THE ECOLOGY OF MANAGEMENT CONCEPTS

ABSTRACT

How does the popularity of a concept depend on how it contrasts with and complements existing concepts? We argue that being similar to existing concepts, being located in a popular domain, and being combined with similar existing concepts is important for gaining attention early on but less important and even negative for sustaining popularity. To examine this question, we focus on the rise and fall of management concepts. We analyze data on the rise and fall of keywords in the Harvard Business Review between 1922 and 2010. Multiple tests confirm our hypotheses. The implication is that lessons learned from studies of popular concepts can be misleading as guides for how to make novel concepts popular.

INTRODUCTION

The question why certain practices and concepts become popular have long interested sociologists and organizational scholars. A long tradition of diffusion research in organization studies has examined how management practices and concepts spread (Abrahamson 1996; Carson et al. 2000; David and Strang 2006; Rogers 2003; Strang and Soule 1998). Studies of fads and fashions have explored how fads are impacted by the external environment, supporting institutions such as consulting firms, and the prevailing ethos (Abrahamson 1996; Carson et al. 2000).

Researchers have typically focused on the diffusion of one or a few management practices in isolation and paid less attention to relationships between the management practices and concepts undergoing diffusion (Denrell and Kovacs, 2008; Denrell and Kovacs 2015). In this paper, we argue that the popularity of a management concept is partly driven by how it contrasts with and complements existing popular concepts. Moreover, we suggest that the importance of contrasting or complementing existing popular concepts may change over time depending on how popular a concept has become. Connections to an existing concept can attract attention and such attention may be crucial for a novel concept (Kennedy 2008). Being tied to an existing concept may have negative long-term consequences, however, once the novel concept has achieved some level of recognition (Zuckerman et al. 2003). A new management concept that refines an already popular concept has an easier time to get accepted but competition from the popular concept may limit the growth of such a derivative concept. Contrasting with existing popular concepts, or combining existing ideas in a novel way, may initially confuse audiences although the effects may be positive once such a concept has received a given level of popularity.

The idea that the diffusion of an object or a concept depends on how it complements or contrasts with existing objects is not new. Theorists have long acknowledged that such ecological

effects are important. For example, Strang and Soule argue that diffusion studies need to pay more attention to 'How innovations compete and support each other' (Strang and Soule 1998: 285). A few studies have examined the how the fate of novel combinations depends on how they relate to existing concepts, including Kennedy (2008) and Ruef (2000). More common are studies of how the rise of a given management concept, such as total quality management, depends on how the concept resonates with management themes (such as cost cutting or rationalization) prevailing at the time (Abrahamson and Fairchild 1999; Barley and Kunda 1992; David and Strang 2006). Studies of the impact of categories have also explored how evaluations of an object or an innovation depends on whether it adheres to or straddles existing classification schemes (Hannan et al. 2007; Hsu 2006; Rao et al. 2003). Nevertheless, to our knowledge, there are no large-scale empirical studies of how the popularity of management concepts depend on how they compare to existing management concepts. Part of the reason is data limitation and the dominance of the single practice research design in studies of management fashion. Most studies of management fashion examine the trajectories of one or a few practices or concepts. Moreover, most studies focus on practices and concepts that are or once were popular (Denrell and Kovács 2008, 2015). Studying ecological effects requires data on multiple trajectories and data on popular as well as unpopular concepts. If only popular concepts are studied, the effect of unpopular related concepts cannot be explored. Lessons learned from studies of concepts that became popular can also be misleading if contrasting with existing concepts only works well once a concept has reached a certain level of popularity.

The purpose of this paper is to systematically study how affiliation with and contrast to other concepts influence the diffusion of a focal concept and to see if the importance of affiliation and contrast matters more or less for a concept that is already popular. To examine this issue, one needs

to analyze a dataset that includes many different concepts, of different levels of popularity, and which does not suffer from selection bias[1]. To obtain such a dataset, we study the diffusion of management concepts by relying on media mentions. Media mentions have often been used in management studies, especially in studies of fads and fashions (Abrahamson and Fairchild 1999; David and Strang 2006). Past studies have often focused on concepts that have once been popular (such as total quality management). In studies of media mentions it is possible to (mostly) avoid this selection bias, however, by including data on all concepts, popular and less popular, in the analysis. To achieve this, we analyze the article keywords in the archive of the Harvard Business Review. Keywords (or key 'phrases' since it is not just one word) include popular concepts such as 'Total Quality Management', general topics such as 'CEO compensation', as well as less well-known phrases such as 'Cyberschool'. To avoid sampling on popular management concepts, we include all keywords ever used in a Harvard Business Review article (see the Methods section for more detail about our methods).

By using a large dataset including numerous management concepts, we explore how similarity to other concepts and affiliation to popular concepts impact the popularity of a focal concept. By using a dataset that includes less popular and well as popular concepts, we are also able to explore whether affiliation effects are contingent on the level of popularity. For example, being located in a popular domain or being combined with similar existing management concepts may be crucial for novel and less popular concepts but may be of less significance or even negative for already popular concepts. We demonstrate that affiliation with other concepts has an important effect on the popularity of management concepts. Moreover, the effect of affiliation with other concepts is

[1] Fully avoiding a selection bias is not possible even if one studies all concepts mentioned in written archives, as some less used management concepts may not even make it to such archives.

contingent on the level of popularity: being located in a popular domain and being combined with similar existing categories matters much more for novel and less popular concepts.

THEORY AND HYPOTHESES

Studies of diffusion and of fads and fashions have explored how diffusion is influenced by the technical and economic advantages of the object under diffusion (Abrahamson and Fairchild, Armour and Teece 1978; Carson et al, 2000; Chandler 1962; Rogers 2003), the number of past adopters (Lieberson 2000; Salganik et al. 2006; Schelling 1978), as well as the centrality and status of prior adopters (Bothner 2003; Davis 1991; Haunschild and Miner 1997). Less explored, at least empirically, are "ecological effects" in diffusion, i.e., how the diffusion of a focal practice or concept depends on how it relates to other practices or concepts. Nevertheless, theoretical work on management fashion and on diffusion, as well as the literature on competition between firms, suggest several mechanisms by which the diffusion of a practice or a management concept depends on other, simultaneously diffusing, practices or concepts. Here we rely on this broad set of literatures to develop hypotheses about how the popularity of a focal managerial concept depends on the popularity of other managerial concepts. Not all of these literatures have been directly applied to issues of fads and fashions, but as we discuss below, we believe that they all provide useful insights to understand the ecology of management concepts.

Affiliation with Popular Others

The popularity of a novel concept may depend on the popularity of other concepts that the new concept links to and refers to. For example, a novel concept may suggest a different solution to a problem an established concept tries to solve. A novel concept may also criticize and seek to

replace an existing popular concept. How does such affiliation with established popular concepts impact the popularity of a novel concept?

Management researchers have demonstrated that affiliation with popular and high-status other individuals and firms usually provides benefits. Affiliation with high-status firms can provide a quality signal to outsiders (Stuart et al. 1999). High status also increases the size of audiences (Kovacs and Sharkey 2014), thereby increasing the potential pool of adopters. Affiliation with resourceful individuals or firms can also provide direct material benefits (access to capital) and informational advantages (inside information about value opportunities). Being associated with high-status others, even if such association provides no resources and has no signal-value, can also lead to more positive evaluations of an actor or object because the audience has more positive memories of such actors and objects (Cialdini et al. 1976).

Many of these arguments, which were developed about the association between organizations, can also apply to management concepts. To gain attention, it is likely important for a novel concept to affiliate with existing popular concepts. A novel concept can also gain attention by providing a novel solution to a problem made famous by an established concept. Another tactic for gaining attention is to criticize a popular concept. Even such a tactic relies on affiliation with a popular concept if affiliation is defined as linking to (but not necessarily affirming) a popular concept. Linking to already popular concepts is also a way to signal the relevance of the new concept. These arguments suggest a positive effect of affiliation with popular concepts.

There are reasons to believe that such a positive effect is less relevant for popular concepts. Gaining attention may be crucial for novel concepts but less important for already popular concepts. Thus, the positive effect of affiliation might be small or insignificant for popular concepts. One could also argue that the effect of affiliation with popular others can be negative for

popular concepts. The reason is that novel concepts may be overshadowed by association with a popular concept: while the new concept gains attention it never establishes an identity of its own. For example, in a study of the survival of firms, Kennedy (2008) shows that entrants benefit from press coverage that makes a few, but not too many, links to other entrants, because making such links help audiences perceive an emerging category. Press coverage that makes several links to other entrants, however, is associated with lower growth and decreased survival chances for entering firms (Kennedy 2008). These arguments about competitive effects can also apply to management concepts. A negative competitive effect is most relevant for already popular concepts, that do not benefit from any increased attention that comes with linking to popular concepts. A study of book sales provide evidence broadly consistent with this: Berger and colleagues (2010) find that even negative reviews in the New York Times benefit books by less well-known authors due to the publicity such reviews generate. For books by established authors, however, negative reviews hurt book sales. Because the positive effects of attention that follows from affiliating with popular others, likely only hold for concepts that are not already popular, we hypothesize that:

Hypothesis 1: Affiliation with popular concepts increases future popularity of focal concepts with low levels of popularity, has only a small positive effect on the future popularity of popular concepts, and decreases future popularity of concepts with high levels of popularity.

Hypothesis 1 specifies a causal effect of affiliating with other popular concepts. A positive estimated effect of affiliating with popular concepts, however, may just reflect that audiences like such concepts. Thus, there may be no causal effect of being mentioned with popular other concepts. Such affiliation may merely indicate that the focal concept has features similar to those of popular concepts and it may be this underlying similarity in features that drive the effect. Because our data is associational, we cannot distinguish between these alternative interpretations. Nevertheless, we

believe it is interesting, at least as a first attempt, to study the association between affiliation with popular others and popularity growth even if our research design cannot determine the mechanism responsible for such an association. In addition, note that evidence consistent with Hypothesis 1, which postulates that affiliating with popular others is negative for already popular concepts, is inconsistent with a simple version of the unobserved heterogeneity story. If affiliating with popular others only reflects unobserved heterogeneity in the demand for certain concepts, then the effect would be non-negative for all popularity ranges. (We also note that in the empirics we include fixed effects for the management concepts, in an attempt to rule out this unobserved heterogeneity.)

Local Crowding and the Popularity of Similar Concepts

The popularity of a novel concept is likely to be most influenced by similar other concepts. Whether the novel concept gains attention, acceptance, and resources depends on how the novel concept is positioned relative to similar existing concepts. Does the novel concept try to compete in an already crowded space, in which there are several similar and popular concepts? Or is the novel concept located in a less crowded space, with few other similar and popular concepts? A novel concept about performance-based incentives and bonuses, a topic much discussed recently, might attract attention but the existence of several similar popular concepts might make it less likely that the novel concept gains traction. A concept that tries to introduce a new set of issues, unrelated to existing popular concepts, could make it bigger, but faces an uphill battle since people might be less interested in and aware of the topic.

To theorize about these effects we draw upon the literature on competition and legitimacy among firms and technologies that has been developed in the population ecology tradition within organization theory (Carnabuci 2010; Hannan and Freeman 1989; McPherson 1983; Podolny and

Stuart 1995) as well as the literature on strategic balance in strategic management (Deephouse 1999; Zhao et al 2017; Zuckerman 2016).

Several, but not all, of the theoretical arguments used in these literatures apply here. First, cognitive legitimacy (Suchman 1995) likely matters: being similar to already popular concepts can increase acceptance to a focal concept (Aldrich and Fiol 1994). A concept that refines an existing popular concept, for example, has an existing audience and does not have to explain why the new concept might be relevant. Hence it is not surprising that many popular concepts, such as total quality management, have spawned a series of derivative concepts (David and Strang 2006). Attention also likely matters: people have already heard about a popular concept and similar concept gain from such attention. Being similar to a popular concept probably also matters due to technical complementarities: the effectiveness of one practice depends on the prevalence of other practices (Milgrom and Roberts 1995). For example, studies have shown that flexible manufacturing practices and human resource practices are complementary (Ichniowski et al. 1997). To the extent that the popularity of a management concept is related to the advantages of adopting the management practices the concept describes, the popularity of a management concept would depend on the popularity of complementary practices. Finally, note that the finding that a concept is more likely to become popular if it is similar to other popular concepts can result from unobserved heterogeneity: the fact that there exist many popular concepts similar to the focal concept indicates that there is demand for this type of concepts. All of these arguments suggest that a focal concept will benefit from being similar to other popular concepts.

There are also theoretical arguments for why being similar to other popular concepts can reduce the popularity of a focal concepts. Theories of density dependence (Hannan and Freeman 1989) and strategic balance (Deephouse 1999), which focus on firm performance, emphasize

crowding and competition. Their argument is that performance is lower if there are many firms offering similar services or products, because the availability of substitutes reduces demand and the price a firm can charge. For example, McPherson (1983) demonstrates that non-profit organizations that target similar audiences (e.g., similar age groups) will face higher competition. To gain a competitive advantage, firms thus need to focus on rare competencies (Barney 1991).

To what extent do these mechanisms apply to the popularity of management concepts? On the one hand, management concepts are often promoted by for-profit firms, such as consultancies (Strang et al 2014), and such firms do strive to achieve a competitive advantage and in doing so they may want to focus on unique ideas. Similarly, adopters to management concepts are for-profit firms that may want to be the first adopters of unique ideas, to gain competitive advantage. On the other hand, the popularity of concepts does not solely depend on its performance consequences. Due to fads a concept with negative performance effects may still become widely discussed. Moreover, even if adopting a widely diffused concept does not provide a firm with a competitive advantage, adopting it may be necessary to avoid a disadvantage and obtaining a performance below the average. Diffusion of a management practice thus differs from its impact on profitability, with early adopters experiencing performance improvements while later adopters do not (Armour and Teece 1978). It follows that competitive uniqueness does not necessarily drive popularity. Still, the general idea of crowding, due to limits on attention and resources, does apply to popularity. There is likely a crowding effect that limits the probability that a new concept will become very popular. If a concept such as Total Quality Management has become popular and well-known, then a new concept, which is very similar and also focuses on quality, is unlikely to become equally popular due to the psychological first-mover advantage an established concept has. Such a crowding effect is likely only relevant for concepts that have reached a high level of

popularity. Moreover, such a crowding effect may not exist for derivative concepts, which are similar to a popular concept but seek to build a popular concept. Consider, for example, a concept focused on how to implement TQM. Such a concept only seems to gain from being similar to TQM in all aspects except the crucial aspect that this concept is focused on implementation.

Given these competing predictions, what can be said about the main effect of being similar to other popular concepts? As recently stressed in the literature on strategic balance by Haans (2019; see also Hannan and Carroll 1992), this depends on the functional forms relating legitimacy and competition effects to similarity. We believe the legitimacy (and attention) effects are dominant for most levels of similarity, except possibly at very high levels of similarity. We thus predict that being similar to popular concepts increases the future popularity of a focal concept, except at very high levels of similarity where being similar to popular concepts may decrease the future popularity of a focal concept. Our focus is not on the main effect of similarity, however, but on how the effect of being similar to other popular concepts depends on the popularity of a concept. We argue that the positive, attention and legitimacy enhancing, effects will dominate for concepts that are not yet very popular. Such concepts can benefit a lot from gaining acceptance and attention by being located in a domain with many similar popular concepts. Moreover, the growth of a concept which is not yet very popular is not constrained much by the popularity of similar concepts. The reverse holds for an already popular concept. Popular concepts do not benefit much from increased awareness. The competitive effect may also matter for popular concepts: the growth of a popular concept is likely constrained by being similar to other popular concepts. Overall, these arguments suggest that the effect of being similar to other popular concepts depends on the popularity of a focal concept:

Hypothesis 2: Similarity to other popular concepts increases future popularity of focal

concepts with low levels of popularity, has only a small positive effect on the future popularity of popular concepts, and decreases future popularity of concepts with high levels of popularity.

How is this hypothesis about the effect of being similar to popular others different from hypothesis 1, about the effect of affiliating with popular others? The answer is that affiliation and similarity are not the same constructs. A concept A is affiliated with concept B if discussion about concept A mentions concept B. This can occur even if concept A and B are not similar. Moreover, two concepts may be similar in content and application even if they are never discussed together. Hence, concepts A and B may be similar even if discussions about A never mention B or vice versa.

Combining Dissimilar Concepts

The popularity of a novel cultural concept not only depends on whether it affiliates with popular others (Hypothesis 1) and how similar it is to existing popular concepts (Hypothesis 2) but also on whether it combines similar or very different elements (Goldberg 2011; Hannan et al. 2007). Consider, for example, a novel concept *i* that occurs together with two other keywords, A and B. Suppose the focal concept *i* is similar to A and that A is a popular concept. Suppose the focal concept *i* is not at all similar to B but B is an unpopular concept. The similarity weighted popularity of the concept that the focal concept is linked to is high, but the focal concept is linked to a concept which it is not similar to (i.e., linked to B). Does this link to B make the focal concept more popular?

Research on consumer products and organizations have argued that while objects that crosses cultural classifications and combines unusual elements may attract attention, they are often devalued for two reasons (Hannan et al. 2007; Hannan et al. 2019). First, category spanning objects

violate audience expectations. Such violations lead to confusion and such confusion, they postulate, mainly has negative consequences. A recent restatement of the theory (Hannan et al. 2019) proposes that the reason for this negative effect of confusion is that audiences cannot be sure that an object which is difficult to evaluate have the characteristics that the audiences care about. Zuckerman (1999) proposed a similar idea: objects containing elements that few evaluators have experience in evaluating will be devalued because there are few evaluators who can assess these objects. A second theoretical mechanism behind devaluation is that the skills required for high performance may differ across categories. If there are benefits to specialization, an object which is not specialized but combines distinct elements, is unlikely to perform well. Audiences may also suspect that an object that is not specialized will perform poorly, which matters if performance cannot be perfectly observed before purchase.

Consistent with this theory, empirical research on consumer products, organizations, and individuals has shown that objects that span distinct categories are often evaluated less favorably than objects that adhere to established cultural genres (Hannan 2010, Kovacs and Hannan 2015). For example, a movie that contains elements associated with westerns, horror movies, comedy, and documentaries, is predicted to be devalued and consistent with this, Hsu (2006) shows that movies that combines many genres are rated lower. Similarly, Zuckerman et al. (2003) show that actors who cross genres progress slower in their careers.

We propose that similar theoretical mechanisms apply to management concepts. First, a concept that combines elements that are seldom combined will confuse audiences. The implication is that few members of the audience will feel competent to evaluate this concept. Consider, for example, a category spanning management concept about organizational culture that referred both to ideas about shared values and to ideas about optimization. While such a category spanning

concept stands out and might generate attention, few readers will be able to evaluate this concept. We here use 'evaluate' in a general sense: "coming up with an evaluation of." The point is that it is less likely that many members of an audience will become highly enthusiastic about a concept if the discourse about this concept contain several elements they do not understand (the possible exception is when people, perhaps academics, get excited about concepts because they are difficult to understand; managers generally seem less susceptible to this). It is more likely that members of an audience will become highly enthusiastic about a concept if they can relate to and understand most of the points made in the discourse about this concept. Second, the skills of promoters that lead to positive evaluations may differ substantially between two audiences. If there are benefits to specialization, it is then unlikely that a concept combining elements from these two audiences will be successfully marketed to both audiences. Audiences may also suspect that if a keyword from a distinct tradition is mentioned (optimization, say) then this indicates that the writer cannot fully understand a distinct concept such as organizational culture. We thus suggest that the main effect of being combining similar elements is positive.

While the main effect of combining similar elements is positive, the effect may vary with the level of popularity. Popular concepts may suffer less from the penalties of spanning categories and may even benefit. For example, Zuckerman et al. (2003) show that actors early in their career did better if they focused on a single genre, being perceived as a generalist who could perform well in several genres was beneficial in later stages of actors' careers. Moreover, studies show that high-status actors have greater latitude to exhibit categorically non-conforming behavior (Phillips and Zuckerman 2001). Rao et al. (2003), for example, find that acclaimed chefs were celebrated for straddling the categorical boundary between Nouvelle and classic French cuisine.

Hypothesis 3: Similarity between the elements a concept combines increases its future

popularity at low levels of popularity, has only a small positive effect on the future popularity of an already popular concept, and decreases future popularity of a concepts with high levels of popularity.

Controlling for other determinants of popularity

Studies of diffusion and fashions have explored how popularity is influenced by a wide range of variables in addition to affiliation and contrast with existing practices. Several studies have focused on the content of the practice, its economic advantages, and effects on profitability (Armour and Teece 1978; Chandler 1962; Rogers 2003). Other studies have examined the impact of external events and trends, including how novel concepts fit with prevailing dominant ideas and institutions (Barley and Kunda 1992; DiMaggio and Powell 1983). In addition to content effects and external determinants there are endogenous effects: popularity depends on the level of and change in past popularity (Bourdieu 1984; Lieberson 2000; Schelling 1978). Popularity may beget popularity, such as when popular practices are more discussed and seem more attractive (Fast et al. 2009; Salganik et al. 2006). An important theme in recent research is how the effect of past popularity depends on the network position of adopters: the effect of prior adoption depends on the centrality and status of prior adopters (Bothner 2003; Davis 1991; Haunschild and Miner 1997).

To the extent possible, it is important to control for these other determinants of popularity in our models. Having said that, our research design, which focuses on collecting data on a wide range of concepts, makes it difficult for us to explore the impact of content effects and the impact of external events. We have little information about the details of each of the management concepts we analyze. For example, we know little about their effects in practice, about who adopted them etc. Such information would be difficult to collect for the wide range of concepts we analyze. We

also have little information about external drivers of popularity specific to the concepts we analyze. Studies focused on one or a few management concepts, in contrast, can collect data on external trends likely to have influenced the spread of these concepts. For example, to analyze how the rise and fall of quality circles were influenced the perceived threat of Japanese manufacturing, Abrahamson and Fairchild (1999) collected data on media mentions of the Japanese threat.

While our data on each management concept is limited, we attempt to control for unobserved heterogeneity and other possible mechanisms in two ways. First, as we explain later, we include in our models keyword fixed effects, which mostly control the constant, unchanging differences across management concepts. Second, our data allows us to examine the effect of some frequently studied variables in diffusion and fashion studies. In particular, we can include the effect of the past popularity and changes in popularity as control variables in our models.

Contagion: past level of popularity: Most models of diffusion and contagion assume that the level of popularity in period $t + 1$ is influenced by the level of popularity in period t (Barabasi and Albert 1999; Bass 1969; Granovetter 1978; Mahajan and Peterson 1985; Schelling 1978;). Specifically, the probability that an agent who has not yet adopted a practice will do so is an increasing function of the number of existing adopters (Burt 1987; Davis 1991; Davis and Greve 1997; DiMaggio and Powell 1983; Greve 1995; Haunschild and Miner 1997; Marsden and Friedkin 1993). The underlying mechanisms include conformity, legitimacy, coordination, and exposure (Deutsch and Gerard 1955; Festinger et al. 1963; Schelling 1978). Many of these arguments apply to management concepts: authors are more likely to be aware of popular concepts and are more likely to feel compelled to discuss them and compare their ideas to them. Therefore, to distinguish our arguments from this previous line of work, we control for concept's previous level of popularity, and following previous research, we expect that *the effect of the past level of*

popularity on popularity is positive.

Changes in popularity: In addition to the level of popularity, we control for the trend in popularity, whether it is increasing or decreasing. The literature on fashion has suggested a 'momentum' effect: the propensity to adopt a practice is an increasing function of past changes in popularity (Abrahamson 1996; Blumer 1969). The implication is that authors of management articles, who desire to be seen as fashionable, may be more likely to adopt concepts that have recently increased in popularity both because such concepts are likely to be regarded as fashionable and because authors are likely to pay attention to such 'rising stars'. Alternatively, if adopters want to avoid being seen as chasing the latest trends, they may avoid practices that recently has increased in popularity, implying a negative effect of the change in popularity (Berger and Le Mens 2009). Using data on media mentions in the New York Times, Denrell and Kovács (2015) show that estimates of the effect of the change in popularity is negative if data on a wide range of practices, both popular and unpopular, is used. Thus, to distinguish our arguments from this previous line of work, we control for the change in the concept's previous level of popularity, and following previous research, we expect that *the effect of the change in popularity on popularity is negative*.

DATA

In line with prior studies of management fashions (Abrahamson 1996; David and Strang 2006), we study the popularity of management concepts by using data on media mentions and word counts. The rationale for using media mentions is that interest in a phenomenon can be measured by tracking how often a concept is mentioned in the business press (e.g., see Abrahamson and Eisenman 2008). Media mentions, scholars have argued, both reflect and impact the popularity of a practice among managers (Kieser 2002). For example, David and Strang (2006) traced the rise

and fall of Total Quality Management (TQM) by calculating the how often this phrase, or similar phrases, was mentioned in the ABI/Inform archive. Surveys of implementation of total quality management programs (Lawler et al. 2001) show that usage of TQM peaked at about the same time. Media mentions of TQM peaked in the early 1990's.

A limitation of most prior studies using media mentions is that they have only examined the popularity of practices that are currently popular or once were popular. This leads to a selection bias (Denrell and Kovács 2008). For example, Abrahamson (1996) uses media mentions to trace the rise and fall of interest in quality circles, a once very popular practice. Using data on media mentions of a wider set of concepts, however, is possible to avoid such a selection bias. Text archives contain data on media mentions on all concepts discussed in the business press. Instead of identifying a subset of words or phrases (such as "quality circles" or "Total Quality Management") and then track media mentions of these phrases, we argue that researchers could track media mentions for a much larger set of management concepts, including those that never became popular (although they have to become popular enough to be mentioned at least once in the media archive used).

Here we follow this approach. Specifically, we analyze the keywords of the Harvard Business Review (HBR). HBR is arguably the most influential business journal, which, since its founding in 1922, provides a mirror of what is current in the management world. Note that we do not claim that HBR is representative of all media, not even of the business media at large. Testing our theory does not necessarily require that the data source is representative of all media. Rather, what it requires is a source that contains long histories of management concepts both that have become popular and that have not become popular. The HBR archive satisfies this criterion.

We have collected the metadata of HBR articles using EBSCO's web interface, which lists for

each article the author(s), the title, the keyword(s)[2], and the date when the article appeared. Using the keywords in HBR, we can trace how ideas emerge, catch on, and go out of fashion by tracking how often management concepts are mentioned. Because we have access to all the articles, we do not have to selectively track a few phrases but can construct a dataset on the popularity of a wide range of management concepts.

Given these data, we still have to decide which concepts to track. One possibility would be to construct a list of management concepts that could have become popular and then track their popularity over time. This is an approach that Carson et al. (2000) followed. This approach works well when researchers want to explore how external determinants influence the popularity of management concepts. A potentially problematic aspect of this approach, however, is how to construct such a list. Should researchers rely on their own judgment? Should they rely on some established list of well-known management concepts? Both approaches likely suffer from hindsight bias and selection bias. Also, if the intention is to study how a concept relates to others, it is important to include many concepts, popular as well as unpopular. To do so, researchers cannot only collect data on a few concepts.

An alternative approach to identifying possible management concepts is to track all distinct phrases. That is, to avoid selection and hindsight bias, a researcher may decide to include all

[2] Keywords, or as EBSCO calls them, "subject headings" are assigned to all articles by the (human) curators of EBSCO who are trained in the subject matter (e.g., business and management in our case). Curators choose the keywords from a long list of available keywords which may change as new concepts and subjects are added. This list is designed not to include close synonyms, e.g., "Total Quality Management" is included but not "TQM" or "total quality control." See more details at https://connect.ebsco.com/s/article/How-does-EBSCO-create-subject-headings-for-EBSCOhost-articles (accessed on 9/20/2019). The benefit of such curation of keywords is consistency across a long time period. The disadvantage, for the purposes of our analyses, is that the keywords are assigned retrospectively for all articles in our sample (EBSCO started indexing Harvard Business Review in 2010)

possible words and phrases. Each of these words, it could be argued, has some chance of becoming a popular management buzzword. The advantage of this approach is that it is not subject to any selection bias nor requires subjective judgments about suitable management concepts. A disadvantage of this approach is that the resulting list of phrases could be far too wide: it may include phrases that have are not really management concepts, such as "midlife crisis" (although the extent to which managers worry about midlife crisis may also be influence by fads and fashions).

To give an example of keywords, consider the article by Dan Ariely, titled "You Are What You Measure" in the June 2010 issue. This article has the following keywords (separated by semicolons): "Performance standards; executives - Salaries, etc.; Chief executive officers; Performance - Management; Innovation management." Because only a few keywords are used, selected to reflect the content of articles and to indicate the relation to existing management topics and concepts, we chose to use the set of distinct keywords as our list of management concepts. There are 14,700 articles in total during the period our data covers: from 1922 to 2010. During this period, there are 16,613 unique keywords. but many keywords are mentioned multiple times, so we have 123,515 mentions, so the average number keywords per article is 7.43. And because co-occurrence is dyadic, we have many more co-occurrences. For example, the above-mentioned article lists five keywords, then this contributes 5*4/2=10 co-occurrences. Altogether, we have 726,656 pairwise keyword co-occurrences in the data.

We track the yearly frequency of each of these distinct keywords. Thus, our unit of analysis is distinct keywords-year.

Figure 1 shows on a log-log scale the distribution of the total number of articles that mentioned distinct keywords in Harvard Business Review. As Figure 1 shows, the distribution of keyword

counts is skewed: most words are mentioned only once or a few times, and there is only a handful of words in our sample that are mentioned more than a few hundred times. In fact, 92% are mentioned less than ten times and 61% of the keywords in the HBR dataset are only mentioned once. Such a skewed distribution of popularity is common in other areas: the number of citations for academic papers, web-links, or downloads all follow a power-law distribution (Newman 2005; Salganik et al. 2006).

Figure 2 illustrates the trajectories of 16 selected keywords that reflect important relevant management concepts or concepts that are relevant to management and thus often discussed in HBR. These keywords are not a random sample of all keywords - rather, our goal with this figure is to illustrate the variety of trajectories over time and to demonstrate how the distribution of keyword counts reflect management trends. Consider for example the concept of "business cycles" - this concept was not popular in the very beginning of HBR, in 1922, but surges in the 1930s, which is clearly related to the Great Depression. The concept has been less talked about since then, except for slight increases in the 1970s, around the 1973 and 1979 economic crises. Or consider the concept of "leadership," which has been occasionally discussed since the early days of HBR in the 1920s, slowly gaining popularity from the 1950s on, finally getting a surge in popularity from the mid-1990s until the recent times, peaking around 2000, with 61 articles in 2000 discussing leadership. Contrast that trajectory with the concept of "strategic planning," which is one of the most commonly mentioned keyword in HBR. Strategic planning has also been around since the 1920s, continuously gaining popularity, peaking in 2003 with 70 mentions. Other concepts are more faddish. For example, the keyword "Japan" was quite popular from the mid-1970s to the early-1990s, peaking in the 1980s, but has not really been discussed in HBR since the mid-1990s.

Insert Figures 1 and 2 about here

Studies of diffusion and fashion and fads tend to focus on the upper tail of the distribution in Figure 1. For example, consider Total Quality Management, a concept studied by several management researchers interested in popularity and fads (Abrahamson 1996; Carson et al. 2000; David and Strang 2006). Nine HBR articles used the keyword "Total Quality Management": only 8% of keywords reached this level. In this respect, total quality management is unrepresentative of the population of management concepts. More generally, studies of diffusion and fads and fashions tend to sample a select set of practices and concepts that are or once were popular (Denrell and Kovács 2015). Because studying ecological effects about the impact of affiliating with and contrasting to other concepts require data on multiple trajectories, and data on popular as well as unpopular concepts, few researchers have examined these effects empirically. If only a few practices are studied, the sample size might be too small to obtain significant effects. If only popular practices are studied, the effect of unpopular related practices cannot be explored. For example, a new management concept associated with unpopular past concepts is unlikely to become popular but only studies with data on unpopular past practices can control for this important effect.

Some of the keywords included in our data may not seem to represent a management concept, including "Canada" and "Stanford University", and could perhaps have been excluded from the analysis. But given the popularity of Japanese management methods during the 1980s ("Japan" is one of the most frequently used keywords) and the Carnegie-school in organization theory ("Carnegie Mellon University" is a keyword), it is possible that other countries and universities

could have become equally popular. To avoid selection bias based on hindsight, we choose to include them.

How useful and representative is the Harvard Business Review as a data source? We do not claim that HBR is fully representative of all (business) media, but as we discussed, perfect representativeness is not required to test our theoretical propositions. What is required is to have data on the full popularity trajectories of successful and unsuccessful management concepts. HBR as a data source satisfices this criterion. Yet, it is interesting to explore whether media mentions in Harvard Business Review correspond to media mentions used by prior researchers. In order to do so, we calculated the correlation between the number of mentions of keywords in our data and the number of mentions in other data sources that have been used to study fads and fashions. For example, Abrahamson (1996) plots the media mentions of quality circles. We examined the number of mentions of this term in the keyword HBR data base. The correlation between Abrahamson's numbers and ours was 0.71 (if we include all the zeros and 0.6 if we do not include the zeros). Similarly, David and Strang (2006) examined the number of mentions of total quality management. We examined the yearly counts of mentions of the keyword "total quality management" in HBR database and the correlation was 0.8. While admittedly only indicative, these findings suggest that popularity trajectories in the Harvard Business Review correspond fairly well to popularity trajectories in other media outlets used to study management fashion.

It should be clear that our research design sacrifices depth for breadth: we have little contextual information or data on external events for the concepts that we include in the analysis. As a result of our research design, we have very limited data on determinants of popularity beyond the variables included in the research design. In particular, we know very little about the actual adoption in firms of the management concepts we analyze. An ideal design would combine depth

with breadth, but this is seldom possible because such data are typically only available for once popular concepts, such as quality circles (Cole 1989). Most studies of diffusion and fads sacrifice breadth for depth: they focus on one or a few practices or concepts, usually practices and concepts that were once popular, and study these practices in depth. In contrast to such a design, our study may seem to be lacking in richness, but we believe the advantages of breadth are considerable.

MEASURES AND METHOD

Yearly panel data structure

We structure the data in a year-keyword panel structure. That is, the unit of analysis is the keyword-year, starting from the first year the keyword was mentioned. For example, if a keyword was first mentioned in 2001, we include in the panel data 10 yearly observations for this keyword (for the years 2001, 2002,…, 2010). Table 1 below illustrate our data structure on the example of the management concept of "Quality Circles." The first column shows the focal year, the second column shows the "age" of the concept in that year. The third column, "count of mentions" captures the number of HBR articles in the focal year that are assigned that keyword – as we explain below, this is our dependent variable. "Lagged mentions" is the number of times the keyword was listed in the previous year. The rightmost three columns capture the three ecological variables of interest, lagged by one year – we explain these variables below.

Insert Table 1 about here

In estimating the models, we pool all observations, for all keywords and all years. Because we have count data, we estimate Poisson and negative binomial models. While the data are overdispersed (which would suggest that we use negative binomial models), we also present the Poisson models as the statistics literature (e.g., Wooldridge 1999) recommends against using fixed effects with negative binomial regressions because these estimators are often not consistent. Therefore, for each test, we present Poisson models with keyword fixed effects and negative binomial models with keyword random effects.

The dependent variable

The main outcome variable is the popularity of a keyword in a given year. We measure *popularity* of keyword *i* in year *t* by the count of articles in year *t* that include *i* as a keyword.

Independent variables

To measure the extent to which a management concept *i* is affiliated with other popular concepts, *Affiliation with popular others*, we sum the popularity of the keywords keyword *i* is mentioned together with (i.e., listed together as a keyword on a given article) in period *t*-1. For example, if keyword A is listed as a keyword in two articles in 1984, and these articles list one additional keyword each such that article 1 lists "A, B" and article 2 list "A, C", then the value of *Affiliation with popular others* for keyword A in year 1985 will be calculated as the sum of the count of mentions of keyword B and keyword C in year 1984. Other functions than the sum could be used (such as the maximum) but give the same results (see the robustness checks).

To measure *Local crowding* and *Combination with similar concepts*, we first need to compute the similarity of keywords. We use a co-occurrence-based approach to measuring the similarity of

keywords (Cf. Kennedy 2008). We assume that two keywords that are frequently mentioned together, in the same article, are similar. Specifically, we compute the pairwise similarity of all keywords by calculating their Jaccard-similarity (Jaccard 1901), a commonly used similarity index. The Jaccard similarity of two keywords is calculated as the proportion of the overlap and union of the articles to which the two focal keywords are associated. Formally, if $|i \cap j|$ denotes the number of articles citing both keywords *i* and *j*, and $|i \cup j|$ denotes the denotes the number of articles citing keyword i and/or keyword j, then $Sim(i,j) = |i \cap j|/|i \cup j|$. For example, 15 articles mention "Total Quality Management" as a keyword, 9 articles mention "employee stock options" as a keyword, but no article mentions both keywords, so the Jaccard-similarity of the two keywords is zero. The Jaccard index takes values in the [0,1] range, with 0 denoting perfect dissimilarity and 1 denoting perfect similarity.[3]

Local crowding, for keyword *i*, is then computed as $\sum sim(i,j)P_j$ where P_j is the popularity of keyword j, where the sum only includes keywords that were used together with *i* in year *t*-1. This measure captures the extent to which a keyword is affiliated with and similar to popular keywords. Finally, we measure *Combination with similar concepts* of keywords *i* as the average Jaccard similarity between *i* and all the keywords that *i* is ever mentioned with. This measure captures the extent to which a keyword is mentioned with similar or dissimilar keywords. Because similarity is based on co-occurrence a high level of *Combination with similar concepts* implies that a keyword is frequently used with a few other keywords while a low value implies that a keyword is mentioned with keywords that are seldom combined.

Table 2 shows descriptive statistics and Pearson correlations for the main variables. Note that

[3] In computing the pairwise similarities we use data from all years. The alternative would be to use data from only the most recent years, but the sample size would then be very small.

for the ease of interpretability, the values of the variables *Affiliation with popular others*, *Local crowding*, and *Combination with similar concepts* are all standardized to mean of zero and standard deviation of one. In all subsequent regressions and figures, we will use the standardized version of these three variables. Also, note that all independent variables are lagged by one year.

Insert Table 2 about here

Control variables

Keyword fixed effects. As we discussed in the Introduction and in the theory section, some management concepts may be more popular than others just because they are of higher quality or for example because they may have been introduced by a high-status academic or journalist who is affiliated with a famous university or company. Because our interest in this paper is to understand the ecological effects in the diffusion of management concept, we control for such unobserved heterogeneities by including in our analyses keyword fixed effects.

Year fixed effects and the age of the management concepts. To account for possible time variation of the data, we include year fixed effects. Such fixed effects control for external variations such as the idiosyncrasies in HBR publications, e.g., change in editorship or changes in the number of issues and articles across the years. Year fixed effects also control for changes in the overall level of competition in the concept space, and for other variations in the economic and societal environment. We also include a *keyword age* control, measured as the number of years since the first mention of the keyword in HBR. We note that it is not possible to include simultaneously in the regressions keyword fixed effects, age effects, and year fixed effects – this is because for any given keyword, year and age are perfectly multicollinear. Therefore, in the

Poisson models with keyword fixed effects, we only include the age control but not the year fixed effects.

Finally, we control for (a) *Past level of popularity* (the number of times the keyword was mentioned in the previous year, and (b) *Change in popularity*, measured as popularity in year *t-1* minus popularity in year *t-2*. We control for change in popularity in order to control for possible endogenous trends in the popularity of concepts.

RESULTS

Table 3 shows the main set of regression results. The left panel shows Poisson panel model estimates with keyword fixed effects; the right panel shows the results for negative binomial panel model estimates with keyword and year random effects. Models 1 and 5 show the baseline specifications with the control variables only. Consistent with previous research, we find that past popularity is a strong positive predictor of future popularity. Also in line with previous research (Denrell and Kovács 2015), we find a negative effect of the change in popularity: an increase in the popularity of the focal concept from year *t*-2 to *t*-1 is associated with lower levels of popularity in year *t*.

In models 2 and 6, we explore the consequences of being mentioned together with other popular concepts, *Affiliation with popular others*, and how this effect interacts with the level of popularity. Consistent with Hypothesis 1, the effect of *Affiliation with popular others* depends on how popular a concept is. Figure 3a illustrates this interaction effect. As shown, being mentioned together with popular concepts makes a focal concept more popular if the focal concept is currently not very popular. The effect of being mentioned together with popular concepts becomes negative,

however, if the focal concept is already popular. Note that the effect turns negative only for really high levels of popularity.

Models 3 and 7 in Table 3 test Hypothesis 2 about the effect of *Local crowding.* Consistent with the hypothesis, the effect of *Local crowding* depends on the level of popularity: the effect of *Local crowding* is positive for a concept with a low level of popularity and becomes negative for a concept with a very high level of popularity. Figure 3b plots this interaction effect. Again, the effect turns negative only for really high levels of popularity.

Finally, Models 4 and 8 in Table 3 test Hypothesis 3 about the effect of *Combination with similar concepts.* Consistent with Hypothesis 3, we find that the effect of *Combination with similar concepts* is positive for a concept with a low level of popularity but becomes negative for a concept with a very high level of popularity. Figure 3c plots this interaction effect.

Insert Table 3 and Figure 3 about here

In terms of effect sizes, two major patterns are worth discussing. First, while we do find evidence for the predicted patterns of the decreasing effect of the three ecological variables on future popularity of the concept as a function of the keyword's prior popularity, the effects are almost always positive and only turn negative at very high levels of popularity. In other words, the results indicate that it is almost always beneficial for a management concept to affiliate with other popular concepts, to position itself in crowded conceptual areas, and to be combined with similar other concepts. Second, while we do find evidence for the predicted patterns, the importance of the three ecological variables differ significantly. By far the strongest effect is exhibited by *local crowding*, followed by *combination with similar concepts*, and the weakest effect in terms of effect

size is that of *affiliation with popular others*. We did not theorize a priori about such differences in effect size, and we do not want to engage in post hoc rationalization. Yet, given the large differences in effect sizes, we call for future research to explore the stability of these results and to investigate whether the patterns we uncovered here hold in other settings as well.

Robustness checks and additional analyses

To ensure the robustness of our results to alternative measures and models specifications, we conducted a set of additional analyses. We report the results of these analyses below.

Aggregating the yearly data to 5-year periods

Yearly count of mentions of management concepts may exhibit larger levels of stochasticity given that HBR on average only publishes 150 articles in a year. As an additional robustness check, we collapsed our data to five-year periods. For each five-year period, we summed the count of mentions of the keyword and calculated the average of the *Affiliation with popular others*, *Local crowding*, and *Combination with similar concepts* variables. We then re-estimated the Poisson and negative binomial model on this collapsed data. See Table A1 for the results. The results confirm our hypotheses.

Removing keywords once they have not been mentioned for 10 years

One may argue that an alternative way of conceptualizing the risk-set of the concepts under diffusion would be to remove from the risk-set those concepts that have not been mentioned for a long while. In Table A2, we present the results of a specification in which we dropped from the panel data a keyword 10 years after its last mention. For example, if a management concept was first mentioned in 1971 and last mentioned in 1987, then for this concept we include years between 1971 and 1997. Our results hold also under this specification as well.

Possible ceiling effects

One may also argue that there exists some limit to how popular a concept can become, due to the limited amount of attention readers will give to management terms as a whole[4]. If so, then it is possible that the popular concepts in our data are bumping up against that limit, and this may account for the negative interaction terms we find. To rule out this possibility, we re-estimated our models on the set of concepts that during their lifetime have received less than 1000 mentions (which, given the total article count of 14,700, is very far from the ceiling). See Table A3 for the results with this specification. The estimated coefficients are highly similar to the estimates we obtain using the whole sample.

Controlling for the fame of the author(s) who mention the management concept

Beside the hypothesized ecological effects, it may also matter who writes the articles. For example, if the author of an article is well-known or comes from a famous university, then one might predict that the concepts will spread faster. The keyword fixed effects capture the prominence of the author(s)' at the concept's first mention but may not capture the prominence of the authors in later mentions. Therefore, we conducted further analyses to investigate whether the prominence of the authors of the article matters, and more importantly, whether our results hold even after controlling for the authors' prominence. As we mentioned, we do know the name of the authors but unfortunately we do not have data on their affiliations and whether they are academics or journalists. Given that we have more than 10,000 authors in the dataset, hand coding their affiliations would be an onerous exercise (and given the historical nature of the data, it would be hard to track down the affiliation of authors from, say, the 1930s). Instead, we decided to proxy the prominence of an author by the number of articles they contributed to HBR (cumulatively,

[4] We thank an anonymous reviewer for calling our attention to this possibility.

prior to the focal article that mentions the focal keyword). We then included this variable as a control in our regressions. We find that our results hold even after the inclusion of this control. We also find that, not surprisingly, this construct has a strong positive effect on the future count of mentions of the concept. See Table A4 for details.

An alternative measure for Affiliation with popular other

As an alternative measure for *Affiliation with popular others* we used not the sum but the maximum of the popularity of the keywords that were mentioned together with the focal keyword in period *t*—1. As Table A5 shows, the results are qualitatively unchanged.

Testing for non-monotonic effects of combination with similar concepts

One may ask why H2 did not predict a curvilinear relationship between similarly and popularity. Indeed, our arguments about the competing pressures of legitimacy and crowding may remind the reader of the curvilinear effects documented in the density dependence (Hannan and Carroll 1992) and strategic balance (e.g., Deephouse 1999) literatures. We note, however, that unlike in the case of density dependence and strategic balance, our focus is not on the main effect of a concept being similar to other concepts; our focus is on whether this effect is moderated by the popularity of the concept. Our claim is that being similar increases popularity for less popular concept, while it decreases popularity for popular concepts. This interaction effect with popularity is theoretically distinct from a non-monotonic main effect of similarity on future popularity. We argue that the attention and legitimacy benefits of being similar are important for less popular concept. The competitive effect may also matter, but likely only for popular concepts: only the growth of a popular concept is likely constrained by being similar to other popular concepts.

In any case, we reanalyzed our data to test curvilinear effects of being similar to others. Specifically, instead of a linear term, we included in our models dummy variables for each

percentile of the distribution of the popularity of keywords. We also re-run our models with adding a squared term for *Combination with similar concepts*. In neither of these tests do we find support for a curvilinear effect.

Log-linear models

In addition, because some researchers prefer log-linear models to count models, we re-estimated our models with log-linear models. Table A6 shows the results, which are fully consistent with the results obtained in the Poisson and negative binomial specifications.

Segmented regression models

Shaver (2019) demonstrates that panel fixed effects models that include interaction effect cannot necessarily be interpreted as purely within-effects and recommends a split-sample segmented regression approach instead. To ensure that our results are robust to such a split-sample approach, we have re-estimated the models of Table 3 that included an interaction effect, splitting the sample at log(lagged_count+1)=1. We find that, consistent with our hypotheses, the effect of all three ecological variables are stronger for concepts with low levels of popularity.

CONCLUSION

In this paper, we systematically study how affiliation and contrast with other management concepts influence the diffusion of a focal management concept. We analyzed a dataset that includes many different concepts and does not suffer from selection bias. To obtain such a dataset, we study the diffusion of management concepts by relying on mentions in the text-archive of the Harvard Business Review.

Our data shows that the effect of being affiliated with and similar to other concepts and combination with similar concepts varies with the popularity of a focal concept. Specifically, (1) the effect of affiliation with popular concepts is positive for concepts with low levels of popularity

but such affiliation matters much less for already popular concepts, and the effect can become negative for concepts with high levels of popularity; (2) the effect of being similar to other popular concepts is positive for concepts with low levels of popularity but similarity matters much less for already popular concepts and the effect can become negative for concepts with high levels of popularity; (3) combination with similar existing concepts increases popularity, and the effect of combination with similar concepts is larger for concepts with low levels of past popularity but can become negative for concepts that are already highly popular.

The fact that the effect of contrasting or complementing existing management concepts is different for popular and unpopular concepts implies that lessons learned from popular concepts can be misleading. Studies of popular concepts may show that it may not matter whether a concept contrast with existing concepts and or locates in unchartered territories where few other concepts are located. Our results show that such a conclusion only holds for concepts that are already popular and that being similar to existing popular concepts is important for novel concepts.

For practitioners, our findings imply that managers who base their impressions only on successful concepts might underestimate the advantages of affiliation and similarity. While the most successful concepts may not have these traits, most concepts that lack these traits do not become popular. The ideal strategy for making a novel concept popular may be to affiliate with popular other concepts initially and be similar to such concepts. Later on, if the focal concept becomes popular, the concept can perhaps be altered to make affiliate less with exiting popular concept and to contrast more, rather being similar, to popular concept. This strategy may not work, however, if it is difficult or illegitimate to change a concept after it has been introduced.

Our results also have implications for theories of management fashions. Theories of management fashions describe the mechanisms by which popularity of management concepts

increased and then decrease in popularity (Abrahamson, 1996; Abrahamson and Fairchild, 1998; Barley and Kunda, 1992; David and Strang, 2006; Strang and Macy, 2001; Strang et al, 2014). Most empirical work on management fashion, however, focus on a few concepts that once became popular and then declined in popularity (Abrahamson and Fairchild, 1998; Carson et al, 2000; David and Strang, 2006). As a result of this empirical focus, the literature on management fashion has not addressed the issue of how fashions arise from the large pool of management concepts that exists at any one point in time. Indeed, conclusions about the determinants of the *rise* in popularity from such a sample of concepts that did become popular suffers from a selection bias (Denrell and Kovacs, 2015) since most concepts never become popular. Our findings here suggest that studies (quantitative or qualitative) that speculate about the determinants of the rise in popularity on the basis of studies of once popular concepts may underestimate the benefits of being similar to existing concepts and locating in territories with many previous concepts. Such tactics may be important for concepts that have not yet become popular.

More generally, our findings raise the issue of how concepts can navigate the conflicting challenges of i) acquiring some initial level of popularity and ii) leveraging this initial popularity and becoming a highly popular concept? One can imagine at least two different strategies: a) an initial bet on contrast or b) shifting over time. The first strategy involves contrasting with existing concepts even early on or at least not choosing an area or topic very similar to existing popular concepts. This is a risky strategy since it may only work well once a concept has reached some level of popularity. The second strategy may combine the best of all worlds, by initially avoiding contrast and then strategically shift to emphasize contrast. Audiences may react negatively to such a shift, however, as changing identity is often risky (Hannan et al. 2006). It would be interesting to study the pre-history of popular concepts, and contrast them with a sample of less popular

concepts, to see if concepts that became popular did initially contrast with existing concepts (a risky strategy initially) or whether the contrast only developed gradually, as popularity increased.

Once the focus shifts from explaining individual trajectories to the distribution of trajectories observed and their dynamics it also becomes clear that existing quantitative models of diffusion and fashions are incomplete. While theoretical ideas and models exist that help to explain why skewed distributions in popularity emerge (Barabasi and Albert 1999; Watts 2002) and why faddish behavior and eventual decline in popularity emerges (Strang and Macy 2001), there is no combined model that is compatible with all these phenomena and describes, not just qualitatively but also quantitatively, how popularity distributions evolve over time.

One way future research could expand on our results is by delving more into the audience-side mechanisms of the ecological effects of the diffusion trajectories. Our approach to the ecology of diffusion trajectories is in line with McPherson (1983)'s approach to the ecology of affiliations. Audiences and niches could be reconceptualized as potential authors, readers, or citers of a management concept. And, as McPherson argues that organizations compete as their niches overlap, one could naturally extend our arguments to explore more directly how management concepts' niches overlap, and how affiliation to popular or similar other concepts would affect the focal concept's niches. Affiliation with popular other concepts, for example, on the one hand would lead to an increase in the audience of the focal concept, but on the other hand would lead to higher overlap with the audiences of other concepts.

We believe that the findings of this paper may be applicable beyond the scope of the diffusion of management concepts. For example, the fields of strategic positioning (Rumelt et al 1994) and strategic categorization (Pontikes 2018) investigate how firms should position themselves in markets. One aspect of this decision is whether they should emphasize their similarity or affiliation

to other popular firms, products, or product categories. Our results, to the extent they are generalizable to other settings, would indicate that the answer depends on the current popularity of the firm or product at hand, and that affiliating with other similar and popular products, market segments, or product categories is most important and beneficial for new entrants and unknown products.

Finally, we believe our empirical approach, relying on large-scale data available in an electronic archive, is a useful avenue for future research on diffusion and management fashion. The reason much previous research has focused on one or a few diffusion trajectories is the difficulty of obtaining data on multiple trajectories. With the emergence of wide-ranging electronic archives new data sources appeared. We hope that this paper has persuaded future researchers to study complete records of diffusion and popularity trajectories, which we believe would spur a new wave (fad?) in diffusion and fad research.

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TABLES AND FIGURES

Table 1: Illustrating the yearly panel data structure using the example of "quality circles." The panel data for "quality circles" starts in the first year the keyword was mentioned (in 1982).

Year	Keyword age	Count of mentions	Lagged mentions	Affiliation with popular others (t-1)*	Local crowding (t-1)*	Combination with similar concepts (t-1)**
1982	0	1	0	0	0	0
1983	1	0	1	74	0.587	0.0007
1984	2	0	0	0	0	0
1985	3	10	0	0	0	0
1986	4	0	10	886	1.161	0.0078
1987	5	0	0	0	0	0
1988	6	0	0	0	0	0
1989	7	0	0	0	0	0
1990	8	0	0	0	0	0
1991	9	0	0	0	0	0
1992	10	1	0	0	0	0
1993	11	0	1	50	1.156	0.0019
1994	12	0	0	0	0	0
1995	13	0	0	0	0	0
1996	14	0	0	0	0	0
1997	15	0	0	0	0	0
1998	16	0	0	0	0	0
1999	17	1	0	0	0	0
2000	18	0	1	33	0.531	0.00074
2001	19	1	0	0	0	0
2002	20	0	1	14	0.894	0.00074
2003	21	0	0	0	0.587	0.0007
2004	22	0	0	0	0	0
2005	23	0	0	0	0	0
2006	24	0	0	0	0	0
2007	25	0	0	0	0	0
2008	26	0	0	0	0	0
2009	27	0	0	0	0	0
2010	28	0	0	0	0	0

*Note that the values of these variables shown here are the unstandardized values, while the regression models are estimated with the standardized values.

Table 2: Descriptive statistics and correlations

Variable	Mean	S.D.	Min	Max	Correlations			
					1	2	3	4
1. Popularity (t-1), logged	0.039	0.205	0.000	4.466				
2. Affiliation with popular others	0.000	1.000	-0.086	156.731	0.668			
3. Local crowding	0.000	1.000	-0.139	52.598	0.594	0.639		
4. Combination with similar concepts	0.000	1.000	-0.069	249.844	0.221	0.255	0.433	
5. Change in popularity	0.002	0.529	-72.000	56.000	0.389	0.361	0.055	0.055

All correlations are significant at the 1% level.

Figure 1: Harvard Business Review keywords: distribution of total mentions, on a log-log scale

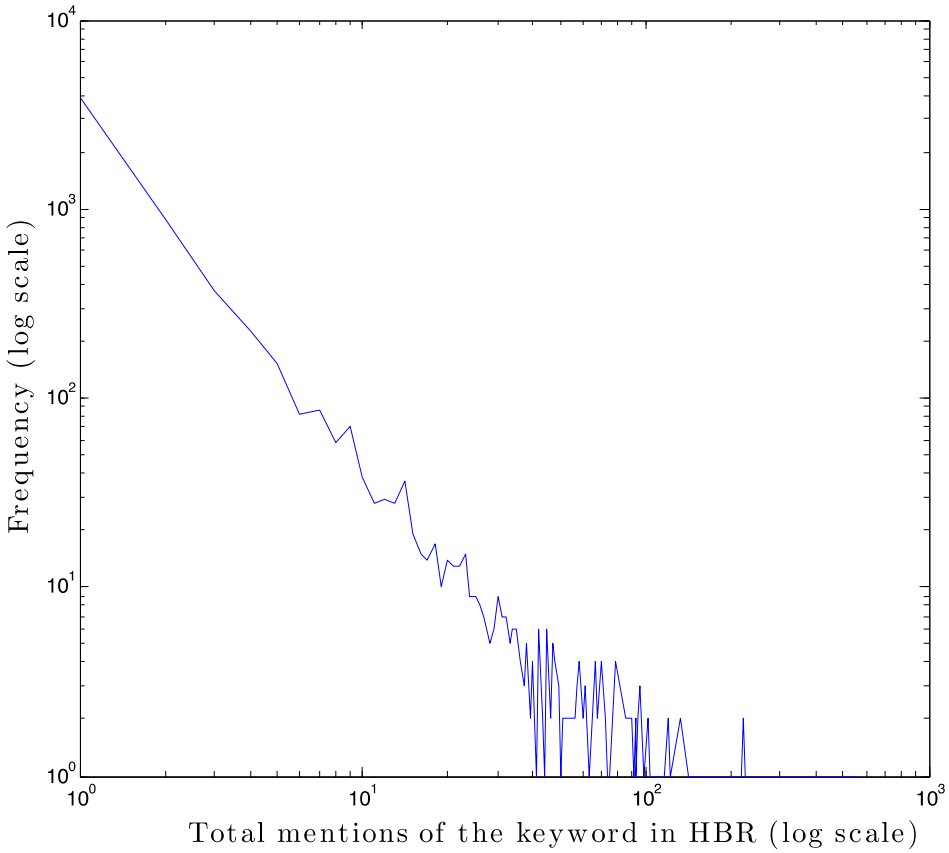


Figure 2. Illustration: The popularity (count of mentions) of 16 keywords in the Harvard Business Review.

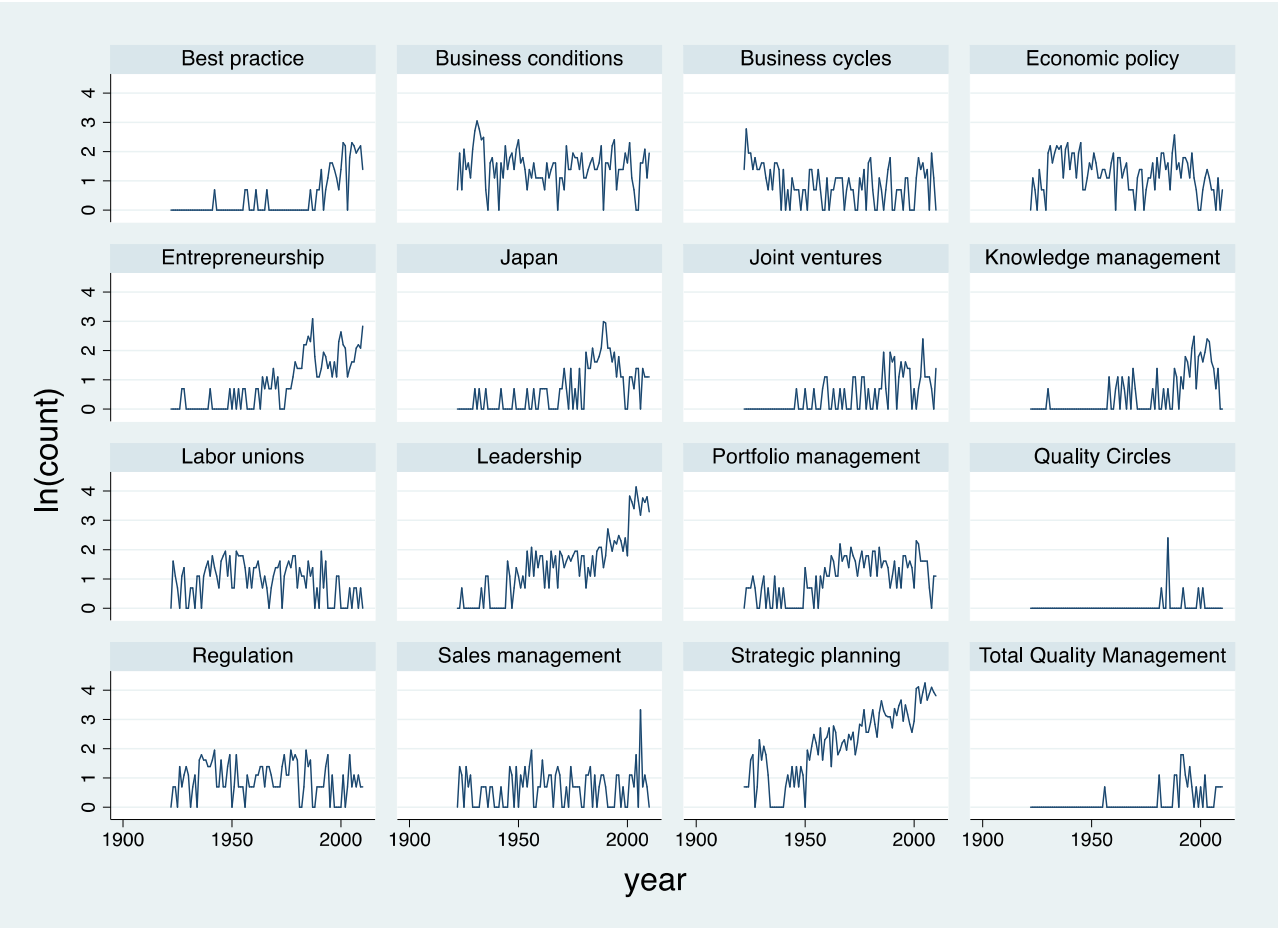


Table 3: Estimates of count models with endogenous and ecological variables, HBR keywords data

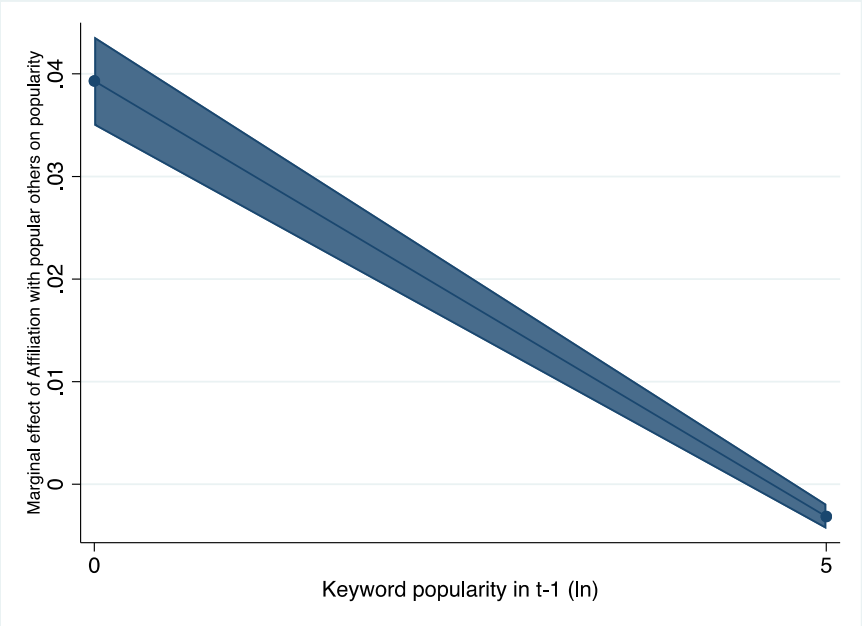
	Poisson models Keyword FE				Negative binomial models Keyword RE, Year FE			
	M1	M2	M3	M4	M5	M6	M7	M8
Keyword age	0.008***	0.008***	-0.005***	0.008***	0.001***	0.001***	-0.010***	0.001***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Change in popularity from t-2 to t-1	-0.033***	-0.028***	0.004***	-0.028***	-0.032***	-0.032***	-0.004***	-0.027***
	[0.000]	[0.001]	[0.001]	[0.000]	[0.001]	[0.001]	[0.001]	[0.001]
Keyword popularity in t-1 (ln)	1.701***	1.834***	1.545***	1.706***	1.698***	1.814***	1.609***	1.709***
	[0.003]	[0.005]	[0.005]	[0.003]	[0.004]	[0.007]	[0.007]	[0.004]
Affiliation with popular others		0.025***				0.050***		
		[0.002]				[0.003]		
Popularity in t-1 (ln) X Affiliation with popular others		-0.012***				-0.020***		
		[0.001]				[0.001]		
Local crowding			0.322***				0.363***	
			[0.001]				[0.001]	
Popularity in t-1 (ln) X Local crowding			-0.092***				-0.115***	
			[0.000]				[0.001]	
Combination with similar concepts				0.058***				0.059***
				[0.000]				[0.000]
Popularity in t-1 (ln) X				-0.017***				-0.017***
Combination with similar concepts				[0.000]				[0.000]
Constant					-22.536***	-16.322	-15.876	-15.264
					[1.048]	[1,693.321]	[1,748.914]	[997.676]
Observations	680,090	680,090	680,090	680,090	680,098	680,098	680,098	680,098
Log-likelihood	-271,066	-268,733	-218,512	-263,742	-246,527	-245,511	-209,251	-242,254

Standard errors in brackets

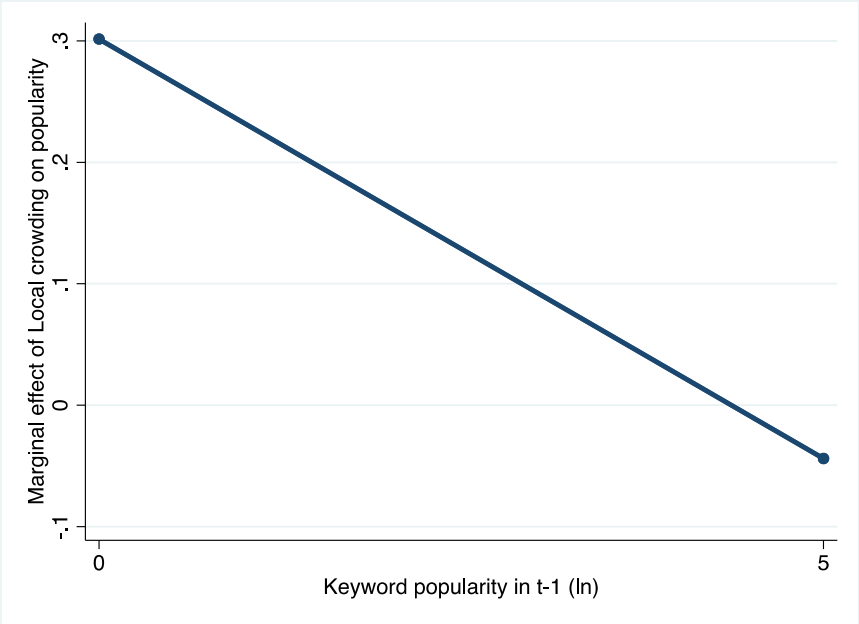
*** p<0.01, ** p<0.05, * p<0.1

Figure 3: Plotting the interaction effects. The X axes are plotted along their observed ranges.

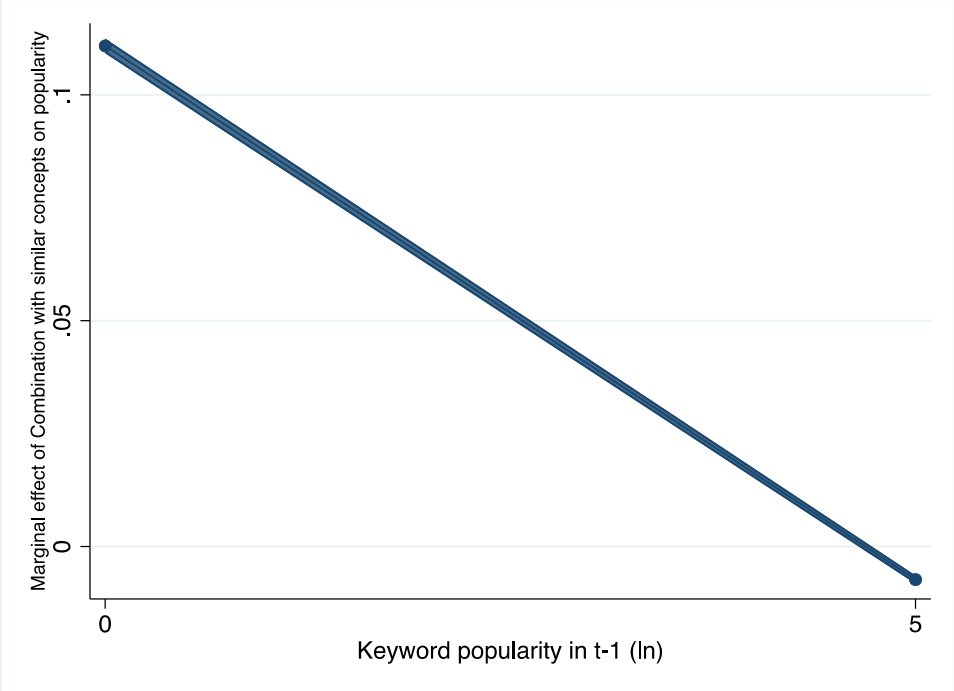
(a) Marginal effect of "Affiliation with popular others" on keyword popularity (based on Model 2 in Table 3). The shaded area indicates the 95% confidence intervals.



(b) Marginal effect of "Local crowding" on keyword popularity (based on Model 3 in Table 3). The shaded area indicates the 95% confidence intervals.



(c) Marginal effect of “Combination with similar concepts” on keyword popularity (based on Model 4 in Table 3). The shaded area indicates the 95% confidence intervals.



Appendix

Table A1: Results with 5-year periods collapsed

	Poisson models Keyword FE			NBReg models Keyword RE, Year FE		
	M1	M2	M3	M4	M5	M6
Keyword age	-0.006***	-0.013***	-0.002***	-0.013***	-0.017***	-0.012***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Keyword popularity in t-1	0.337***	0.405***	0.431***	0.438***	0.450***	0.536***
	[0.005]	[0.005]	[0.005]	[0.008]	[0.008]	[0.008]
Change in popularity from t-2 to t-1	0.003***	0.003***	0.001***	0.002**	0.006***	0.002***
	[0.000]	[0.000]	[0.000]	[0.001]	[0.000]	[0.000]
Affiliation with popular others	0.243***			0.467***		
	[0.002]			[0.005]		
Popularity in t-1 X Affiliation with popular others	-0.044***			-0.109***		
	[0.000]			[0.001]		
Local crowding		0.334***			0.405***	
		[0.002]			[0.003]	
Popularity in t-1 X Local crowding		-0.053***			-0.072***	
		[0.000]			[0.001]	
Combination with similar concepts			0.109***			0.084***
			[0.002]			[0.001]
Popularity in t-1 X Combination with similar concepts			-0.013***			-0.012***
			[0.000]			[0.000]
Constant				0.112***	0.229***	-0.057***
				[0.016]	[0.017]	[0.015]
Observations	137,132	137,132	137,132	151,757	151,757	151,757
Log-likelihood	-89,869	-83,433	-94,959	-116,637	-112,380	-119,138

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table A2: Truncating keyword trajectories 10 years after last mention

	Poisson models Keyword FE			NBReg models Keyword RE, Year FE		
	M1	M2	M3	M4	M5	M6
Keyword age	0.006***	-0.009***	0.005***	0.005***	-0.007***	0.005***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Keyword popularity in t-1	0.589***	0.762***	0.641***	0.675***	0.766***	0.690***
	[0.007]	[0.006]	[0.005]	[0.010]	[0.008]	[0.007]
Change in popularity from t-2 to t-1	-0.007***	0.006***	-0.005***	-0.016***	0.015***	-0.012***
	[0.000]	[0.000]	[0.000]	[0.001]	[0.001]	[0.001]
Affiliation with popular others	0.022***			0.002		
	[0.002]			[0.004]		
Popularity in t-1 X Affiliation with popular others	-0.005***			0.000		
	[0.000]			[0.001]		
Local crowding		0.278***			0.325***	
		[0.001]			[0.001]	
Popularity in t-1 X Local crowding		-0.064***			-0.077***	
		[0.000]			[0.000]	
Combination with similar concepts			0.106***			0.098***
			[0.001]			[0.001]
Popularity in t-1 X			-0.022***			-0.022***
Combination with similar concepts			[0.000]			[0.000]
Constant				0.457***	0.445***	0.594***
				[0.040]	[0.041]	[0.040]
Observations	363,316	363,316	363,316	364,885	364,885	364,885
Log-likelihood	-179,379	-151,172	-170,717	-202,556	-177,819	-196,914

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table A3: Re-estimating the models using the subset of keywords with less than 1000 total mentions

	Poisson models Keyword FE			NBReg models Keyword RE, Year FE		
	M1	M2	M3	M4	M5	M6
Keyword age	-0.000***	-0.016***	-0.002***	-0.007***	-0.019***	-0.006***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Keyword popularity in t-1	0.642***	0.772***	0.776***	0.799***	0.836***	0.901***
	[0.009]	[0.007]	[0.006]	[0.013]	[0.009]	[0.008]
Change in popularity from t-2 to t-1	-0.027***	0.033***	-0.020***	-0.041***	0.050***	-0.035***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
Affiliation with popular others	0.047***			0.042***		
	[0.003]			[0.006]		
Popularity in t-1 X Affiliation with popular others	-0.010***			-0.010***		
	[0.001]			[0.002]		
Local crowding		0.345***			0.431***	
		[0.001]			[0.002]	
Popularity in t-1 Local crowding		-0.086***			-0.106***	
		[0.001]			[0.001]	
Combination with similar concepts			0.168***			0.159***
			[0.001]			[0.001]
Popularity in t-1 X Combination with similar concepts			-0.043***			-0.044***
			[0.001]			[0.001]
Observations	664,376	664,376	664,376	674,773	674,773	674,773
Log-likelihood	-190,481	-155,965	-179,607	-219,807	-187,640	-211,845

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A4: Controlling for the productivity of the article authors

	Poisson models Keyword FE			NBReg models Keyword RE, Year FE		
	M1	M2	M3	M4	M5	M6
Keyword age	-0.003***	-0.013***	-0.004***	-0.006***	-0.016***	-0.007***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Keyword popularity in t-1	0.956***	1.055***	0.940***	1.054***	1.159***	1.035***
	[0.007]	[0.007]	[0.005]	[0.008]	[0.009]	[0.006]
Change in popularity from t-2 to t-1	-0.010***	0.018***	-0.011***	-0.015***	0.016***	-0.014***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
Affiliation with popular others	0.031***			0.036***		
	[0.002]			[0.003]		
Popularity in t-1 X Affiliation with popular others	-0.010***			-0.012***		
	[0.001]			[0.001]		
Local crowding		0.285***			0.323***	
		[0.001]			[0.001]	
Popularity in t-1 X Local crowding		-0.077***			-0.095***	
		[0.000]			[0.001]	
Combination with similar concepts			0.050***			0.052***
			[0.000]			[0.000]
Popularity in t-1 X			-0.014***			-0.015***
Combination with similar concepts			[0.000]			[0.000]
Author productivity	0.462***	0.268***	0.456***	0.400***	0.227***	0.398***
	[0.003]	[0.003]	[0.002]	[0.003]	[0.003]	[0.003]
Constant				0.283	2.126***	0.447**
				[0.205]	[0.715]	[0.225]
Observations	615,596	615,596	615,596	615,596	615,596	615,596
Log-likelihood	-231,306	-197,443	-226,728	-218,643	-191,544	-215,573

Standard errors in brackets

*** p<0.01, ** p<0.05, * p<0.1

Table A5: Models using an alternative measure for “Affiliation with popular others”: Max popularity of co-mentioned keywords in year t-1.

	Poisson model Keyword FE	NBReg model Keyword RE, Year FE
Keyword age	0.009***	0.002***
	[0.000]	[0.000]
Keyword popularity in t-1	1.763***	1.716***
	[0.004]	[0.006]
Change in popularity from t-2 to t-1	-0.031***	-0.032***
	[0.001]	[0.001]
Max pop. of co-mentioned keywords (t-1)	0.132***	0.094***
	[0.002]	[0.002]
Popularity in t-1 X	-0.053***	-0.034***
(max pop. of co-mentioned keywords)	[0.001]	[0.001]
Constant		-14.549
		[2,023.656]
Observations	676,719	676,720
Log-likelihood	-265,553	-244,162

Standard errors in brackets

*** p<0.01, ** p<0.05, * p<0.1

Table A6: Re-estimating the models with log-linear specification. OLS models with keyword fixed effects, the DV is ln(count+1).

	M1	M2	M3	M4
Keyword age	-0.000***	-0.000***	-0.001***	0.000***
	[0.000]	[0.000]	[0.000]	[0.000]
Keyword popularity in t-1	0.253***	0.118***	0.045***	0.223***
	[0.001]	[0.002]	[0.001]	[0.001]
Change in popularity from t-2 to t-1	-0.023***	-0.032***	0.017***	-0.019***
	[0.000]	[0.000]	[0.000]	[0.000]
Affiliation with popular others		0.067***		
		[0.001]		
Popularity in t-1 X		-0.009***		
Affiliation with popular others		[0.000]		
Local crowding			0.245***	
			[0.000]	
Popularity in t-1 X Local crowding			-0.048***	
			[0.000]	
Combination with similar concepts				0.105***
				[0.000]
Popularity in t-1 X Combination with similar concepts				-0.021***
				[0.000]
Constant	0.066***	0.079***	0.079***	0.057***
	[0.001]	[0.001]	[0.000]	[0.000]
Observations	676,720	676,720	676,720	676,720
R-squared	0.051	0.076	0.656	0.229

Standard errors in brackets

*** p<0.01, ** p<0.05, * p<0.1

Table A7: Re-estimating the models of Table 3 with a split-sample approach.

(a) Poisson models with keyword fixed effects

	M1	M2	M3	M4	M5	M6
	ln(popularity_t-1)<=1	ln(popularity_t-1)>1	ln(popularity_t-1)<=1	ln(popularity_t-1)>1	ln(popularity_t-1)<=1	ln(popularity_t-1)>1
Affiliation with popular others	0.259***	0.014***				
	[0.005]	[0.000]				
Local crowding			0.625***	0.069***		
			[0.002]	[0.001]		
Combination with similar concepts					0.380***	0.016***
					[0.003]	[0.000]
Keyword age	-0.006***	0.010***	-0.028***	-0.001***	-0.008***	0.013***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Change in popularity from t-2 to t-1	-0.113***	-0.001	0.103***	0.002***	-0.064***	0.008***
	[0.003]	[0.001]	[0.004]	[0.001]	[0.004]	[0.001]
Observations	651,974	15,585	651,974	15,585	651,974	15,585
Log-likelihood	-157755	-31629	-115802	-27668	-144249	-31024

(b) Negative binomial models with keyword random effects and year fixed effects

	M7	M8	M9	M10	M11	M12
	"ln(popularity_t-1)<=1"	"ln(popularity_t-1)>1"	"ln(popularity_t-1)<=1"	"ln(popularity_t-1)>1"	"ln(popularity_t-1)<=1"	"ln(popularity_t-1)>1"
Affiliation with popular others	0.286***	0.016***				
	[0.005]	[0.001]				
Local crowding			0.629***	0.073***		
			[0.002]	[0.001]		
Combination with similar concepts					0.271	0.015***
					[0.000]	[0.000]
Keyword age	-0.013***	0.010***	-0.027***	0.001**	-0.012***	0.012***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Change in popularity from t-2 to t-1	-0.149***	-0.007***	0.107***	0.001	-0.112***	0.003**
	[0.004]	[0.001]	[0.004]	[0.001]	[0.004]	[0.002]
Constant	-0.032**	0.183***	1.555***	0.515***	0.170***	0.182***
	[0.016]	[0.029]	[0.062]	[0.032]	[0.019]	[0.029]
Observations	662,397	17,701	662,397	17,701	662,397	17,701
Log-likelihood	-191333	-33121	-151258	-30974	-181414	-33018

Standard errors in brackets

*** p<0.01, ** p<0.05, * p<0.1