0183)***	0.9379 (0.0183)***	0.9330 (0.0183)***	0.8938 (0.0185)***
Proportion of voters talked to (log)	12.7770 (0.1644)***	12.7948 (0.1643)***	12.4817 (0.1638)***	12.7353 (0.1643)***	12.3535 (0.1642)***
Talk centrality	−1.2049 (0.0628)***	−1.2185 (0.0626)***	−1.1521 (0.0626)***	−1.3314 (0.0628)***	−1.2047 (0.0632)***
Difference candidate-voter talk centrality	0.8789 (0.0282)***	0.9237 (0.0280)***	0.9316 (0.0281)***	0.7548 (0.0285)***	0.7776 (0.0286)***
Mainspace edits 2 months before (log)	0.4845 (0.0035)***	0.4833 (0.0035)***	0.4837 (0.0035)***	0.4844 (0.0035)***	0.4841 (0.0035)***
Total edits up to election (log)	0.5909 (0.0059)***	0.5875 (0.0061)***	0.5609 (0.0060)***	0.5782 (0.0060)***	0.5625 (0.0061)***
Difference candidate-voter in total edits	0.0203 (0.0002)***	0.0209 (0.0002)***	0.0210 (0.0002)***	0.0190 (0.0002)***	0.0190 (0.0002)***
Years since first edit	−0.0280 (0.0028)***	−0.0270 (0.0028)***	−0.0188 (0.0028)***	−0.0285 (0.0028)***	−0.0199 (0.0029)***
Was reverted by the candidate	0.1771 (0.0337)***	0.1755 (0.0336)***	0.1773 (0.0336)***	0.1761 (0.0336)***	0.1788 (0.0338)***
Reverted the candidate	0.2182 (0.0345)***	0.2210 (0.0344)***	0.2211 (0.0345)***	0.2256 (0.0344)***	0.2201 (0.0346)***
Year of election: 09-14 (Ref.: 03-08)	0.0093 (0.0120)	−0.0046 (0.0119)	0.0150 (0.0119)	0.0557 (0.0120)***	0.0360 (0.0121)**
Year of election: 15-20 (Ref.: 03-08)	0.2805 (0.0229)***	0.2772 (0.0228)***	0.2760 (0.0228)***	0.3065 (0.0228)***	0.2782 (0.0229)***
Log Likelihood	−389343.0627	−390687.2183	−390027.0893	−389898.2272	−388172.2940
Deviance	778686.1253	781374.4366	780054.1785	779796.4544	776344.5881
Num. obs.	2219322	2219322	2219322	2219322	2219322

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$.

A.4.4 Voting Supportively in Elections

A.4.4.1 Bivariate LPMs

Table A107: Voting supportively, bivariate LPM.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Intercept	0.7139 (0.0054)***	0.7155 (0.0054)***	0.7065 (0.0055)***	0.7340 (0.0054)***	0.7200 (0.0053)***	0.7536 (0.0046)***
Met candidate (cm)	1.5047 (0.1815)***					
Met candidate (cwc)	0.1418 (0.0065)***					
Been at meetings (cm)		0.0191 (0.0017)***				
Been at meetings (cwc)		−0.0010 (0.0011)				
Proportion of pro voters met (log, cm)			0.0168 (0.0012)***			
Proportion of pro voters met (log, cwc)			0.0123 (0.0008)***			
Proportion of anti voters met (log, cm)				0.0029 (0.0024)		
Proportion of anti voters met (log, cwc)				−0.0197 (0.0011)***		
Meetup centrality (cm)					0.3313 (0.0362)***	
Meetup centrality (cwc)					−0.0012 (0.0128)	
Difference candidate-voter meetup centrality (cm)						−0.3482 (0.0354)***
Difference candidate-voter meetup centrality (cwc)						0.1147 (0.0065)***
AIC	114945.4304	115636.8246	114220.3540	111361.8967	115654.4112	114791.0960
BIC	114993.7202	115685.1144	114268.6438	111410.1865	115702.7010	114839.3858
Log Likelihood	−57467.7152	−57813.4123	−57105.1770	−55675.9483	−57822.2056	−57390.5480
Num. obs.	115608	115608	115608	115608	115608	115608
Num. groups: id	2939	2939	2939	2939	2939	2939
Var: id (Intercept)	0.0366	0.0371	0.0365	0.0393	0.0375	0.0373
Var: Residual	0.1526	0.1535	0.1516	0.1477	0.1535	0.1523

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$.

A.4.4.2 REWB LPM

Table A108: Voting supportively, main LPM.

	Empty model	Model 1	Model 2	Model 3	Model 4	Full model
Intercept	0.7372 (0.0047)***	0.6668 (0.1046)***	0.6675 (0.1049)***	0.6555 (0.1019)***	0.5806 (0.1303)***	0.5615 (0.1252)***
Met candidate (cm)		1.0594 (0.1761)***				0.9248 (0.6002)
Met candidate (cwc)		0.1168 (0.0059)***				0.0076 (0.0057)
Been at meetings (cm)			0.0131 (0.0016)***			0.0081 (0.0023)***
Been at meetings (cwc)			0.0005 (0.0011)			−0.0001 (0.0011)
Proportion of pro voters met (log, cm)				0.0263 (0.0034)***		0.0271 (0.0042)***
Proportion of pro voters met (log, cwc)				0.0151 (0.0008)***		0.0175 (0.0012)***
Proportion of anti voters met (log, cm)				−0.0308 (0.0068)***		−0.0289 (0.0071)***
Proportion of anti voters met (log, cwc)				−0.0189 (0.0012)***		−0.0174 (0.0011)***
Meetup centrality (cm)					0.7615 (0.4830)	0.0796 (0.4853)
Meetup centrality (cwc)					0.1496 (0.0139)***	−0.0051 (0.0236)
Difference candidate-voter meetup centrality (cm)					0.5660 (0.4828)	0.4246 (0.4671)
Difference candidate-voter meetup centrality (cwc)					0.1386 (0.0056)***	0.1067 (0.0054)***
Collaborated with the candidate (cm)		0.0674 (0.0246)**	0.0774 (0.0247)**	0.0584 (0.0248)*	0.0769 (0.0247)**	0.0570 (0.0249)*
Collaborated with the candidate (cwc)		0.0127 (0.0035)***	0.0161 (0.0035)***	0.0138 (0.0033)***	0.0151 (0.0035)***	0.0126 (0.0033)***
Proportion of pro voters collaborated with (log, cm)		0.0036 (0.0012)**	0.0036 (0.0012)**	0.0032 (0.0011)**	0.0037 (0.0012)**	0.0035 (0.0011)**
Proportion of pro voters collaborated with (log, cwc)		0.0027 (0.0003)***	0.0027 (0.0003)***	0.0021 (0.0003)***	0.0029 (0.0003)***	0.0023 (0.0003)***
Proportion of anti voters collaborated with (log, cm)		0.0007 (0.0012)	0.0006 (0.0012)	0.0009 (0.0012)	0.0007 (0.0012)	0.0009 (0.0012)
Proportion of anti voters collaborated with (log, cwc)		−0.0004 (0.0001)**	−0.0005 (0.0001)***	−0.0001 (0.0001)	−0.0004 (0.0001)**	−0.0000 (0.0001)
Collaboration centrality (cm)		−0.3601 (0.2437)	−0.3697 (0.2446)	−0.2096 (0.2367)	−0.3873 (0.2541)	−0.2592 (0.2467)
Collaboration centrality (cwc)		−0.1578 (0.0490)**	−0.1697 (0.0488)***	−0.1362 (0.0473)**	−0.1735 (0.0487)***	−0.1335 (0.0471)**
Difference candidate-voter collaboration centrality (cm)		0.1275 (0.2028)	0.0970 (0.2039)	0.2248 (0.1994)	0.1007 (0.2163)	0.1675 (0.2120)
Difference candidate-voter collaboration centrality (cwc)		0.1835 (0.0167)***	0.1746 (0.0169)***	0.1939 (0.0158)***	0.1964 (0.0168)***	0.2147 (0.0158)***
Talked to candidate (log, cm)		−0.0329 (0.0350)	−0.0252 (0.0353)	−0.0266 (0.0356)	−0.0209 (0.0353)	−0.0319 (0.0356)
Talked to candidate (log, cwc)		0.0335 (0.0051)***	0.0411 (0.0052)***	0.0378 (0.0050)***	0.0387 (0.0051)***	0.0348 (0.0050)***
Proportion of pro voters talked to (log, cm)		0.0343 (0.0045)***	0.0347 (0.0046)***	0.0305 (0.0048)***	0.0346 (0.0046)***	0.0306 (0.0047)***
Proportion of pro voters talked to (log, cwc)		0.0188 (0.0011)***	0.0189 (0.0011)***	0.0159 (0.0011)***	0.0190 (0.0011)***	0.0157 (0.0011)***
Proportion of anti voters talked to (log, cm)		−0.0488 (0.0040)***	−0.0490 (0.0040)***	−0.0446 (0.0040)***	−0.0491 (0.0040)***	−0.0441 (0.0039)***
Proportion of anti voters talked to (log, cwc)		−0.0120 (0.0007)***	−0.0120 (0.0007)***	−0.0095 (0.0007)***	−0.0120 (0.0007)***	−0.0096 (0.0007)***
Talk centrality (cm)		0.2640 (0.3969)	0.3580 (0.3978)	0.2040 (0.3984)	0.5979 (0.5559)	0.5789 (0.5440)
Talk centrality (cwc)		−0.2537 (0.0301)***	−0.2513 (0.0303)***	−0.2025 (0.0305)***	−0.2896 (0.0303)***	−0.2202 (0.0301)***
Difference candidate-voter talk centrality (cm)		−0.4399 (0.3897)	−0.3516 (0.3911)	−0.5783 (0.3831)	−0.1123 (0.5445)	−0.1683 (0.5264)
Difference candidate-voter talk centrality (cwc)		−0.1502 (0.0124)***	−0.1414 (0.0125)***	−0.1247 (0.0122)***	−0.1905 (0.0124)***	−0.1633 (0.0122)***
Mainspace edits 2 months before (log, cm)		0.0148 (0.0063)*	0.0131 (0.0063)*	0.0123 (0.0062)*	0.0138 (0.0063)*	0.0111 (0.0062)+
Mainspace edits 2 months before (log, cwc)		0.0067 (0.0029)*	0.0065 (0.0030)*	0.0066 (0.0028)*	0.0062 (0.0030)*	0.0067 (0.0028)*
Total edits up to election (log, cm)		−0.0024 (0.0088)	−0.0021 (0.0088)	−0.0017 (0.0086)	−0.0033 (0.0089)	−0.0004 (0.0086)
Total edits up to election (log, cwc)		−0.0013 (0.0066)	0.0017 (0.0067)	−0.0028 (0.0064)	−0.0048 (0.0068)	−0.0023 (0.0064)
Difference candidate-voter in total edits (cm)		0.0002 (0.0012)	0.0004 (0.0012)	0.0001 (0.0011)	0.0002 (0.0012)	0.0004 (0.0011)
Difference candidate-voter in total edits (cwc)		0.0029 (0.0002)***	0.0030 (0.0002)***	0.0029 (0.0002)***	0.0025 (0.0002)***	0.0025 (0.0002)***
Years since first edit (cm)		0.0047 (0.0030)	0.0045 (0.0030)	0.0041 (0.0029)	0.0056 (0.0030)+	0.0042 (0.0029)
Years since first edit (cwc)		0.0096 (0.0018)***	0.0089 (0.0018)***	0.0084 (0.0018)***	0.0092 (0.0018)***	0.0079 (0.0018)***
Was reverted by the candidate (cm)		−2.4294 (0.8696)**	−2.4221 (0.8719)**	−2.3912 (0.8380)**	−2.3745 (0.8778)**	−2.5478 (0.8376)**
Was reverted by the candidate (cwc)		−0.0418 (0.0094)***	−0.0419 (0.0095)***	−0.0387 (0.0092)***	−0.0408 (0.0094)***	−0.0379 (0.0090)***
Reverted the candidate (cm)		−2.2007 (0.8617)*	−2.1433 (0.8548)*	−2.2209 (0.8417)**	−2.3063 (0.8692)**	−2.0128 (0.8357)*
Reverted the candidate (cwc)		−0.0629 (0.0097)***	−0.0639 (0.0097)***	−0.0575 (0.0097)***	−0.0630 (0.0097)***	−0.0566 (0.0097)***
Year of election: 09-14 (Ref.: 03-08)		−0.0081 (0.0078)	−0.0115 (0.0078)	−0.0012 (0.0076)	0.0049 (0.0079)	0.0062 (0.0076)
Year of election: 15-20 (Ref.: 03-08)		−0.0499 (0.0119)***	−0.0505 (0.0120)***	−0.0397 (0.0116)***	−0.0449 (0.0120)***	−0.0381 (0.0115)**
AIC	115694.0121	105477.1492	105985.3539	100912.0739	105076.1827	100244.0317
BIC	115722.9860	105853.8097	106362.0144	101308.0503	105472.1591	100717.2718
Log Likelihood	−57844.0060	−52699.5746	−52953.6770	−50415.0369	−52497.0913	−50073.0159
Num. obs.	115608	115608	115608	115608	115608	115608
Num. groups: id	2939	2939	2939	2939	2939	2939
Var: id (Intercept)	0.0387	0.0253	0.0255	0.0244	0.0255	0.0241
Var: Residual	0.1535	0.1408	0.1414	0.1353	0.1402	0.1344

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$.

A.4.4.3 REWB GLM

Table A109: Voting supportively, GLM.

	Empty model	Model 1	Model 2	Model 3	Model 4	Full model
Intercept	1.3300 (0.0298)***	0.7012 (0.6346)	0.8258 (0.6337)	0.6618 (0.6257)	−0.0068 (0.8070)	0.0534 (0.7890)
Met candidate (cm)		6.0007 (1.3511)***				−5.0574 (4.6770)
Met candidate (cwc)		1.2998 (0.0566)***				0.5249 (0.0659)***
Been at meetings (cm)			0.0871 (0.0127)***			0.0716 (0.0204)***
Been at meetings (cwc)			−0.0021 (0.0036)			−0.0081 (0.0046)$^{+}$
Proportion of pro voters met (log, cm)				0.3328 (0.0194)***		0.4125 (0.0279)***
Proportion of pro voters met (log, cwc)				0.1834 (0.0038)***		0.2236 (0.0058)***
Proportion of anti voters met (log, cm)				−0.3770 (0.0298)***		−0.3658 (0.0304)***
Proportion of anti voters met (log, cwc)				−0.1803 (0.0030)***		−0.1637 (0.0032)***
Meetup centrality (cm)					6.1543 (3.2076)$^{+}$	1.7113 (3.3018)
Meetup centrality (cwc)					1.1767 (0.0650)***	−0.3833 (0.1172)**
Difference candidate-voter meetup centrality (cm)					5.0838 (3.2056)	3.9711 (3.1420)
Difference candidate-voter meetup centrality (cwc)					1.1268 (0.0375)***	0.9065 (0.0397)***
Collaborated with the candidate (cm)		0.4599 (0.1811)*	0.5465 (0.1802)**	0.4092 (0.1794)*	0.5180 (0.1817)**	0.3128 (0.1790)$^{+}$
Collaborated with the candidate (cwc)		0.0692 (0.0208)***	0.0922 (0.0206)***	0.0846 (0.0215)***	0.0864 (0.0208)***	0.0755 (0.0216)***
Proportion of pro voters collaborated with (log, cm)		0.0316 (0.0082)***	0.0298 (0.0081)***	0.0256 (0.0080)**	0.0305 (0.0082)***	0.0301 (0.0080)***
Proportion of pro voters collaborated with (log, cwc)		0.0142 (0.0014)***	0.0143 (0.0014)***	0.0111 (0.0014)***	0.0159 (0.0014)***	0.0122 (0.0014)***
Proportion of anti voters collaborated with (log, cm)		−0.0111 (0.0073)	−0.0099 (0.0072)	−0.0065 (0.0072)	−0.0093 (0.0073)	−0.0083 (0.0072)
Proportion of anti voters collaborated with (log, cwc)		−0.0040 (0.0008)***	−0.0042 (0.0008)***	−0.0000 (0.0009)	−0.0036 (0.0008)***	0.0004 (0.0009)
Collaboration centrality (cm)		−1.7350 (1.5450)	−2.0621 (1.5446)	−0.4209 (1.5199)	−2.0014 (1.6404)	−1.2582 (1.6048)
Collaboration centrality (cwc)		−0.5497 (0.2102)**	−0.5996 (0.2099)**	−0.5707 (0.2187)**	−0.6528 (0.2103)**	−0.5380 (0.2198)*
Difference candidate-voter collaboration centrality (cm)		0.6673 (1.2984)	0.0823 (1.2984)	1.4641 (1.2803)	0.2305 (1.4165)	0.4873 (1.3931)
Difference candidate-voter collaboration centrality (cwc)		1.2699 (0.0669)***	1.2048 (0.0667)***	1.3790 (0.0693)***	1.3525 (0.0672)***	1.5740 (0.0700)***
Talked to candidate (log, cm)		−0.2900 (0.2814)	−0.2013 (0.2805)	−0.2174 (0.2798)	−0.2334 (0.2820)	−0.1674 (0.2796)
Talked to candidate (log, cwc)		0.2861 (0.0373)***	0.3401 (0.0370)***	0.3262 (0.0386)***	0.3208 (0.0372)***	0.2986 (0.0390)***
Proportion of pro voters talked to (log, cm)		0.4144 (0.0206)***	0.4147 (0.0206)***	0.3883 (0.0206)***	0.4302 (0.0209)***	0.3847 (0.0207)***
Proportion of pro voters talked to (log, cwc)		0.2082 (0.0041)***	0.2092 (0.0041)***	0.1851 (0.0042)***	0.2094 (0.0041)***	0.1839 (0.0042)***
Proportion of anti voters talked to (log, cm)		−0.4211 (0.0161)***	−0.4206 (0.0161)***	−0.3908 (0.0162)***	−0.4366 (0.0163)***	−0.3888 (0.0162)***
Proportion of anti voters talked to (log, cwc)		−0.0920 (0.0018)***	−0.0921 (0.0018)***	−0.0823 (0.0018)***	−0.0924 (0.0018)***	−0.0828 (0.0018)***
Talk centrality (cm)		0.3907 (2.5592)	1.2376 (2.5559)	0.3331 (2.5083)	3.5463 (3.7144)	3.2965 (3.6248)
Talk centrality (cwc)		−2.5510 (0.1402)***	−2.5424 (0.1397)***	−1.9560 (0.1470)***	−2.8236 (0.1409)***	−2.1834 (0.1484)***
Difference candidate-voter talk centrality (cm)		−0.7419 (2.5346)	0.2841 (2.5315)	−1.2114 (2.4837)	2.4224 (3.6802)	1.6418 (3.5972)
Difference candidate-voter talk centrality (cwc)		−1.1341 (0.0772)***	−1.0634 (0.0768)***	−0.9860 (0.0798)***	−1.4147 (0.0783)***	−1.3707 (0.0814)***
Mainspace edits 2 months before (log, cm)		0.0819 (0.0402)*	0.0615 (0.0402)	0.0650 (0.0394)$^{+}$	0.0649 (0.0407)	0.0416 (0.0396)
Mainspace edits 2 months before (log, cwc)		0.0298 (0.0134)*	0.0217 (0.0133)	0.0280 (0.0137)*	0.0221 (0.0134)$^{+}$	0.0300 (0.0138)*
Total edits up to election (log, cm)		−0.0195 (0.0549)	−0.0232 (0.0549)	−0.0269 (0.0542)	−0.0248 (0.0556)	−0.0114 (0.0545)
Total edits up to election (log, cwc)		−0.0836 (0.0225)***	−0.0527 (0.0232)*	−0.0891 (0.0237)***	−0.1062 (0.0232)***	−0.0864 (0.0242)***
Difference candidate-voter in total edits (cm)		0.0011 (0.0073)	0.0036 (0.0073)	0.0024 (0.0071)	0.0025 (0.0074)	0.0032 (0.0071)
Difference candidate-voter in total edits (cwc)		0.0195 (0.0006)***	0.0201 (0.0006)***	0.0202 (0.0006)***	0.0166 (0.0006)***	0.0171 (0.0006)***
Years since first edit (cm)		0.0489 (0.0184)**	0.0456 (0.0184)*	0.0371 (0.0180)*	0.0562 (0.0187)**	0.0401 (0.0182)*
Years since first edit (cwc)		0.0733 (0.0083)***	0.0690 (0.0083)***	0.0650 (0.0086)***	0.0718 (0.0084)***	0.0631 (0.0086)***
Was reverted by the candidate (cm)		−12.5175 (5.6589)*	−11.1936 (5.6490)*	−11.9436 (5.5131)*	−12.6243 (5.7333)*	−12.5869 (5.5049)*
Was reverted by the candidate (cwc)		−0.3145 (0.0666)***	−0.3140 (0.0661)***	−0.2945 (0.0688)***	−0.3120 (0.0664)***	−0.3005 (0.0692)***
Reverted the candidate (cm)		−15.0752 (5.6018)**	−15.4133 (5.5861)**	−16.4889 (5.4501)**	−15.8118 (5.6771)**	−14.3451 (5.4479)**
Reverted the candidate (cwc)		−0.4584 (0.0660)***	−0.4476 (0.0657)***	−0.4443 (0.0686)***	−0.4490 (0.0659)***	−0.4304 (0.0691)***
Year of election: 09-14 (Ref.: 03-08)		−0.0143 (0.0340)	−0.0509 (0.0338)	−0.0359 (0.0355)	0.0571 (0.0345)$^{+}$	0.0143 (0.0360)
Year of election: 15-20 (Ref.: 03-08)		−0.2957 (0.0621)***	−0.3203 (0.0619)***	−0.3081 (0.0639)***	−0.2882 (0.0623)***	−0.3187 (0.0643)***
AIC	112868.2278	101330.2195	101996.6550	95887.8268	101024.3145	94915.8615
BIC	112887.5437	101697.2220	102363.6575	96274.1452	101410.6329	95379.4436
Log Likelihood	−56432.1139	−50627.1097	−50960.3275	−47903.9134	−50472.1572	−47409.9308
Num. obs.	115608	115608	115608	115608	115608	115608
Num. groups: id	2939	2939	2939	2939	2939	2939
Var: id (Intercept)	1.4764	0.9936	0.9961	0.9140	1.0138	0.9034

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$.

A.4.4.4 FE LPM

Table A110: Voting supportively, FE LPM.

	Model 1	Model 2	Model 3	Model 4	Full model
Met candidate	0.1144 (0.0060)***				0.0069 (0.0057)
Been at meetings		0.0003 (0.0011)			−0.0001 (0.0011)
Proportion of pro voters met (log)			1.5075 (0.0793)***		1.7596 (0.1240)***
Proportion of anti voters met (log)			−1.8861 (0.1164)***		−1.7410 (0.1120)***
Meetup centrality				0.1472 (0.0141)***	−0.0067 (0.0240)
Difference candidate-voter meetup centrality				0.1376 (0.0057)***	0.1060 (0.0054)***
Collaborated with the candidate	0.0130 (0.0035)***	0.0163 (0.0035)***	0.0141 (0.0033)***	0.0154 (0.0035)***	0.0129 (0.0033)***
Proportion of pro voters collaborated with (log)	0.2692 (0.0348)***	0.2671 (0.0348)***	0.2138 (0.0341)***	0.2888 (0.0348)***	0.2281 (0.0342)***
Proportion of anti voters collaborated with (log)	−0.0433 (0.0136)**	−0.0464 (0.0137)***	−0.0056 (0.0129)	−0.0381 (0.0135)**	−0.0015 (0.0127)
Collaboration centrality	−0.1603 (0.0500)**	−0.1720 (0.0498)***	−0.1376 (0.0482)**	−0.1764 (0.0497)***	−0.1336 (0.0481)**
Difference candidate-voter collaboration centrality	0.1807 (0.0169)***	0.1721 (0.0171)***	0.1912 (0.0160)***	0.1937 (0.0170)***	0.2119 (0.0160)***
Talked to candidate (log)	0.0335 (0.0051)***	0.0410 (0.0052)***	0.0377 (0.0050)***	0.0386 (0.0051)***	0.0347 (0.0050)***
Proportion of pro voters talked to (log)	1.8779 (0.1139)***	1.8924 (0.1151)***	1.5899 (0.1061)***	1.9009 (0.1149)***	1.5701 (0.1066)***
Proportion of anti voters talked to (log)	−1.1961 (0.0707)***	−1.2016 (0.0710)***	−0.9511 (0.0666)***	−1.2017 (0.0710)***	−0.9603 (0.0669)***
Talk centrality	−0.2565 (0.0305)***	−0.2542 (0.0307)***	−0.2049 (0.0309)***	−0.2918 (0.0307)***	−0.2222 (0.0305)***
Difference candidate-voter talk centrality	−0.1508 (0.0126)***	−0.1425 (0.0126)***	−0.1255 (0.0124)***	−0.1910 (0.0126)***	−0.1638 (0.0123)***
Mainspace edits 2 months before (log)	0.0070 (0.0031)*	0.0069 (0.0031)*	0.0068 (0.0030)*	0.0065 (0.0031)*	0.0068 (0.0030)*
Total edits up to election (log)	−0.0008 (0.0069)	0.0025 (0.0071)	−0.0021 (0.0067)	−0.0042 (0.0071)	−0.0017 (0.0068)
Difference candidate-voter in total edits	0.0029 (0.0002)***	0.0030 (0.0002)***	0.0029 (0.0002)***	0.0025 (0.0002)***	0.0025 (0.0002)***
Years since first edit	0.0094 (0.0019)***	0.0088 (0.0019)***	0.0083 (0.0018)***	0.0090 (0.0019)***	0.0078 (0.0018)***
Was reverted by the candidate	−0.0395 (0.0094)***	−0.0396 (0.0095)***	−0.0366 (0.0092)***	−0.0387 (0.0094)***	−0.0358 (0.0091)***
Reverted the candidate	−0.0623 (0.0098)***	−0.0631 (0.0098)***	−0.0568 (0.0098)***	−0.0621 (0.0097)***	−0.0559 (0.0097)***
Year of election: 09-14 (Ref.: 03-08)	−0.0075 (0.0079)	−0.0108 (0.0080)	−0.0006 (0.0078)	0.0055 (0.0081)	0.0068 (0.0078)
Year of election: 15-20 (Ref.: 03-08)	−0.0483 (0.0123)***	−0.0490 (0.0124)***	−0.0384 (0.0119)**	−0.0427 (0.0123)***	−0.0365 (0.0119)**
R^2	0.08	0.08	0.12	0.09	0.12
Adj. R^2	0.06	0.05	0.10	0.06	0.10
Num. obs.	115608	115608	115608	115608	115608

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$.

A.4.4.5 FE GLM

Table A111: Voting supportively, FE GLM.

	Model 1	Model 2	Model 3	Model 4	Full model
Met candidate	1.2851 (0.0576)***				0.5808 (0.0668)***
Been at meetings		0.0002 (0.0034)			−0.0065 (0.0045)
Proportion of pro voters met (log)			18.2678 (0.3789)***		21.8222 (0.5873)***
Proportion of anti voters met (log)			−18.4963 (0.3055)***		−16.9158 (0.3324)***
Meetup centrality				0.9927 (0.0594)***	−0.3849 (0.1150)***
Difference candidate-voter meetup centrality				0.9159 (0.0291)***	0.7750 (0.0302)***
Collaborated with the candidate	0.0778 (0.0175)***	0.0927 (0.0174)***	0.0895 (0.0179)***	0.0917 (0.0175)***	0.0852 (0.0180)***
Proportion of pro voters collaborated with (log)	1.2856 (0.1178)***	1.2657 (0.1176)***	1.0747 (0.1219)***	1.4215 (0.1180)***	1.1795 (0.1227)***
Proportion of anti voters collaborated with (log)	−0.0999 (0.0705)	−0.1175 (0.0703)+	0.1909 (0.0741)**	−0.0590 (0.0706)	0.2305 (0.0743)**
Collaboration centrality	−0.7092 (0.1791)***	−0.7650 (0.1788)***	−0.7418 (0.1842)***	−0.7903 (0.1792)***	−0.7332 (0.1850)***
Difference candidate-voter collaboration centrality	1.2749 (0.0540)***	1.2330 (0.0539)***	1.3475 (0.0552)***	1.3621 (0.0542)***	1.4864 (0.0556)***
Talked to candidate (log)	0.2594 (0.0334)***	0.3015 (0.0331)***	0.2852 (0.0342)***	0.2859 (0.0333)***	0.2544 (0.0345)***
Proportion of pro voters talked to (log)	26.2595 (0.3878)***	26.4749 (0.3882)***	24.6583 (0.3962)***	26.4973 (0.3884)***	24.6869 (0.3972)***
Proportion of anti voters talked to (log)	−11.9089 (0.1694)***	−11.8782 (0.1688)***	−11.2599 (0.1733)***	−11.9898 (0.1697)***	−11.3295 (0.1739)***
Talk centrality	−3.0903 (0.1332)***	−3.1108 (0.1329)***	−2.6531 (0.1387)***	−3.3545 (0.1339)***	−2.8431 (0.1399)***
Difference candidate-voter talk centrality	−1.1053 (0.0616)***	−1.0539 (0.0614)***	−1.0319 (0.0627)***	−1.3791 (0.0625)***	−1.3340 (0.0640)***
Mainspace edits 2 months before (log)	0.0354 (0.0093)***	0.0359 (0.0093)***	0.0343 (0.0095)***	0.0323 (0.0094)***	0.0345 (0.0095)***
Total edits up to election (log)	−0.0308 (0.0146)*	−0.0137 (0.0150)	−0.0241 (0.0152)	−0.0465 (0.0150)**	−0.0341 (0.0154)*
Difference candidate-voter in total edits	0.0227 (0.0005)***	0.0231 (0.0005)***	0.0234 (0.0005)***	0.0202 (0.0005)***	0.0207 (0.0005)***
Years since first edit	0.0637 (0.0066)***	0.0607 (0.0066)***	0.0548 (0.0067)***	0.0603 (0.0066)***	0.0536 (0.0068)***
Was reverted by the candidate	−0.3977 (0.0591)***	−0.3920 (0.0588)***	−0.3912 (0.0606)***	−0.3891 (0.0590)***	−0.3909 (0.0608)***
Reverted the candidate	−0.5283 (0.0603)***	−0.5284 (0.0600)***	−0.5284 (0.0621)***	−0.5200 (0.0602)***	−0.5142 (0.0624)***
Year of election: 09-14 (Ref.: 03-08)	−0.0340 (0.0287)	−0.0506 (0.0286)+	−0.0511 (0.0296)+	0.0429 (0.0291)	0.0076 (0.0300)
Year of election: 15-20 (Ref.: 03-08)	−0.3202 (0.0513)***	−0.3265 (0.0512)***	−0.3247 (0.0524)***	−0.2888 (0.0514)***	−0.3141 (0.0526)***
Log Likelihood	−76196.2081	−76512.0505	−73616.6600	−75982.3908	−73092.1527
Deviance	152392.4161	153024.1011	147233.3199	151964.7815	146184.3054
Num. obs.	175765	175765	175765	175765	175765

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$.

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