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Yardstick Competition in the Digital Age: Unveiling New Networks in Tax Competition

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Abstract

We exploit a data disclosure project by the Italian government (OpenCivitas) which allowed mayors to view each other's detailed expenditure data through a dedicated website. We interpret views on the website as generating a directed network. Mayors in the network are on average younger, more educated, they are more likely to come from larger cities which more often are in the northern regions and are more likely to be affiliated to traditional parties, although populist parties usually rely more on the web for communication and political activities. Using directed dyadic models we find that mayors tend to form links with mayors of similar age who manage similar-sized cities and most often in their same region. However, links are more likely to be formed when mayors don't share the same gender, education and party affiliation. Mayors in this network do not engage in yardstick competition with neighbouring municipalities while all the other mayors do, and rather compete with each other, despite the physical distance. We show that this network existed before the website opened, but we find that after data disclosure yardstick competition within the network becomes strongly driven by mayors who are up for re-election. This was not the case before data disclosure. For the other municipalities, yardstick competition between neighbours remains uncorrelated with mayors' term limits.

JEL codes: H11, H71, H77

Keywords: yardstick competition, tax competition, network, open data, property tax, municipalities, italy

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1 Introduction

There is now a large empirical literature on the effect of increased information via the media on government policy. Early well-known contributions include Besley, Burgess (2002) who show that state governments in India are more responsive to falls in food production and crop flood damage via public food distribution and calamity relief expenditure where newspaper circulation is higher, and Strömberg (2004), who finds that U. S. counties with many radio listeners received more relief funds a major New Deal relief program. More recently, Repetto (2018) showed that a reform that required Italian municipalities to disclose their balance sheets before elections reduced the effect of the size of the political budget cycle in spending.

However, there are two possible channels by which increased media coverage affects the setting of economic policies. One, which is the focus of existing literature, is that voters become better informed about government policies and so incumbent politicians change their behaviour accordingly, by becoming more "responsive", in order to secure re-election. A second possibility, which has received, as far as we are aware, no attention at all, is that other political decision-makers have more information via the media about what their peers in other jurisdictions are doing. Of course, to study this second channel in isolation, what is required is a policy experiment where *only other politicians, not voters*, become better informed about policies of their peers.

In this paper, we exploit just such a policy experiment in Italian local government. This was a data disclosure project by the Italian government, called OpenCivitas, which allowed only mayors of Italian municipalities, not the general public, to view each other's detailed expenditure data through a dedicated website over the period July to November 2014. Between July 16th and November 18th of that year, the access to the system was fully monitored, and we have recording more than 63000 'access events' involving 13% of Italian municipalities. An access event occurs when the mayor or council member of one municipality opens the page of another municipality, or his own.

In this paper, we interpret views on the website as generating a directed network of

municipalities. An initial analysis reveals that mayors who participate in the network i.e. access the OpenCivitas website, are on average younger, more educated, are more likely to come from larger cities which more often are in the northern regions, and are more likely to be affiliated to traditional parties. We then estimate a dyadic model of network formation. We find not surprisingly, that if two mayors share the same region, age bracket or city size, this increases the chances of a link being created. However, the opposite happens for gender, political affiliation and higher education. We also see that if both mayors are term limited, the chances of creating a link decrease.

The main purpose of this paper is to study whether mayors in the OpenCivitas network have different fiscal behaviour from the others. We focus on strategic interaction in the setting of property tax rates by mayors, by estimating tax reaction functions. Our main finding is that municipalities in the network interact in a different way than municipalities outside the network. First, those in the network were strategically interacting with others in the network even before the OpenCivitas initiative. After the initiative, the nature of the interaction changed somewhat, with strong evidence of strategic interaction only for non-term limited mayors. Both before and after OpenCivitas, municipalities in the network did not react with those outside. On the other hand, municipalities outside the network appear to react only to the tax rates of their geographical neighbors, both before and after the OpenCivitas initiative.

The layout of the remainder of this paper is as follows. Section 2 discusses related literature, section 2 gives the institutional background and details about the OpenCivitas initiative, Section 4 describes the data that we use to construct the network and estimate fiscal reaction functions, Section 5 has the results on network formation, and finally 6 and 7 describe the reaction functions we estimate and our main results on how membership of the network affects strategic interaction in the setting of property taxes.

2 Literature

This paper speaks to three literatures. First, there is the literature on estimation of the determinants of network formation (see De Paula (2020)). Here, there are two approaches, descriptive and structural.

The first approach studies correlations between the pairwise or dyadic network links and characteristics of the linked individuals. In particular, dyadic models focus on the estimation of individual parameters, i.e. degree heterogeneities, and common parameters between nodes, namely homophily parameters. The latter category often refers to similarities or dissimilarities in nodes' characteristics (municipalities/mayors' features in our case). As jointly estimating both kinds of parameters is extremely challenging and often leads to biases and incorrect inference, we focus on models which estimate homophily parameters while treating the node-specific characteristics as fixed effects (Jochmans (2018). Other models focus on estimating the individual-specific parameters (Yan et al. (2019), although in our setting this class of parameters are less relevant for our analysis.

The second approach explicitly models network formation as the equilibrium outcome of a non-cooperative game between n individuals. This game is usually formalised so that the equilibrium decision rules are linear functions of observed and unobserved characteristics (Blume et al. (2015), Canen, Trebbi (2016)), where the reduced-form coefficients in these decision rules depend on both the underlying structural coefficients, such as parameters of the utility function, and network links. Then, the question is under what conditions the structural coefficients can be identified from the reduced form. As our focus in this paper is simply to describe the Opencitivas network and explore its implications for strategic interaction in taxes between municipalities, this structural approach is beyond the scope of this work.

Second, there is the literature on tax competition and fiscal competition more generally. This literature dates back to the seminal contribution of Case et al. (1993) and can usefully be divided into two generations. First generation contributions, such as Bordignon et al.

(2003), Devereux et al. (2008), and Allers, Elhorst (2005), estimate a simultaneous system of reaction functions for taxes or other fiscal variables. To avoid problems with degrees of freedom and overfitting, the number of coefficients is substantially reduced by assuming that the tax set by one authority (municipality, state, country) depends on a *weighted average* of the other authorities' taxes, where the weights are exogenously given. This eventually means that only one coefficient, the reaction coefficient, needs to be estimated, along with the effects of other covariates of authority i on the tax. Such a system has been typically estimated in two ways.

First, an instrumental variables approach has been taken, where the weighted average of other taxes is instrumented by the weighted average of characteristics of other authorities that are unlikely to affect authority i's tax directly e.g. demographic variables of other authorities. Well known examples of this first approach include Devereux et al. (2008), (more?). Second, some papers take a maximum likelihood approach, by estimating what is known as the spatial lag model, for example, Allers, Elhorst (2005).

However, this first-generation approach has been critiqued in a well-known article by Gibbons, Overman (2012), who say that "in many situations of interest this achieves, at best, only very weak identification. Worse, in many cases, such an approach will be uninformative about the causal economic processes at work, rendering much applied spatial econometric research "pointless," unless the main aim is description of the data." Specifically, it is not clear which taxes are influencing which, as there is no exogenous variation in taxes of any units in any of these studies. Moreover, results are often very sensitive to the somewhat arbitrary choice of weighting matrix. A third problem is that to achieve identification, the assumption that characteristics of other authorities other than the tax do not affect i's tax setting directly.

A small second-generation literature has started to address these problems by leveraging reforms that generate exogenous variation in local or regional taxes. For example, Baskaran (2014) exploits an exogenous reform of the local fiscal equalization scheme in the German

State of North Rhine-Westphalia to identify tax mimicking by municipalities in the neighboring state of Lower Saxony. Parchet (2019) exploits the fact that local jurisdictions located close to a state border in Swtizerland have some neighbors in another state and instruments the tax rate of neighbor jurisdictions with the state-level tax rate of the neighboring state. He uses this instrument to identify strategic personal income tax setting by local jurisdictions in Switzerland and find that tax rates are strategic substitutes.

In our context, there are no reforms that generate exogenous variation in municipal taxes, but we improve on the first-generation approach in two ways. First, the OpenCivitas access data allow us to *directly* observe a possible weighting matrix. Second, using the network structure of the OpenCivitas links, we are able to achieve identification without assuming that characteristics of other authorities other than the tax do not affect i's tax setting directly, as explained in more detail in Section 6 below. This relates our work to a third literature, on identification in networks.

Identification in networks is generally problematic because unit j may affect unit i's choice of endogenous variable (say y_i) both through its own endogenous choice y_j and some exogenous variable(s) relating to j, say z_j. The identification issue in this type of model is that these two effects cannot be distinguished, as these endogenous effects can act as conduits for the reverberation of exogenous changes in z_j, leading to a multiplier effect. This is known as the reflection problem (Manski (1993)).

As already remarked, in the tax competition literature, the reflection problem is eliminated by making the very strong assumption that characteristics of other authorities other than the tax do not affect i's tax setting directly. In our case, we use the known structure of the OpenCivitas network to establish that for every municipality i that looks at some other municipalities, at least one of the municipalities j accessed by i itself accesses a set of municipalities that include some municipalities that are not accessed by i (and also not i itself). As we show below, this is enough to solve the reflection problem in our context. This condition also relates to necessary and sufficient conditions for identification developed

by Bramoullé et al. (2009).

3 Institutional Setting

3.1 Structure of Italian Local governments

As reported in Marattin et al. (2021), Italy is a unitary Republic with three layers of sub-national governments. As a first layers the territory is divided in 20 Regions (five of which with a special statute that gives them higher autonomy from the central government); the second layer of the institutional system is represented by 93 Provinces (17 of which within special regions) and 14 Metropolitan districts (4 of which within special regions). The third and most important layer of the institutional system is represented by municipalities (*Comuni*), which have a long and important historical tradition in Italy. Municipal governments are ruled by a city council and an executive committee appointed by the elected mayor (*Sindaco*). The council and the mayor are directly elected for a five-year term and are subject to a two-term limit.[1] As in many other European countries, also in Italy, there is a high level of fragmentation at the municipal level. There exist 7,978 municipalities (1,351 of which within special regions); 85% of all municipalities have less than 10,000 inhabitants, 75% less than 5,000, 24% less than 1,000 inhabitants, while only 6 cities have more than 500,000 inhabitants. At this level of government is allocated 6.8% of total current public expenditure (52.2 billion euros), by which a wide range of essential public services are provided: environment protection and waste management, social services to elderly and disabled persons, childcare and nursery schools, school-related services (such as school meals and transportation), local police, maintenance of municipal roads, management of civil registries, town planning, culture, recreation, and economic development.

In our analysis, we focus on municipalities within normal-statute regions, as they share the same set of fiscal rules and participated to the opnecivitas network. In particular, the

[1]The electoral system is different according to the population: in small municipalities (below 15,000 inhabitants) there is single-round plurality system; instead, in larger municipalities (above 15,000 inhabitants) there is a run-off system.

current expenditure of these municipalities is fully financed by local taxes and fees plus horizontal (non earmarked) equalization grants allocated with a system based on historical expenditure up to 2014; after that year a new equalization system based on the difference between standard expenditure needs and fiscal capacity has been gradually introduced in 2015 with the goal of completely replacing the previous method in 2030. Specific grants are exceptional and earmarked; they are a residual source of funding provided by the central or the regional government, in favor of municipalities with specific investment needs.

Municipalities' own fiscal revenues come from two main sources: (1) local taxes, among which the most relevant are the Property Tax (called "ICI" until 2011 and "IMU" afterward), the tax on waste disposal (called "TARSU" until 2011 and "TARI" afterward), and the local income tax surcharge; (2) local fees related to road and traffic, libraries, theaters and culture, burial services, and other services such as the occupation of public spaces, public billboards, certificates. According to the Italian Constitution, all local governments are subject to a balanced-budget constraint and fiscal deficit is allowed only to finance capital expenditure.

In the aftermath of the financial crisis, starting in 2010, the Italian government has implemented an intense program of spending cuts. In the period 2010–2015, approximately one third of the fiscal consolidation occurred through a permanent cut in transfers to municipal governments, which were reduced by 8.6 billion euros, corresponding to roughly 16% of current expenditure or 33% of capital expenditure at the municipal level. As a result of these cuts, in 2015 the vertical component of the equalization grants was abolished, and the equalization system became horizontal.

During the fiscal consolidation period, we also observe an increase in the level of the property tax, mainly due to the 2012 reform passed by the central government as one of the main pillar of the fiscal consolidation program implemented to cope with the consequences of the financial crisis. Between 2011 and 2012, total revenues from the property tax passed from 9.8 billion to 23.8 billion euros, thanks to the revaluation of the cadastral values and to the taxation of the owner-occupied dwellings previously exempted in 2008 and recently

exempted again in 2016 (see Marattin et al. (2021) for more details).

After a reform in 2012, the Italian property tax worked as follows: the baseline tax rate was fixed at 0.76% by the central government and gave mayors the ability to modify it locally by adding or subtracting 0.3%. The final range of possible tax rates goes from 0.46% to 1.06% of the house value. The rate is reduced for the main house of residence: the baseline rate is 0.4%, with a local flexibility of $+/-0.2\%$ decided by the mayor.

3.2 Fiscal equalization and the OpenCivitas project of online data disclosure

In May 2009 (Law no. 42/2009) the Parliament reformed the local governments' financing structure, introducing a new equalization system based on standard expenditure needs and fiscal capacity.

In the end of 2013, the Italian government produced the first wave of the assessment of Standard Expenditure Needs (SEN from now on) for 6702 municipalities. This marked the beginning of a radical reform of intergovernmental relations in Italy, taking the first and necessary step towards the construction of a new and more efficient mechanism for the distribution of equalisation grants to finance the essential functions of municipalities (34 billion euros in 2010) . As part of this process, the Italian government decided to integrate the information provided by official sources (Budget Sheets, National Institute of Statistics, Ministry of Education, Land Registry Office, etc.) with new data by sending all authorities a specific questionnaire for each service. In this way a new database was built collecting, for the first time, detailed information on outputs, inputs, methods of management and organisational decisions made in the production process of local services by local governments. The survey questionnaire, in addition to representing valuable information in itself, represents an innovation in international techniques to evaluate SEN.

As a complementary exercise, besides the evaluation of SEN, the data collected through the questionnaires have been used to produce a simple system of performance indicators, pro-

viding basic information on how each municipality uses its resources for the provision of the essential services. In the first wave of the analysis of the data, between 2004 and 2015, the main computed indicator was the gap between the standard and actual expenditure for each service, while other indicators are, for example, the labour cost for employee, the share of labour costs on total expenditure or the level of services per capita. It is important to note that, although the comparison between standard and actual expenditure is not a perfect indicator of efficiency, it provides a good reference point to judge the level of expenditure of each municipality against the level of expenditure of other local authorities. In order to overcome this limitation, in the second wave of the analysis, which started 2016, also a second performance indicator was computed based on the evaluation of output efficiency considering the the gap between the standard and actual level of services. Finally, the combination between the expenditure and the output efficiency indicators was used to produced an overall index of municipal efficiency.

After the computation of Standard Expenditure Needs and performance indicators, the Italian government decided to publish on the web the data collected through the questionnaires along with the system of performance indicators. This has been done using a business intelligence model named OpenCivitas, with the purpose of providing local authorities with an innovative online tool for information-management, and citizens with the opportunity to know how local public services are provided. Crucially for our purposes, OpenCivitas allows each local authority to display its data and compare them with the data of other authorities with similar characteristics. The web site www.OpenCivitas.it was opened the 16th July 2014, on the same day each municipality received an official e-mail by the Ministry of Finance advertising the new initiative. In order to test the system, for a period of four months information was only visible to local administrators (the mayor and member of the council) who received a password to access the system. On November 18th, the website was opened to the public thus removing the need to sign in through credentials.

Between July 16th and November 18th, the access to the system has been fully monitored,

recording more than 63000 'access events' involving 13% of Italian municipalities (see Figure 1). An access event occurs when the mayor or council member of one municipality opens the page of another municipality, or his own. It has been possible to track, for each access, which pages of the website each mayor viewed e.g. those relating to particular services, etc., and for how long they were viewed. For example, we know that the most visited webpages concern the local police service. Figure C.1 summarize the main information published online for each local authority and report the methodology followed for the performance evaluation of each local authority.

4 Data

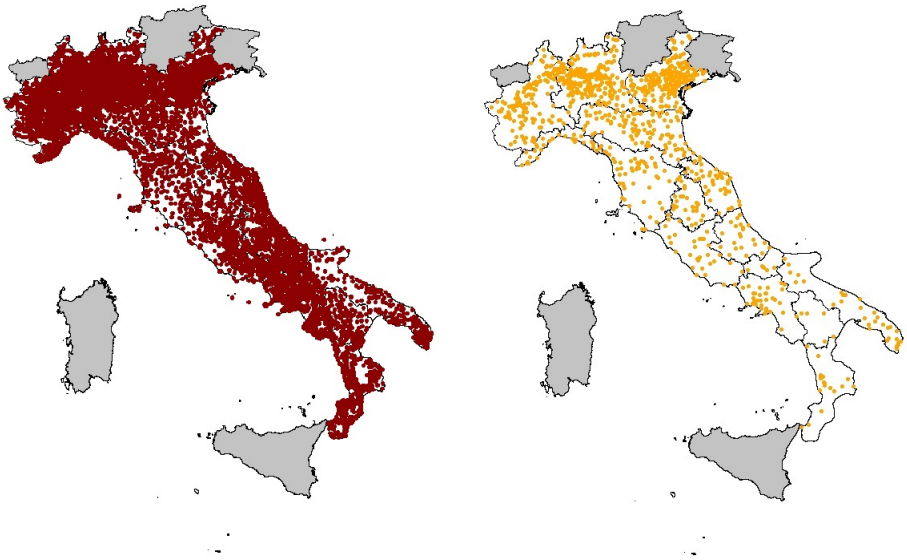
4.1 Clicks

Second by second observations of every action taken by mayors on the website ($\sim$ 63'000 single events). Collected by the Ministry of Finance (MoF) during the testing period (July-November 2014). For each click, the data reports the username of the account, the exact timing of the click and what information was accessed through the click. There were in total 22712 accesses to other mayors' spending information.

Figure 1 shows a graphical comparison between all the Italian municipalities and the ones who were active on OpenCivitas.

We exploit the information accessed by each mayor to construct our network: whenever mayor i accesses expenditure information of any other mayor j, we assign a direct link between i and j. Out of the 6660 municipalities in our sample, 652 looked at other mayors' information, and 2516 were viewed. The total amount of mayors involved, including both active and passive nodes, is 2740. The total amount of direct links created is 4768. Figure 2 provides a graphical representation of the network. Figure 3 shows the partial network which satisfies the conditions for the instrumental variable approach (see Section 6), and hence this represents the main sample in our analysis.

Figure 1: Total number of municipalities vs Municipalities active on OpenCivitas



4.2 Property Tax Rates

Mayors in Italian municipalities can choose to marginally increase or decrease the baseline rate for the property tax, within a certain range. We collect the information of the final property tax rates chosen by mayors for the years 2011 to 2015.

4.3 Expenditure, Output, Performance

For the years 2011, 2013 and 2015, we collect from OpenCivitas.it the levels of expenditure for each category of public spending, the levels of public goods and services provided by the municipalities, for each good and service, and the efficiency for all these variables as a difference between actual expenditure and the standard estimated one. We also collect overall performance, which is a function of spending efficiency, output efficiency and the average cost of the public good.

4.3.1 Municipalities Characteristics

We collect characteristics of each municipality from the Ministry of Interior (MINT) and ISTAT for the year 2014. These characteristics include population, share of population over 65 (over 75), degree of urbanization, elevation, income and property tax rates, average declared income of citizens, transfers from the central government.

4.3.2 Mayors Characteristics

We collect characteristics of each mayor in 2014 from the Ministry of Interior (MINT): age, education, party affiliation and description of their job before becoming a mayor. Many mayors were elected in May 2014, 2 months before the introduction of the website. For municipalities which held election in 2014, we use data for the new mayors.

Table 1: Descriptive Statistics

		Total municipalities				OpenCivitas Network		Outside OpenCivitas Network	
		Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Mean	Std. Dev.
Dependent variables									
Property tax rate variation (2013-2011)	per thousands	2.574	1.059	-1.4	6.1	2.588	1.037	2.576	1.065
Property tax rate variation (2012-2014)	per thousands	0.427	0.854	-4.6	4.6	0.401	0.908	0.425	0.848
Property tax rate variation (2015-2013)	per thousands	0.240	0.718	-3.3	5.1	0.207	0.756	0.241	0.714
Property tax rate									
2011 tax rate	(per thousands)	6.267	0.719	3.0	8.0	6.491	0.633	6.245	0.724
2012 tax rate	(per thousands)	8.578	1.017	4.6	10.6	8.824	1.094	8.558	1.009
2013 tax rate	(per thousands)	8.849	1.067	4.6	10.6	9.077	1.093	8.829	1.065
2014 tax rate	(per thousands)	9.006	1.115	4.6	10.6	9.224	1.179	8.983	1.109
2015 tax rate	(per thousands)	9.089	1.113	4.6	10.6	9.283	1.165	9.070	1.108
Instrumental and control variables									
Declared income	(euro per taxpayer)	17,256	3,591	6,796	53,973	19,789	2,961	17,035	3,559
Seismic risk level	(discrete scale)	2.730	1.242	1	5	2.680	0.997	2.737	1.264
Municipal surface	(Square km)	34.25	47.47	0.12	1287.36	56.14	98.04	32.61	41.41
Population density	(Inhab. per square Km)	331.7	682.5	0.8	12269.6	617.0	928.4	306.6	653.5
Population	(no.)	7,748	43,652	34	2,617,175	34,914	161,053	5,808	16,570
Municipality below 3000 inhab.	(dummy)	0.548	0.498	0	1	0.180	0.385	0.580	0.494
Municipality above 15000 inhab.	(dummy)	0.096	0.295	0	1	0.309	0.463	0.079	0.269
Left wing mayor	(dummy)	0.096	0.294	0	1	0.253	0.435	0.083	0.276
Right wing mayor	(dummy)	0.069	0.253	0	1	0.147	0.354	0.062	0.241
Local/populist mayor	(dummy)	0.836	0.371	0	1	0.601	0.490	0.855	0.352
Femail mayor	(dummy)	0.139	0.346	0	1	0.180	0.385	0.135	0.342
Mayor age	(years)	50.38	10.63	19.00	86.00	50.00	9.79	50.47	10.68
Mayor with university degree	(dummy)	0.468	0.499	0	1	0.527	0.500	0.463	0.499
Mayor at first term	(dummy)	0.656	0.475	0	1	0.633	0.483	0.659	0.474
Electoral year	(dummy)	0.585	0.493	0	1	0.554	0.498	0.587	0.492

Notes: Total municipal sample = 6359; OpenCivitas network municipalities = 388; Outside OpenCivitas municipalities = 5735.

Figure 2: OpenCivitas network visualization - All municipalities

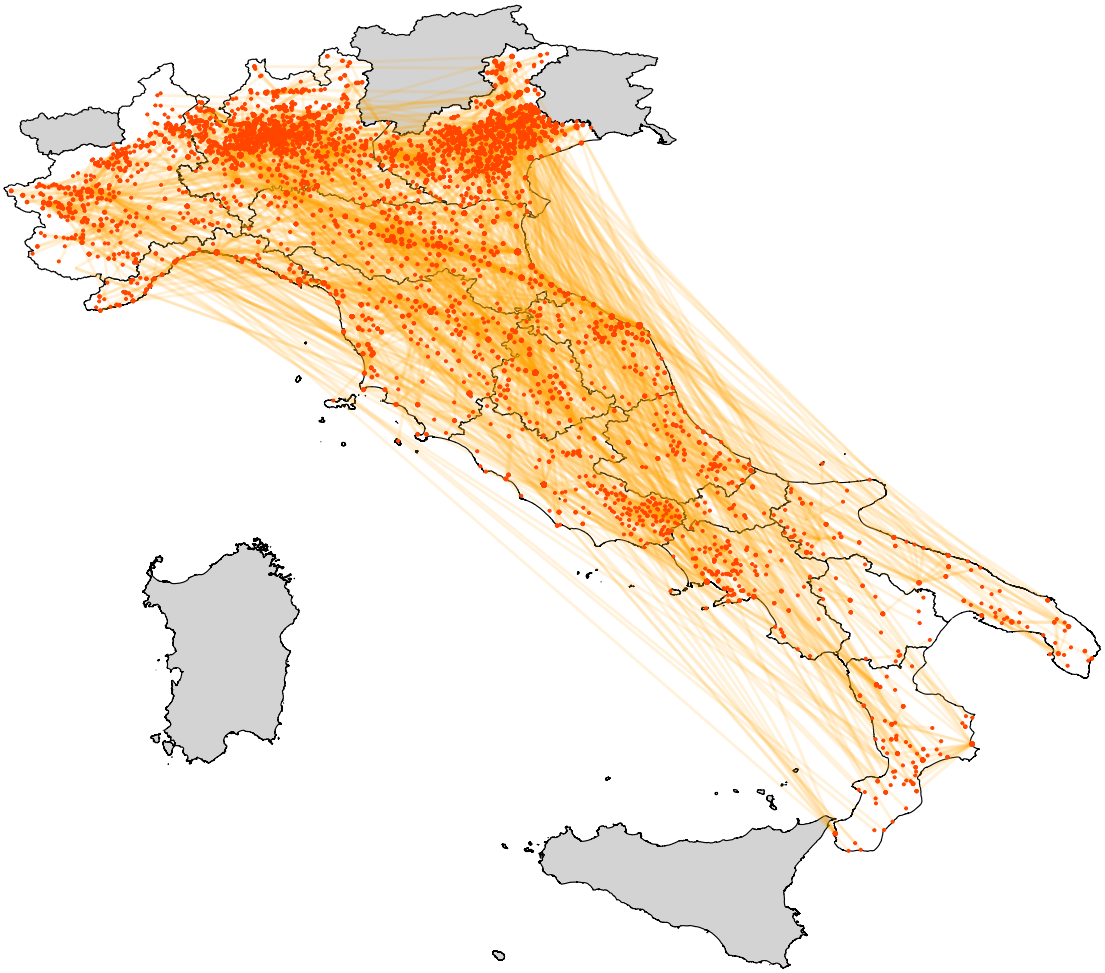


Figure 3: OpenCivitas network visualization - Municipalities included in the first stage.

For information on the selection of the sample for IV estimation, see Section 6

5 Endogenous Network Formation

5.1 Participation to the Network

In this section we investigate the process of endogenous network formation and in particular we focus on analysing which are the characteristics of mayors and cities which better predict participation to the network and the formation of specific links within the network.
We estimate a simple linear model as well as a Probit and a Logit model:

OLS:

$$Yi = \beta X_i + \epsilon_i$$

Probit:

$$Prob[Y_i = 1|X_i] = \Phi(\beta_1 X_i)$$

Logit:

$$Prob[Y_i = 1|X_i] = \frac{e^{\beta_2 X_i}}{1 + e^{\beta_2 X_i}}$$

Where Y is a dummy representing whether the municipality is part of the network and X is a vector of municipality's and mayor's characteristics which act as explanatory variables. Table 2 reports the OLS coefficients, the marginal effects computed from the Probit coefficients and the odds ratios from the logistic model. The results show that the network is composed by younger, more educated mayors, who are more likely to be up for re-election. These mayors are more likely to come from larger cities and from more northern regions. Mayors from the more traditional parties, both right-wing and left-wing, are also more likely to be in the network. This last result is somehow surprising as this network has been revealed through a web platform, and usually members of the populist parties are considered to be the most active on the internet, both in terms of in terms of propaganda and all-around political activity.

Table 2: Network analysis - Probability of participation

Dependent variable	Dummy = 1 if OpenCivitas access>1		
	(1)	(2)	(3)
Northern Region	0.0406***	0.0363***	1.5724***
	[0.010]	[0.010]	[0.195]
Southern Region	-0.0524***	-0.0762***	0.3464***
	[0.010]	[0.013]	[0.063]
Population	0.0010***	0.0005***	1.0055***
	[0.000]	[0.000]	[0.002]
Left-wing Mayor	0.0677***	0.0611***	2.1679***
	[0.016]	[0.011]	[0.284]
Right-wing Mayor	0.0572***	0.0527***	1.8957***
	[0.017]	[0.012]	[0.267]
Populist Party Mayor	0.0406	0.0391	1.7034
	[0.124]	[0.071]	[1.348]
No Term Limit	0.0179**	0.0160*	1.2357**
	[0.009]	[0.008]	[0.126]
Election Next Year	-0.0078	-0.0128	0.8785
	[0.013]	[0.016]	[0.180]
Mayors above age of 60	-0.0265**	-0.0282**	0.7131**
	[0.012]	[0.012]	[0.109]
Female Mayor	0.0111	0.0096	1.1257
	[0.011]	[0.010]	[0.135]
Mayor with University Degree	0.0173**	0.0170**	1.2526**
	[0.007]	[0.007]	[0.116]
Estimator	OLS	Probit	Logistic
Observations	6,328	6,328	6,328

Notes: Standard errors in parenthesis. Column 2 report marginal effects computed from the Probit coefficients. Column 3 reports the odds ratios from the logistic regression.

5.2 Link creation

Secondarily, we investigate the reasons why specific links are created, i.e. why a mayor chooses to look at a municipality and not at another one. For this purpose, we construct a

dataset with $n \times (n-1)$ rows where each municipality is matched with every other municipality. We define W to be a dummy which takes value 1 if municipality i looked at municipality j (a direct link from i to j). We replace all the mayor's personal characteristics, as well as the municipality's characteristics, with dummies which take value 1 whenever the two matched municipalities share the same value or they are similar, e.g. mayors are in the same age bracket. Otherwise, these dummies take value zero.

In addition to OLS and binary response models, in this setting we use dyadic models. In particular, following Jochmans (2018) we consider a model for directed network formation, which estimates the parameters which are commons within pairs of individuals, i.e. the homophily parameters, while treating the node-specific parameters as fixed effects. This model considers the cross-section describing the links as a semi-panel of all the $n \times (n-1)$ possible pairwise interactions between agents $i = 1...n$ and $j \neq i$ and the fixed effects are the in-degree and the out-degree of each node. The strategy behind this model is to difference-out the individual parameters in the logistic regression, namely α^{in} and α^{out}. We consider the estimator proposed by Jochmans (2018) for logistic regression models with two-way fixed effects:

$$\begin{aligned} P(W_{lj} =&1|X, \alpha^{in}, \alpha^{out}, W_{lj} + W_{lk} = 1, W_{ij} + W_{ik} = 1, W_{lj} + W_{ij} = 1) = \\ &= \frac{exp[((X_{lj} - X_{lk}) - (X_{ij} - X_{ik}))^T \beta]}{1 + exp[((X_{lj} - X_{lk}) - (X_{ij} - X_{ik}))^T \beta]} \end{aligned} \tag{1}$$

Where W_{lj} is the (lj) link. Table 3 reports the results for all the specifications. For the dyadic model, we use the *twgravity* Stata command proposed by Jochmans, Verardi (2020) which implements equation 1 as a GMM estimator which is n-consistent, asymptotically normally-distributed, and asymptotically unbiased (Jochmans (2017)).

Table 3: Network formation - Probability of link creation

Dependent variable	Link between municipality i and j			
	(1)	(2)	(3)	(4)
Mayors in the same age bracket	0.0000**	0.0361***	1.1383***	0.0000*
	0.000]	[0.011]	[0.038]	[0.000]
Mayors with same gender	0.0000***	-0.0599***	0.7909***	-0.0000**
	0.000]	[0.009]	[0.033]	[0.000]
Mayors with university degree	0.0000***	-0.0296**	0.8840***	-0.0000**
	0.000]	[0.013]	[0.047]	[0.000]
No term-limited mayors	0	0.0367***	1.1421***	0.0000***
	0.000]	[0.009]	[0.032]	[0.000]
Municipalities in the same region	0.0012***	0.9570***	37.9208***	0.0012***
	0.000]	[0.010]	[0.039]	[0.000]
Municipalities below 3000 inhab.	0.0002***	0.3567***	3.7102***	0.0002***
	0.000]	[0.010]	[0.036]	[0.000]
Left wing mayors	0.0001***	-0.1720***	0.5523***	-0.0001***
	0.000]	[0.010]	[0.037]	[0.000]
Right wing mayors	0.0001***	-0.1354***	0.6261***	-0.0001***
	0.000]	[0.011]	[0.039]	[0.000]
Populist parity mayors	0.0001**	-0.1204***	0.6352***	0.0000**
	0.000]	[0.023]	[0.077]	[0.000]
Mayors with the same electoral cycle	0.0001***	-0.0755***	0.7661***	-0.0001***
	0.000]	[0.009]	[0.032]	[0.000]
Estimator	OLS	Probit	Logistic	TW-FE Exp.
Observations	43,725,154	43,725,154	43,725,154	43,725,154

Notes: Standard errors in parenthesis. Column 2 report marginal effects computed from the Probit coefficients. Column 3 reports the odds ratios from the logistic regression. Column 4 reports the coefficients from exponential regression with two-way fixed effects as in equation 1.

Not surprisingly, sharing the same region, age bracket or city size increases the chances of a link being created. However, it is interesting to notice that the opposite happens for gender, political affiliation and higher education. While having both just a primary education level increases the odds of forming a link, college graduates tend to look less at each other and the same happens for same sex people and for members of the same party, irrespective of the party.

Finally, if mayors i and j are both non term-limited, the odds that i forms a link are higher. This is consistent with the existing evidence: mayors who are up for re-election tend to behave according to political competition, by changing their spending and the provision of salient public good. Hence it is not surprising to find that mayors might want to check how colleagues from other municipalities are facing the electoral challenge.

6 The OpenCivitas Network and Strategic Interaction between Mayors

6.1 Reaction Functions

In the section, we discuss the specification and estimation of our reaction functions. We aim to estimate reaction functions of the form

$$y_i = \alpha \sum_{j \neq i} \omega_{ij} y_j + \beta' \mathrm{X}_i + \gamma' \sum_{j \neq i} \omega_{ij} \mathrm{X}_j + \varepsilon_i \tag{2}$$

for municipalities i =1, ...n, where y_i is an outcome such as a (change in) tax, X_i is a vector of control variables, and ω_{ij} are the elements of an interaction matrix W, assumed known to the modeller. This is sometimes known as the spatial Durbin Model (Gibbons, Overman (2012)).

The "first-generation" literature on fiscal reaction functions made two strong assumptions when estimating (2). First, some ad hoc assumption is invariably made about the interaction matrix W; for example, a common assumption is that any municipality only reacts to its direct geographic neighbours, with which it shares a boundary. Second, it has long been known that without further restrictions on W, coefficients (α, β, γ) are not identified (Bramoullé et al. (2009)). The intuition is simple: if some element of X_j changes, this will also affect y_j and so without further restrictions, α and γ cannot be separately identified. In the first-generation literature, this problem was dealt with by simply assuming that the characteristics of other municipalities cannot influence the fiscal policies of municipality i i.e. $\gamma = 0$. Both of these assumptions are strong and have been criticized, as discussed in section 2 above.

In our approach, we to some extent avoid both these problems. First, the OpenCivitas access data allow us to *directly* observe a possible interaction matrix. In particular, we use the access data in two ways. Let $N(i)$ be the set of municipalities (websites) accessed by i. In the simplest case, we set $\omega_{ij} = 1$ if municipality i accessed $j's$ fiscal data during the period,

and zero otherwise, and then normalize to that the row elements of the matrix sum to one i.e.

$$\omega_{ij} = \begin{cases} \frac{1}{\#N(i)}, & j \in N(i) \\ 0, & j \notin N(i) \end{cases} \tag{3}$$

A refinement is allow the weight to be proportional to c_{ij} is the number of "clicks" i.e. access events when municipality i accesses j, so

$$\omega_{ij} = \frac{c_{ij}}{\sum_{j \in N} c_{ij}}, j \in N$$

We will focus on the simpler case for exposition, so we want to estimate:

$$y_i = \frac{\alpha}{\#N(i)} \sum_{j \in N(i)} y_j + \beta' \mathrm{X}_i + \frac{1}{\#N(i)} \gamma' \sum_{j \in N(i)} \mathrm{X}_j + \varepsilon_i \tag{4}$$

To achieve identification, we make a weaker assumption than exclusion of X_j from (2). Assume for the moment that all i in N access at least one other municipality i.e. $N(i)$ is non empty. We assume:

A1. $S_j^i = N(j)/(N(i) \cup i) \neq \emptyset$, at least one $j \in N(i)$

This says that at least one of the municipalities $j \in N(i)$ accessed by i itself accesses a set of municipalities that include some municipalities that are not accessed by i (and also not i itself). This achieves identification because (i) $\mathrm{X}_k, k \in S_j^i$. does not appear in (2); (ii) when X_k varies, it will affect the setting of y_j. Thus, the X_k can be used as valid instruments for y_j; more precisely, we will use $Z_{ij} = \sum_{k \in S_j^i} \omega_{jk} \mathrm{X}_k$ as an instrument for y_j. So, in this way, we can identify (α, γ) separately without having to exclude X_j from (2). The identification condition A1 can be checked straightforwardly, and it holds in our data for a subsample which is sufficient for inference (see figure 3).

Finally, it should be noted there are weaker identification conditions. For example,

Bramoullé et al. (2009), Proposition 1, shows that (2) is identified if W, W^2 and the identity matrix I are linearly independent. We do not need this weaker condition as the stronger condition A1 is satisfied in the data, and it implies an intuitive procedure for instrumenting the y_j.

Our estimation procedure is as follows. First, we observe that by construction, $cov(Z_{ij},\ \varepsilon_i) = 0, j \in N(i)$, as none of the $\mathrm{X}_k, k \in S^i_j$. appear in (1) and so none of the X_k are affected by the realization of ε_i. So, we can proceed as follows:

- At the first stage, we regress y_j on $Z_{ij}, i \in N, j \in N(i)$. To do this, we construct a pseudo panel with $\sum_{i=1}^{n} N(i)$ observations. This gives a vector of predicted values $\hat{y}^i_j, i \in N, j \in N(i)$.

- At the second stage, we estimate

$$y_i = \frac{\alpha}{\#N(i)} \sum_{j \in N(i)} \hat{y}^i_j + \beta' \mathrm{X}_i + \frac{1}{\#N(i)} \gamma' \sum_{j \in N(i)} \mathrm{X}_j + \varepsilon_i \tag{5}$$

  Equation 5 describes our main estimation equation.

  This is contrast to the standard 2SLS procedure used for estimating reaction functions where:

- At the first stage, we regress the single endogenous variable $Y_i = \frac{1}{\#N(i)} \sum_{j \in N(i)} y_j$ on $\frac{1}{\#N(i)} \sum_{j \in N(i)} Z_{ij}$. This gives a predicted value $\hat{Y}_i, j = 1, ..n$.

- At the second stage, we estimate

$$y_i = \alpha \hat{Y}_i + \beta' \mathrm{X}_i + \frac{1}{\#N(i)} \gamma' \sum_{j \in N(i)} \mathrm{X}_j + \varepsilon_i$$

The difference is obviously at the first stage. If for 2SLS to be valid, we need the instrument for Y_i to be uncorrelated with the error ε_i in (1):

$$cov(\sum_{j \in N(i)} Z_{ij}, \varepsilon_i) = \sum_{j \in N(i)} cov(Z_{ij}, \varepsilon_i) = 0$$

So, 2SLS will also give us unbiased estimates. However, 2SLS would capture different sources of variability as it would exploit the covariance between the mean of y_j^i and the mean of $X_k, k \in S_j^i$. This, although unbiased, would make the estimation arguably meaningless. Section **??** explains in detail why this is the case and why our approach captures the correct source of variability.

7 Results

7.1 Municipalities in the OpenCivitas Network

We first look at at the correlations in the property tax rates considering the two kind of networks before and after data was disclosed through the web platform. Table 4 reports the results. In this and the following tables we include in the sample only the subset of municipalities involved in the OpenCivitas network. For the sake of comparability, we reduce the sample to include only mayors for which a valid instrument exist (see section 6). Moreover, as the online-revealed network is directed, we use all the mayors who are active on the website to construct their directed contiguity network. As, on average, there are more neighbours than links in the online network, the contiguity sample is larger, although the same set of "active" nodes are used, i.e. the same set of $i = 1...n$.

Table 4: Reaction fuction estimates, municipalities in OpenCivitas network before and after data disclosure, OLS estimator.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable = Y_i	Before data disclosure				After data disclosure			
	Property tax rate variation (2013-2011)				Property tax rate variation (2015-2013)			
	OpenCivitas network		Contiguous municipalities		OpenCivitas network		Contiguous municipalities	
Y_j	0.5783***	0.6121***	0.6295***	0.5496***	-0.0304	-0.0574	0.3587***	0.3632***
	[0.084]	[0.088]	[0.094]	[0.091]	[0.109]	[0.129]	[0.137]	[0.138]
No term limit dummy	0.7939**	1.0585***	0.3468	0.3379	0.0270	-0.0301	0.0378	0.0296
	[0.325]	[0.314]	[0.327]	[0.316]	[0.084]	[0.097]	[0.072]	[0.074]
$Y_j *$ No term limit dummy	-0.2829***	-0.3937***	-0.1573	-0.1537	0.1839	0.2176	-0.0342	-0.0362
	[0.108]	[0.106]	[0.124]	[0.120]	[0.139]	[0.157]	[0.171]	[0.173]
Controls	No	Yes	No	Yes	No	Yes	No	Yes
Observation	367	343	592	571	361	335	593	571
R-square	0.262	0.367	0.211	0.295	0.089	0.126	0.106	0.128

Notes: Robust Standard errors in parenthesis. Municipal controls include population, share of population over 65 (over 75), degree of urbanization, surface, own initial level of income and property tax rates, average declared income of citizens, transfers from the central government. Mayoral controls include age, education, party affiliation and description of their job before becoming a mayor, years from the next election.

Columns 3 and 4, 7 and 8 report the results for the same set of municipalities involved in OpenCivitas, and compare them to their neighbours. Before instrumenting the links, this table shows a weaker but consistent correlation with neighbours' tax rates and a stronger but more volatile one with municipalities in the OpenCivitas network.

We then look at the first stage as described in section 6. Table 5 reports the results for 8 different definitions of network. The table shows that the set of valid instruments change over the periods and according to the definition of network. We choose two sets of instruments for the two periods according to which set of variables works more consistently across specifications. Although variables such as income per capita might look like they don't satisfy the exclusion restriction, that concern does not apply in our setting as the characteristics we use as instruments are the ones of municipalities in S_j^i, which are never directly linked to municipality i. Here, the sample is larger than the OLS and IV one: this is due to the fact that each mayor i has a number of first stage equations equal to the number of elements in S_i. This number is usually larger than one and different across municipalities.

Table 5: First stage analysis

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable = Y_j	OpenCivitas Network		Contiguity network (with OpenCivitas access)		Contiguity network (with no OpenCivitas access)		Contiguity network (all municipalities)	
	Property tax rate variation		Property tax rate variation		Property tax rate variation		Property tax rate variation	
	2013-2011	2015-2013	2013-2011	2015-2013	2013-2011	2015-2013	2013-2011	2015-2013
Income	-0.0001***		-0.0000***		-0.0000***		-0.0000***	
	[0.000]		[0.000]		[0.000]		[0.000]	
Sismic risk	-0.1774***	-0.0896***	-0.0653***	-0.0586***	-0.0442***	-0.0536***	-0.0521***	-0.0542***
	[0.044]	[0.029]	[0.020]	[0.013]	[0.006]	[0.004]	[0.006]	[0.004]
Municipal surface	0.0906	-0.8623***	1.2972***	-0.1347	0.8113***	-0.0413	0.8763***	-0.0567
	[0.353]	[0.246]	[0.341]	[0.272]	[0.198]	[0.124]	[0.175]	[0.113]
Population density	0.0001**		0.0001***		0.0000		0	
	[0.000]		[0.000]		[0.000]		[0.000]	
F(instruments, observation)	11.7	9.28	11.22	10.11	23.91	95.26	31.37	105.49
Prob $\geq F$	0.0000	0.0001	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Observations	1,039	1,021	3,325	3,432	26,827	26,432	30,097	29,806
R-squared	0.364	0.144	0.073	0.022	0.049	0.014	0.05	0.015

Notes: Robust Standard errors in parenthesis. Municipal controls include population, share of population over 65 (over 75), degree of urbanization, surface, own initial level of income and property tax rates, average declared income of citizens, transfers from the central government. Mayoral controls include age, education, party affiliation and description of their job before becoming a mayor, years from the next election.

Table 5 shows that different sets of municipalities' characteristics work as excluded instrument according to the period considered and to the kind of network. As there is no differential concerns among these variables in terms of satisfying the exclusion restriction, we choose the two set of instrumental variables which minimise the concerns about having a

weak instrument and which are consistent across the different definitions of network. Using different set of strong instruments does not change the results.

Finally, we consider the IV estimation, as specified in section 6. Table 6 reports the results of our main specification and the main results of the paper. This table shows the coefficients when instrumenting the property tax rate of municipality j by the exogenous characteristics of municipality's k (X_k is the instrument in the model) as per first-stage table. The predicted values from the different first stage equations are averaged over each each mayor i before running the second stage.

There are several conclusions to be drawn from this table. First, once the simultaneity issue is addressed by instrumenting Y_j, there is no evidence that municipalities which are part of the OpenCivitas network engage in yardstick competition with their neighbours. There is a significant coefficient for the change between 2011 and 2013, but that disappears after adding the controls. Second, when instrumenting y_j the results for the OpenCivitas network seem more clearly different before and after data disclosure. Column 2 shows that before the opening of the online platform, the coefficient for yardstick competition within the OpenCivitas network was large and significant, while the coefficients for the term-limit dummy were small and not statistically significant, as was the coefficient for the interaction of the two. The change between 2013 and 2015, instead, i.e. the change in tax rates from the year before data disclosure to the year after, shows that in this case the interaction term between municipality's j instrumented tax rate and the dummy for being up for re-election explains the whole variation.

This result suggest that after data disclosure mayors in the network who can face re-election become more concerned with yardstick competition. Mayors in the OpenCivitas network seem more reactive to online data disclosure and in general more attentive to political competition.

Table 6: Reaction fuction estimates, municipalities in OpenCivitas network before and after data disclosure, IV estimator.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable = Y_i	Before data disclosure				After data disclosure			
	Property tax rate variation (2013-2011)				Property tax rate variation (2015-2013)			
	OpenCivitas network		Contiguous municipalities		OpenCivitas network		Contiguous municipalities	
$\hat{Y}_j$	0.6837***	0.8851***	1.2982***	0.8705	-0.6651**	-0.4895	0.4269	0.2802
	[0.159]	[0.215]	[0.459]	[0.597]	[0.308]	[0.572]	[0.713]	[0.917]
No term limit dummy	0.0997	0.2481	0.4921	0.6380	-0.1850*	-0.2089*	-0.0221	-0.0370
	[0.500]	[0.504]	[1.101]	[1.182]	[0.111]	[0.122]	[0.194]	[0.228]
$\hat{Y}_j *$ No term limit dummy	-0.0302	-0.1087	-0.2172	-0.2742	1.3676***	1.3755***	0.2306	0.2724
	[0.176]	[0.179]	[0.421]	[0.456]	[0.389]	[0.425]	[0.792]	[0.891]
Controls	No	Yes	No	Yes	No	Yes	No	Yes
Observation	358	343	592	571	361	345	593	571
R-square	0.191	0.305	0.131	0.236	0.119	0.150	0.077	0.106

Notes: Bootstrap standard errors in parenthesis with 1000 replications. Municipal controls include population, share of population over 65 (over 75), degree of urbanization, surface, own initial level of income and property tax rates, average declared income of citizens, transfers from the central government. Mayoral controls include age, education, party affiliation and description of their job before becoming a mayor, years from the next election. The excluded instruments are as depicted in table 5.

7.2 Other Municipalities

Tables 7 and 8 reports the results for the OLS and the IV estimations as in section 6. These tables show that municipalities which are not active on the website and thus not part of the network, stick with the traditional competition with their neighbours throughout the periods of analysis. Column 4 in table 7 shows a positive and significant coefficient for the interaction term, suggesting that after data disclosure even in the non-active municipalities the competition seems to be driven for the largest part by mayors who are not term-limited. This effect disappears when instrumenting neighbours' tax rates. One could claim that contiguity networks are exogenous and that thus the OLS should be consistent. Although this network can somehow be considered exogenous, the OLS is still inconsistent because of the simultaneity issue in the determination of the property tax rates.

Table 7: Reaction fuction estimates, municipalities outside OpenCivitas network before and after data disclosure, OLS estimator.

	(1)	(2)	(3)	(4)
Dependent variable = Y_i	Contiguous municipalities			
	Before data disclosure		After data disclosure	
	Property tax rate variation (2013-2011)		Property tax rate variation (2015-2013)	
Y_j	0.4077***	0.3651***	0.2525***	0.2471***
	[0.038]	[0.038]	[0.028]	[0.028]
No term limit dummy	0.0901	0.1215	-0.1260***	-0.1312***
	[0.125]	[0.124]	[0.045]	[0.050]
$Y_j *$ No term limit dummy	-0.0199	-0.0370	0.4671***	0.5221***
	[0.047]	[0.047]	[0.166]	[0.190]
Controls	No	Yes	No	Yes
Observation	5,200	4,966	5,126	4,890
R-square	0.198	0.239	0.113	0.123

Notes: Robust Standard errors in parenthesis. Municipal controls include population, share of population over 65 (over 75), degree of urbanization, surface, own initial level of income and property tax rates, average declared income of citizens, transfers from the central government. Mayoral controls include age, education, party affiliation and description of their job before becoming a mayor, years from the next election.

Table 8: Reaction fuction estimates, municipalities outside OpenCivitas network before and after data disclosure, IV estimator.

	(1)	(2)	(3)	(4)
Dependent variable = Y_i	Contiguous municipalities			
	Before data disclosure		After data disclosure	
	Property tax rate variation (2013-2011)		Property tax rate variation (2015-2013)	
$\hat{Y}_j$	1.0976***	0.7815***	0.9886***	1.2510***
	[0.167]	[0.214]	[0.288]	[0.315]
No term limit dummy	0.0481	0.1433	0.0413	0.0798
	[0.447]	[0.431]	[0.076]	[0.079]
$\hat{Y}_j *$ No term limit dummy	-0.0032	-0.0458	-0.2387	-0.3642
	[0.171]	[0.165]	[0.310]	[0.328]
Controls	No	Yes	No	Yes
Observation	5,197	4,965	5,137	4,901
R-square	0.173	0.210	0.098	0.110

Notes: Bootstrap standard errors in parenthesis with 1000 replications. Municipal controls include population, share of population over 65 (over 75), degree of urbanization, surface, own initial level of income and property tax rates, average declared income of citizens, transfers from the central government. Mayoral controls include age, education, party affiliation and description of their job before becoming a mayor, years from the next election. The excluded instruments are as depicted in table 5.

8 Conclusions

We investigated the existence of a network formed by Italian mayors which was revealed through accesses to an online platform aimed at disclosing expenditure and performance data for Italian municipalities. Mayors who are active in this network seem to have abandoned the standard yardstick competition with neighbouring municipalities which is well established in the literature and of which we still find evidence in our data among the other mayors. This class of politicians are on average younger, more educated and administer on average larger municipalities. The fact that this network was revealed through their actions on a web platform suggests that these local administrators consider more efficient to compete or emulate other mayors which they choose according to criteria that are different from the more standard contiguity. Using binary response and dyadic models we found that mayors who are active in this network look for colleagues who are in their same region but not necessarily close to them, which are on average more similar to them in terms of age, size of the city they manage and in terms of political campaigning needs. However, they seem more interested in mayors of the opposite sex, who are affiliated with different parties and with a different level of education. We found evidence that this network existed before the data disclosure program was implemented, as mayors in the network had already moved away from traditional competition with their neighbours in favor of a different set of municipalities that they chose. Finally, we found that mayors who were active on the web reacted differently to data disclosure: as opposed to the remaining Italian local administrators, mayors in the network changed their tax competition behaviour after the reform. This suggests these local politicians are more careful and attentive to transparency policies and to the information which is available on the internet. Indeed, competition among them becomes stronger and mainly driven mayors who are up for re-election, indicating that differently from other mayors, they consider transparency programs and data disclosure as an important factor in political competition. Further research will explore more in depth how and why they choose to create specific links and whether this makes them more successful as administrators and

benefits them in the elections.

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Appendices

A Difference between 2SLS and our model

For simplicity, let's consider the case without control variables and, for the sake of notation, since neither model considers unweighted X_k as a variable, let us define

$$X^i_{jk} == \sum_{k \in S^i_j} w_{jk} X_k$$

X^i_{jk} represents a vector of instrumental variables in our model. It takes a value for each element in S^i_j.

We want to estimate the following regression equation:

$$y_i = \beta \sum_{j \in N_i} w_{ij} y_j + \eta_i$$

Our model

In our approach, we instrument each $y_j (j \neq i)$, for each i, by X^i_{jk}.

So, our first stage is:

$$y_j = \alpha X^i_{jk} + u_i$$

While our second stage is:

$$y_i = \beta \sum_{j \in N_i} w_{ij} \hat{y}_j + \eta_i$$

So that our $\hat{\beta}$ is the OLS coefficient from:

$$y_i = \beta \sum_{j \in N_i} w_{ij} (\hat{\alpha} X^i_{jk}) + \eta_i$$

Or:

$$y_i = \beta\hat{\alpha} \sum_{j \in N_i} w_{ij} X^i_{jk} + \eta_i$$

And our estimator can be written as:

$$\hat{\beta} = \frac{cov\left(y_i \ , \ \sum_{j \in N_i} w_{ij} X^i_{jk}\right)}{cov\left(y_j \ , \ X^i_{jk}\right)}$$

Traditional 2SLS

Using the 2SLS command, Stata will compute a single first-stage equation for each i. This means that instead of instrumenting each $y^i_j (j \neq i)$, it just instruments

$$\sum_{j \in N_i} w_{ij} y_j$$

by:

$$\sum_{j \in N_i} w_{ij} X^i_{jk}$$

Hence, the first stage, for each i, will be:

$$\sum_{j \in N_i} w_{ij} y_j = \gamma \sum_{j \in N_i} w_{ij} X^i_{jk} + v_i$$

And the second stage is:

$$y_i = \beta_{2SLS} \widehat{\sum_{j \in N_i} w_{ij} y_j} + \mu_i$$

or:

$$y_i = \beta_{2SLS} \left(\hat{\gamma} \sum_{j \in N_i} w_{ij} X^i_{jk} \right) + \mu_i$$

And:

$$\widehat{\beta_{2SLS}} = \frac{cov\left(y_i\ ,\ \sum_{j\in N_i} w_{ij}X^i_{jk}\right)}{cov\left(\sum_{j\in N_i} w_{ij}y_j\ ,\ \sum_{j\in N_i} w_{ij}X^i_{jk}\right)}$$

Differences

The numerator of the estimators is the same (as we can see from the second stage equations), while the denominators, representing the first stage, are not equivalent.

In order to understand this, we need to show that α and γ are different.

First of all, they are estimated from different samples. In the traditional 2SLS the first stage can count on the same number of observations as in the first stage, equal to the number of municipalities for which a valid instrument exist (n=369). In our model, instead, the first stage relies on a much larger sample, as there is a different regression equation for each $j \in S_i$ (n=1110).

More importantly, by averaging over variables, we lose important information on their variance and on the covariance between them. In our model, each first-stage equation captures the correlation between the outcome variable of each municipality j and the exogenous characteristics of each municipality k which j looks at. Hence the coefficient from our model exploit the correct source of variability in the data: to each j its own set of ks. The 2SLS, instead, uses the variability of the average of the outcome among the municipalities $j \in S_i$ and the average of the characteristics of $k \in S^i_j$. By doing this, it loses all the information of which specific j is linked to each specific k, which is the core functioning of the network model.

To see this in practice, consider the following example with data simulated in R (see figure A.1): Y_j has very little variance within $N(i)$, while X^i_{jk} has huge variance within $N(i)$ and the 2 variables are negatively correlated. However, the weighted averages of the 2 variables are highly and positively correlated.

Figure A.1: a simulation

```
## # A tibble: 36 x 5
##      y_i   y_j mean_y_j   x_k mean_x_k
##
##  1     1     8       10   105        5
##  2     1     9       10   105        5
##  3     1    10       10     5        5
##  4     1    11       10   -95        5
##  5     1    12       10   -95        5
##  6     2    13       15   910       10
##  7     2    14       15   910       10
##  8     2    15       15    10       10
##  9     2    16       15  -890       10
## 10     2    17       15  -890       10
## # ... with 26 more rows
```

The two variables have very different variances and negative correlation:

```
var(df$y_j)
```

```
## [1] 704.9206
```

```
var(df$x_k)
```

```
## [1] 577252550
```

```
cor(df$y_j, df$x_k)
```

```
## [1] -0.02358105
```

So, the covariance between the 2 variables is huge and negative, yet the covariance of the averages is large and positive:

```
cov(df$y_j, df$x_k)
```

```
## [1] -15042.37
```

```
cov(df1$mean_y_j, df1$mean_x_k)
```

```
## [1] 805
```

B Robustness

B.2 Analysis on the 2012-2014 period

To check for pre-existence of the OpenCivitas network, so far we considered the period 2011-2013. To alleviate concerns about the OpenCivitas mayors reacting differently to the reform of property tax rates of 2012, as a robustness we replicate the pre-disclosure analysis for the period 2012-2014. This period did not include any new reform in tax rates and it is supposedly not yet affected by the data disclosure of the late 2014. Tables B.1 and B.2 report the results for all the definitions of network, for the years 2012 and 2014.

The results are not different from the 2011-2013 period analysis, suggesting that it was data disclosure which increased competitiveness and incentivised non term-limited mayors to react more.

Table B.1: Reaction fumction estimates, OpenCivitas network municipalities before data disclosure, robustness check analysis after property tax reform.

	(1)	(2)	(3)	(4)
Dependent variable	Property tax rate variation (2014-2012)			
	OpenCivitas network		Contiguous municipalities	
Y_j	0.0735		0.1688	
	[0.130]		[0.145]	
$\hat{Y}_j$		0.7783*		1.2172
		[0.466]		[0.757]
No term limit dummy	-0.1136	0.0882	-0.0649	-0.2201
	[0.120]	[0.197]	[0.116]	[0.362]
$Y_j *$ No term limit dummy	-0.0835		0.0216	
	[0.167]		[0.211]	
$\hat{Y}_j *$ No term limit dummy		-0.6682		0.3773
		[0.500]		[0.877]
Controls	Yes	Yes	Yes	Yes
Observation	343	343	571	571
R-square	0.064	0.073	0.050	0.055

Notes: Robust standard errors in parenthesis, and in columns (2) and (4) bootstrap standard errors in parenthesis with 1000 replications. Municipal controls include population, share of population over 65 (over 75), degree of urbanization, surface, own initial level of income and property tax rates, average declared income of citizens, transfers from the central government. Mayoral controls include age, education, party affiliation and description of their job before becoming a mayor, years from the next election.

Table B.2: Reaction fuction estimates, all municipalities and municipalities outside OpenCivitas network before data disclosure, robustness check analysis after property tax reform.

	(1)	(2)	(3)	(4)
Dependent variable	Contiguous municipalities			
	Property tax rate variation (2014-2012)			
	Outside OpenCivitas Network		All municipalities	
Y_j	0.3271***		0.3130***	
	[0.052]		[0.049]	
$\hat{Y}_j$		0.6429**		0.7019***
		[0.272]		[0.256]
No term limit dummy	0.0084	-0.1487	0.0027	-0.1379
	[0.035]	[0.132]	[0.033]	[0.124]
$Y_j *$ No term limit dummy	-0.0885		-0.0779	
	[0.065]		[0.062]	
$\hat{Y}_j *$ No term limit dummy		0.2970		0.2637
		[0.308]		[0.289]
Controls	Yes	Yes	Yes	Yes
Observation	4,966	4,965	5,537	5,536
R-square	0.028	0.014	0.026	0.015

Notes: Robust standard errors in parenthesis, and in columns (2) and (4) bootstrap standard errors in parenthesis with 1000 replications. Municipal controls include population, share of population over 65 (over 75), degree of urbanization, surface, own initial level of income and property tax rates, average declared income of citizens, transfers from the central government. Mayoral controls include age, education, party affiliation and description of their job before becoming a mayor, years from the next election.

B.2 All the municipalities together

In this section we replicate all the results in section **??** when including all the Italian municipalities in the sample (the ones in ordinary regions). As most of them are not active on OpenCivitas, when using this sample we can only consider the contiguity network. Tables B.3 and B.4 report the results. As expected, as the non-active municipalities are the majority, the aggregate results indicate the presence of the standard yardstick competition and they show no differential effect coming from non term-limited mayors.

Table B.3: Reaction fuction estimates, all municipalities before and after data disclosure, OLS estimator.

	(1)	(2)	(3)	(4)
Dependent variable = Y_i	Contiguous municipalities			
	Before data disclosure		After data disclosure	
	Property tax rate variation (2013-2011)		Property tax rate variation (2015-2013)	
Y_j	0.4376***	0.3939***	0.3067***	0.2878***
	[0.035]	[0.035]	[0.060]	[0.060]
No term limit dummy	0.1118	0.1418	-0.0013	0.0043
	[0.117]	[0.116]	[0.026]	[0.026]
$Y_j *$ No term limit dummy	-0.0319	-0.0478	-0.0487	-0.0331
	[0.044]	[0.044]	[0.066]	[0.067]
Controls	No	Yes	No	Yes
Observation	5,792	5,537	5,720	5,461
R-square	0.188	0.235	0.107	0.117

Notes: Robust Standard errors in parenthesis. Municipal controls include population, share of population over 65 (over 75), degree of urbanization, surface, own initial level of income and property tax rates, average declared income of citizens, transfers from the central government. Mayoral controls include age, education, party affiliation and description of their job before becoming a mayor, years from the next election.

Table B.4: Reaction fuction estimates, all municipalities before and after data disclosure, IV estimator.

	(1)	(2)	(3)	(4)
Dependent variable = Y_i	Contiguous municipalities			
	Before data disclosure		After data disclosure	
	Property tax rate variation (2013-2011)		Property tax rate variation (2015-2013)	
$\hat{Y}_j$	1.1564***	0.7991***	0.9191***	1.2119***
	[0.143]	[0.196]	[0.267]	[0.295]
No term limit dummy	0.1233	0.2004	0.0450	0.0772
	[0.400]	[0.416]	[0.070]	[0.076]
$\hat{Y}_j *$ No term limit dummy	-0.0364	-0.0714	-0.2301	-0.3227
	[0.153]	[0.158]	[0.289]	[0.313]
Controls	No	Yes	No	yes
Observation	5,789	5,536	5,730	5,472
R-square	0.159	0.202	0.093	0.105

Notes: Bootstrap standard errors in parenthesis with 1000 replications. Municipal controls include population, share of population over 65 (over 75), degree of urbanization, surface, own initial level of income and property tax rates, average declared income of citizens, transfers from the central government. Mayoral controls include age, education, party affiliation and description of their job before becoming a mayor, years from the next election. The excluded instruments are as depicted in table 5.

C Additional Figures

Figure C.1: OpenCivitas score system, year 2015 (1=low, 10=high)

For each municipality

	Historic (a)	Standard (b)	Difference (a-b)
Expenditure	y	ŷ	Δy
Level of Service	g	ĝ	Δg

Performance evaluation

- *Expenditure score* = Δy
- *Output score* = Δg
- *Performance score* = $f(\Delta y, \Delta g, c)$

  where: c = average standard cost of overall output