Connecting to Power: Political Connections, Innovation, and Firm Dynamics*

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Abstract

Do political connections affect firm and industry dynamics? We study the Italian firms and their workers to answer this question. Our analysis uses a brand-new data spanning the period from 1993 to 2014 where we merge: (i) firm-level balance sheet data, (ii) universe of social security data on workers, (iii) patent data from the European Patent Office, (iv) registry of local politicians, and (v) detailed data on local elections in Italy. We find that firm-level political connections are widespread, especially among large firms, and that the industries with more politically connected firms feature worse firm dynamics. Market leaders are much more likely to hire a politician and less likely to innovate, compared to their competitors. In addition, connections relate to higher survival and growth in employment and sales but not in productivity. We build a firm dynamics model where we allow firms to invest in innovation and/or rent-seeking to advance their productivity and to overcome regulatory or bureaucratic burden. The model highlights an interaction between static gains and dynamic losses from rent-seeking for aggregate productivity.

Keywords: Political connections, firm dynamics, innovation, productivity.
JEL Codes: O3, O4, D7.

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1 Introduction

In 1978, Silvio Berlusconi founded Fininvest, one of the largest media groups in Italy. After purchasing various local TV stations, Berlusconi wanted to expand his network and create Italy's first private national network. However, there was a major problem that he had to overcome: in the early 80s, the Italian TV industry was heavily regulated and the rights to do nationwide broadcasting was restricted only to Radiotelevisione Italiana (RAI), the national public broadcasting company. Luckily, Berlusconi and the prime minister Bettino Craxi were close friends and thanks to this close friendship, Craxi's government passed, on 20 October 1984, an emergency decree legalising the nationwide transmissions of Berlusconi's television stations. This event opened the door for Fininvest to become the first and the only private country-wide TV network in Italy. This example is a showcase of how political connections could help firms overcome regulations and bureaucratic barriers. An important question is, how widespread are such political connections and how do they affect firm dynamics, market competition, innovation, and the overall productivity process in the economy? This project is aimed at answering these questions both theoretically and empirically.

Our empirical analysis focuses on Italy from 1993 to 2014. There are three main reasons for this. First, as hinted by our opening story, there is ample anecdotal evidence for the link between political power and corporate sector in Italy. Perhaps, the largest manifestation of this presumption has been the historical episode of Mani Pulite ("Clean Hands"), the biggest corruption scandal that uncovered a dense network of corruption and bribery throughout Italy in the early 90s.

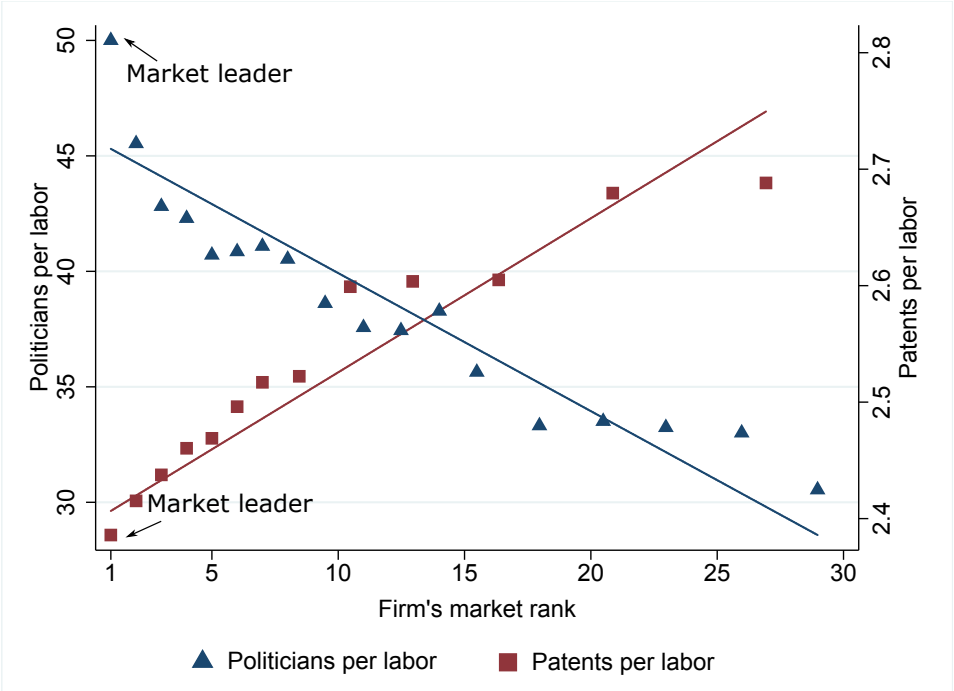
Second, to rigorously study all the channels through which political connections affect firm dynamics, we need a very detailed large-scale micro data on firms and their connections. We construct a brand-new data spanning the whole period from the 90s to 2014 where we merge: (i) firm-level balance sheet data, (ii) universe of social security data on workers, (iii) patent data from the European Patent Office, (iv) registry of local politicians, and (v) detailed data on local elections in Italy. This unique five-way match allows us to examine at the micro level how firms change their competition strategy as they gain market power. In particular, we are able to observe number of innovations and number of politicians hired by the firms – our measure of firm-level political connections. In addition, we study how factor reallocation among incumbents and new entry are affected by political connections of the incumbents.

Third, Italian economy has been performing extremely badly for the last decades. While many reasons could be at play for low and stalling aggregate productivity, we try to shed

some light on aggregate implications of firm-level political connections through their effect on firm dynamics, innovation incentives and competition.

Recent literature on firm dynamics has highlighted the importance of creative destruction whereby unproductive incumbents are replaced by more productive new entrants and the factors of production are reallocated to more productive producers (see Foster et al. (2001, 2006)). Clearly this process comes with a tension between market leaders and their potential competitors. While the followers try to surpass the market leader by innovating better products or technologies that would shift customers to themselves, the market leader would try hard to maintain its leadership and could follow protective defensive strategies. These protective strategies could include political connections which could give an extra advantage to maintain leadership or overcome certain barriers. This fact is indeed born out very visibly in our data. Figure 1 plots the politician intensity, defined as the number of politicians per worker within the firm, and innovation intensity (patent count per worker) against the market position of the firms. Interestingly, it shows that as firms become market leaders (lower market rank), their political connectedness increases, whereas innovation intensity decreases. This finding suggests that firms are following different competition strategies as a function of their position in the market.

Figure 1: Market Leadership, Innovation and Political Connection



Our empirical analysis uncovers the following important facts:

1. *Firm-level connections are widespread.* Politically connected firms hold 32% of employment in the Italian economy. Similarly, among large firms with more than 100 workers, 44% of the firms are politically connected.

2. *Industries with more politically connected firms feature worse firm dynamics.* In particular, industries with more politically connected incumbents have lower entry rate, lower share of young firms, and lower firm growth, and productivity on average.

3. Politically connected incumbents are replaced by politically connected entrants.

4. Market leaders have higher political connection and lower lower innovation intensity.

5. Politically connected firms have higher employment and sales growth but lower productivity growth. Despite having lower productivity, politically connected firms have lower exit rate.

We confirm direction of causality from firm-level political connections to firm-level outcomes in a regression discontinuity setup. We exploit a quasi-random discontinuity caused by local elections decided on a thin margin to estimate the effect of connections with marginally winning relative to marginally losing politicians.

We operationalize our empirical findings in a simple model of firm dynamics and growth. In the model, firms face bureaucratic/regulatory burden that may be alleviated by connecting with politicians. Connections are costly. Static problem implies a threshold rule of productivity (size) above which firms find it profitable to incur cost of connections and get rid of regulations – hence, in line with the evidence, larger firms (and market leaders) are more politically connected. As in the data, we also obtain that firms that get connected enjoy (temporarily) larger employment and sales growth but lower productivity growth.

Dynamic problem implies that industries that have politically connected incumbents face lower entry by new firms. Intuitively, new firms now need to compete with incumbents not just in terms of productivity but they also need to overcome the regulatory or bureaucratic burden that the connected incumbent is already immune to. Crucially, incumbents anticipate this dynamic effect and turn to political connections to preempt competition.

The model highlights the important contrasting facets of firm-level connections for aggregate economy. Statically, connections may be beneficial to overcome certain market frictions, however connections may also entail dynamic losses by distorting competition and firm dynamics. This interplay is at the heart of both our theoretical and empirical construct.

Related literature. Politicians and entrepreneurs have often found themselves along the road to the pursuing of power. Borrowing the definition by Faccio and Parsley (2006), political connection is typically a situation in which a top officer, a relevant shareholder or someone with an important position in the enterprise was (or is) either a holder of a high political office or a prominent politician. Recent evidence shows that political connection is a widespread phenomenon and a positive relationship between political connections and firm value has largely been documented (Fisman, 2001). Moreover, politically connected firms have been observed both in developed and developing countries, like the US, the UK, France, Italy, Turkey, China, Malaysia, Indonesia, Korea, Thailand and Singapore (Johnson and Mitton (2003), Khwaja and Mian (2005), Leuz and Oberholzer-Gee (2006), Fan et al. (2007), Cingano and Pinotti (2013), Schoenherr (2015)).

The reasons that lead a private company to establish a connection with politics are certainly linked to profit maximization and surely the expected benefits exceed the costs of establishing political connections, but the channels through which this is realized are manifold. The range of benefits provided by governments to favored firms include preferential access to credit (Joh and Chiu (2004), Cull and Xu (2005), Johnson and Mitton (2003), Khwaja and Mian (2005)); preferential treatment by government-owned enterprises (Backman (2001), Dinc (2005)) and for procurement (Goldman et al., 2007); relaxed regulatory oversight of the company in question or stiffer regulatory oversight of its rivals (Kroszner and Stratmann, 1998); lighter taxation (De Soto, 1989); and government bailouts of financially distressed firms (Faccio and Parsley, 2006).

While political connections are clearly valued positively in the stock market (Faccio and Parsley, 2006), they become more valuable where there is a high level of regulation, high level of corruption, and high population concentration in the capital city. Political connections are also more valuable in small firms and in firms that rely more on external finance (Do and Levchenko, 2006). However, they have a social cost, but it largely depends on the type of firms that establishes the connection: if higher revenues come from higher productivity - because the connections are aimed at reducing the burden of bureaucracy and administrative regulation - it does not necessarily imply a negative effect on welfare. This mechanism, known also as *greasing wheels hypothesis* (Kaufmann and Wei, 1999) is expected to have a positive effect on welfare, since it increases efficiency through a relief of the burden of regulation (Shleifer and Vishny, 1994). On the contrary, if a connected firm exerts a rent seeking behavior, for example by diverting public demand (Goldman et al., 2007), the entailed social cost is high and possibly magnified by resource misallocation (Hsieh and Klenow, 2009).

This second effect, named *grabbing hand hypothesis* (Shleifer and Vishny, 2002) is consistent with the results provided by Cingano and Pinotti (2013) on political connections in Italy. Using a sample of social security data and data on politicians appointed at the local level, they find that firms' productivity dynamics cannot account for the increase in market power associated with political connections, and that the gains in market power come from public demand shift towards politically connected firms.

While the existing empirical literature on the consequences of political connections through moonlighting politicians (i.e. the fact that in most modern democracies elected officials can work in the private sector during their appointment) is at the firm level, less is known on the relationship between political connections, firms dynamics and growth.

2 Model

Political connections might affect firms through various channels. As it was exemplified in the opening paragraph, political connections might help overcome regulatory or bureaucratic burden. In order to understand if this is the case systematically, we examine if in industries that are more heavily regulated or face higher bureaucracy firms are also more politically connected. For that, we develop our industry-level bureaucracy index that measures the level of regulatory burden based on newspaper articles from Factiva, building on Pellegrino and Zingales (2014).

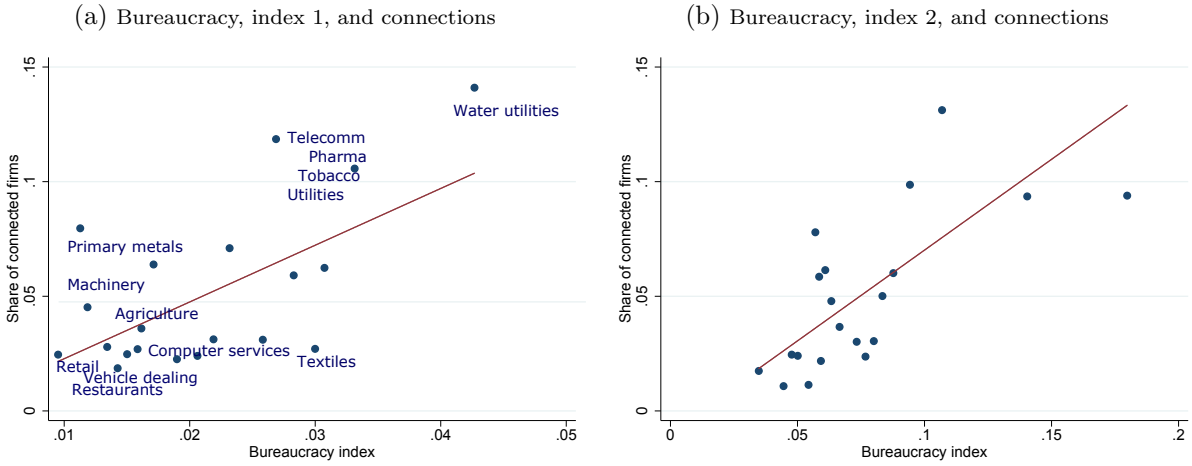
We look at newspaper articles from 4 large news providers (Bloomberg, Dow Jones Adviser, Financial Times, The Wall Street Journal), and count number of articles that contain set of words that proxy for government intervention or bureaucracy level that sectors are facing. Using international newspapers alleviates concerns of endogeneity and reverse causality if we were just to look at Italian news. We focus on 58 broad sectors that roughly correspond to 2-digit nace rev 2 industry classification. We focus on articles starting from 1991 and experiment with two lists of words, List 1 and List 2[1].

Our measures of a sector's regulation/bureaucracy, that we refer to as simply Bureaucracy index 1(2), is then a share of newspaper articles in a sector that have some words from the List 1 (List 2). The two bureaucracy indices are highly positively correlated with correlation of 0.56. Figure 2 confirms that there is a strong and positive relationship between industry's

[1]List 1 includes the following words: regulation*, regulated, regulator, bureaucracy, bureaucratic, deregulation, deregulated, paperwork*, red tape, license and licenses. List 2 includes the same words as List 1, plus authority, authorities, liberaliz*, reform*, Agency, Agencies, Commission, Commissions, policy maker*, policymaker*, government, official form*, official procedure*. The * is a jolly character.

Bureaucracy index 1 and 2 and share of firms that are politically connected. Appendix Figure 12 shows similar relationship for high-rank politicical connections.

Figure 2: Bureaucracy and Connections across Industries



Notes: Binscatter plots (split into 20 quantiles) and linear fits between bureaucracy indices and share of connected firms across 52 industries. Sector-level bureaucracy index 1(2) is defined as share of newspaper articles about a sector from Factiva News search that have government regulation or bureacracy-related words as listed in the List 1(2) in the main text. Panel (a) uses index 1, while panel (b) uses index 2. Y axis is share of connected firms across industries.

2.1 Static Environment

The economy features continuum of producers who produce an identical good with different productivities according to the following production function

$$y_i = q_i^{\alpha} l_i^{1-\alpha}$$

where we index each producer by i. In this production function, y_i, q_i and l_i denote output, productivity and production workers, respectively. Workers are hired at the same labor market clearing wage w. However, firms are subject to regulation which we capture as a wedge τ per each worker. Hence, the profit maximization of each firm can be stated as

$$\pi^n = \max_{l_i} \left\{ q_i^{\alpha} l_i^{1-\alpha} - (1+\tau)\, w l_i \right\}.$$

This maximization delivers the following equilibrium labor, output and profit for firms that are not politically connected

$$\begin{aligned} l_i^n &= \left[\frac{(1-\alpha)}{(1+\tau)\,w}\right]^{\frac{1}{\alpha}} q_i, \\ y_i^n &= \left[\frac{(1-\alpha)}{(1+\tau)\,w}\right]^{\frac{1-\alpha}{\alpha}} q_i, \\ \pi^n &= \left[\frac{(1-\alpha)}{(1+\tau)\,w}\right]^{\frac{1-\alpha}{\alpha}} \alpha q_i \equiv \tilde{\pi}^n q_i \end{aligned}$$

Firms can avoid regulations by hiring a politician. If firm i hires a politician, it can avoid paying the wedge τ, yet it has to compensate the politician with the wage rate w_p. However, in order to be able to hire a politician, a firm has to become familar with the network of politicians. We capture the ability of hiring a politician by assuming that firms are in two states $s_i \in \{0,1\}$. $s_i = 0$ implies that firm i is not yet familiar with the politician network, whereas $s_i = 1$ implies that firms are already familiar with the network and can hire a politician if they want to. In that case, a firm that is in state $s_i = 1$ and decides to hire a politician solves the following maximization problem

$$\pi^p = \max_{l_i} \left\{ q_i^{\alpha} l_i^{1-\alpha} - w l_i - w_p \right\}.$$

This problem delivers the following optimal labor, output, and profit:

$$\begin{aligned} l_i^p &= \left[\frac{(1-\alpha)}{w}\right]^{\frac{1}{\alpha}} q_i, \\ y_i^p &= \left[\frac{(1-\alpha)}{w}\right]^{\frac{1-\alpha}{\alpha}} q_i, \\ \pi^p &= \left[\frac{(1-\alpha)}{w}\right]^{\frac{1-\alpha}{\alpha}} \alpha q_i - w_p \equiv \tilde{\pi}^p q_i - w_p \end{aligned}$$

Comparing these optimal decisions, we can now state our first result.

Prediction 1 *Connected firms have higher sales and employment, yet lower labor productivity*

$$l_i^p > l_i^n, y_i^p > y_i^n, \frac{y_i^p}{l_i^p} < \frac{y_i^n}{l_i^n}.$$

2.2 Dynamics

In every sector i, there is a potential entrant who receives a new innovative idea with probability p with quality $\lambda \sim U\left[0, \bar{\lambda}\right]$. A new idea of quality λ improves the existing productivity q_i according to the following law of motion

$$q_i^{new} = (1 + \lambda)\, q_i.$$

Accessing the network of politicians takes time. We assume that α_0 of the entrants start with $s_i = 1$ and $1 - \alpha_0$ start with $s_i = 0$. Firms switch from being $s_i = 0$ to 1 at the Poisson arrival rate ζ.

A new entrant replaces an existing incumbent if its regulation-adjusted quality of innovation is superior to that of incumbent. If incumbent quality is less than the threshold $q_i < q^*$, incumbent gets replaced with probability p.

If the firm is above the threshold, then the probability of being replaced depends on the quality of the innovation and also the connection status of the incumbent and the new entrant. If the incumbent is in status $s_i = 0$, we are again in the above case and the incumbent gets replaced with probability p.

If the incumbent is already connected, now the entrant has to also overcome the regulatory burden that the incumbent is immune to thanks to its political connection. In this case, a connected incumbent will get replaced by a connected entrant with probability p and by an unconnected entrant with probability $p\frac{\lambda^*}{\bar{\lambda}}$ where

$$\lambda^* \equiv \frac{\tilde{\pi}^p - w_p/q_i}{\tilde{\pi}^n} - 1.$$

Prediction 2 *Connected incumbents are less likely to exit.*

Prediction 3 *In connected industries, average firm size if bigger.*

Prediction 4 *In connected industries, entry rate is lower.*

Now we can solve for the value of being connected. First, consider a firm with $q < q^*$ and denote its value by V_{-1}. Then

$$rV_{-1} = \tilde{\pi}^n q - pV_{-1}$$

which implies

$$V_{-1} = \frac{\tilde{\pi}^n q}{r + p}.$$

Now we can solve for the value of a firm that is in state $s_i = 0$ with $q \geq q^*$:

$$rV_0 = \tilde{\pi}^n q - pV_0 + \zeta (V_1 - V_0)$$

and a firm that is in state $s_i = 1$ with $q \geq q^*$:

$$rV_1 = \tilde{\pi}^p q - w_p - p\frac{\lambda^*}{\bar{\lambda}} V_1$$

This implies:

$$V_1 = \frac{\tilde{\pi}^p q - w_p}{r + p\frac{\lambda^*}{\bar{\lambda}}}.$$

Comparing V_1 to V_{-1}, firms connect politically if and only if

$$q_i > q^* \equiv \frac{w_p}{\tilde{\pi}^p - \frac{r+p\frac{\lambda^*}{\bar{\lambda}}}{r+p}\tilde{\pi}^n}$$

This result predicts that large firms with $q_i > q^*$ are more likely to be connected. In addition, note that $\tilde{\pi}^n$ is decreasing in τ and λ^* is also decreasing in $\tilde{\pi}^n$. Hence the cutoff q^* is decreasing in τ, which implies that firms in more regulated industries are more likely to be connected. Now we list these predictions.

Prediction 5 *In more regulated industries (large τ), firms are more likely to be politically connected.*

Prediction 6 *Large firms are more likely to be connected.*

3 Data Description

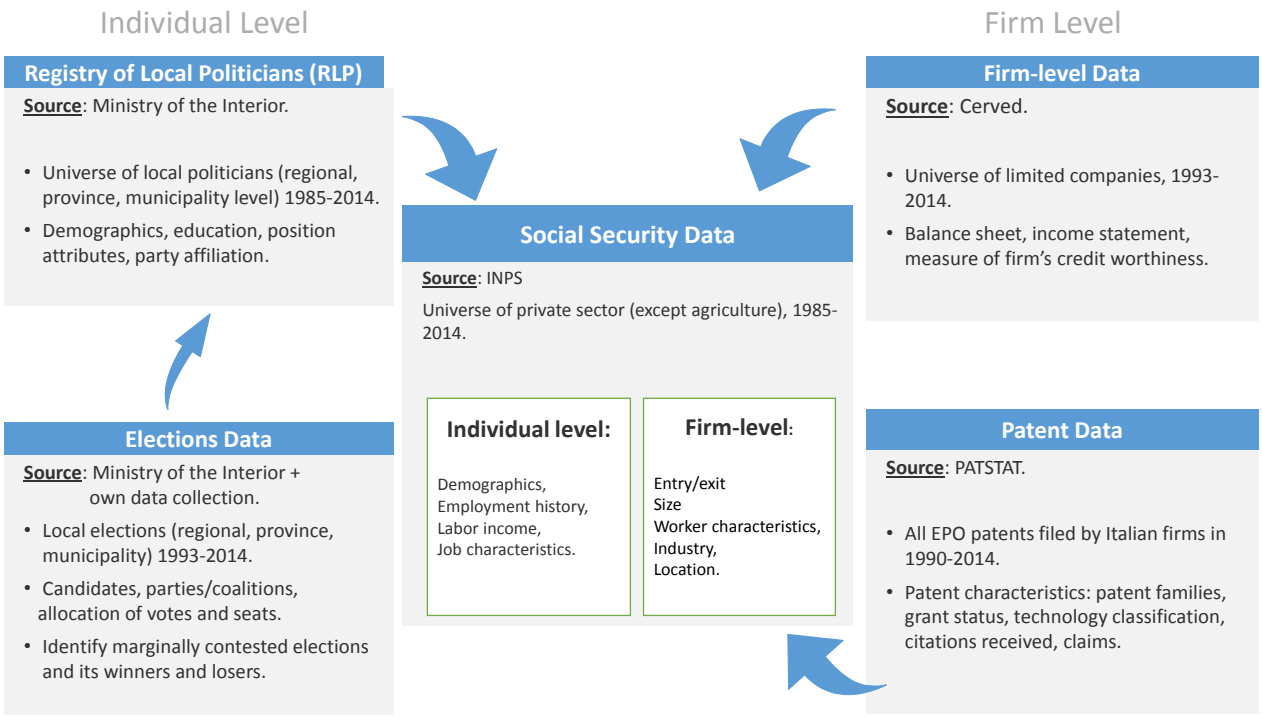
We match multiple administrative datasets to build a comprehensive dataset on firms, workers and local politicians in Italy for the period of 1993-2014. Central piece of this data construction is individual-level data from the Italian Social Security Administration (INPS)[2]. We combined a rich Social Security (SS) data with administrative data on firms' balance sheet (Cerved) to obtain a detailed matched employer-employee dataset for Italy. On the firms' side, data is further augmented with information on firm-level innovation activities derived from patent records in PATSTAT. On the workers' side, we combine SS data with individual records on local politicians from the Italian Registry of Local Politicians (RLP). This allows us to track whether a politician works in private sector while holding an office.

[2]Data became available through the VisitINPS Scholars program initiated in 2016.

Literature has coined a term "moonlighting politicians" to refer to such politicians. It is exactly moonlighting politicians that help us to identify political connections at the firm level. Finally, we also construct a new data on all local elections in Italy held in 1993-2014. Together, RLP and elections data allow us to define various attributes of individual political careers, such as type of position and rank, party affiliation, and participation in marginally contested elections.

Below, we provide an overview of the main steps undertaken during the data construction. Figure 3 gives a graphical illustration of data construction[3]. We delegate a more detailed discussion to Appendix A.

Figure 3: Data Construction



[3]For RLP, we thank Massimiliano Baragona of the Ministry of Interior, for election data, we thank Roberto Brocchini for providing archive on Italian elections, Marco Chiurato for his help in complementing the data with information taken from Wikipedia and from local newspapers.

3.1 Politicians Data (RLP and Elections Data)

We build a dataset on local politicians in Italy by making use of Italian Registry of Local Politicians (RLP) and the data that we collect on local elections over time. Table 1 provides short descriptive statistics, while below we overview construction and variable definitions.

3.1.1 Registry of Local Politicians (RLP)

We obtain administrative data on local politicians (RLP) from the website of the Ministry of the Interior[4]. RLP contains information on all local politicians at the municipality (more than 8,000 municipalities), province (110 provinces) and regional (20 regions) level in Italy. Data spans a period from 1985 to 2014. For each individual, we have his/her detailed demographic information, attributes of their political positions - location, position description (like council member, mayor, regional president, vice-president, etc), appointment date.

We proceed in the following steps described in more details in Appendix A.1.1. First, in order to link individual politicians to Social Security data on private-sector employees, we recover social security numbers from the demographic information on politicians. Second, we clean and standardize political party names and define majority parties at local level. This lets us identify whether a politician is a member of a majority at local level. Finally, based on politician's position attributes, we define a politician's *position level* for whether he/she is a politician at the municipality, province or regional level. We also define *position rank* for whether a politician holds a high-rank position as mayor/president/vice-president, or not.

3.1.2 Elections Data

We obtain data on elections at the regional, province and municipality level from the Ministry of Interior. Data generally covers period of 1993-2014. However, the electronic archives we got from the Ministry did not have data on province-level elections for the 1993-2004 period. We hand-collected that data from various sources online (online election archives, Wikipedia). Five special-status regions were not included in the Ministry's data either. We hand-collected information for those elections as well. In the end, for each election, we have

[4]This data has been used in several other studies. Among others, Gagliarducci and Manacorda (2016) link RLP to the sample of INPS private sector workers to study the effect of being in office on labor market outcomes of family members. Cingano and Pinotti (2013) link this data with a sample of Italian firms (INVIND) and find that political connections help firms to increase sales by shifting public demand to connected firms.

information on identities of all the candidates (names and demographics); parties/coalitions running for elections and candidates that they support; votes obtained (for candidates and parties) in each election round, if multiple; allocation of seats in the council.

This data serves two purposes. First, we define winning/majority parties for each election - this complements and in a way verifies majority parties constructed using the previous source of data, RLP. Second and more importantly, we identify marginally contested elections and party affiliations of marginally losing and winning parties or coalitions.

Institutional Background:

We outline a brief note on the electoral system and administrative elections in Italy for the period of interest with an emphasis on electoral rules that are important for our purpose.

Elections at the municipality level. Elections generally take place every five years and voters are asked to choose a mayor and members of the local council. There are around 8,100 municipalities in Italy with population ranging from as small as 100 inhabitants to as much as 3 million. Electoral law somewhat differs based on the size of municipality, however main features are as follows.

Elections generally take place through the "one-shot" voting mechanism with a majoritarian system for both the mayor and the council members. Votes are casted both for mayor candidates and parties that support those candidates (usually, separate voting is not allowed so that voters cannot pick candidates and parties from competing tickets, except for large municipalities). For larger municipalities (with population $> 15,000$), if none of the candidates gets an absolute majority ($> 50\%$), election goes to the second round. Votes casted for the candidates not only determine identity of a mayor but also determine allocation of seats to parties associated with the candidates. Importantly, winning candidate is generally guaranteed to have a majority of seats in the council (2/3 in case of smaller municipalities and at least 60% in larger municipalities). Existence of this majority premium generally implies that definition of a majority using mayor's affiliation should be similar to definition of a majority using council members' affiliations. After determining total allocation of seats to a winning coalition, further allocation of seats within a winning coalition or outside of it is determined by votes casted for each party.

Elections at the province level. Elections are generally held every 5 years and voters choose a president of a province and a council composition. Electoral rules for province-level elections are very similar to the ones for large municipalities (with population $> 15,000$) as

described above[5].

Elections at the regional level. Regional elections are generally held every 5 years in twenty regions of Italy. Before 1995, voters did not directly choose a regional president. Instead, they casted votes for parties/coalitions that formed a council. Allocation of seats between parties was based on a proportional system. However, since 1995, voters cast votes for a presidential candidate as well as for parties/coalitions forming a government (with lists running at district or regional level). There is no possibility of runoff. Coalition associated with a winning president is generally assured a majority of seats in the government (at least 55%). The rest of seats is determined by votes casted for parties[6].

Identifying marginally contested elections.

Our detailed elections data allows to identify elections that have been contested on a thin margin. As described above, votes casted for the candidates (not for parties) determine margin of victory in a particular election[7]. In most cases, threshold percent of votes is 50% and if that threshold is not reached by anyone, the runoff is expected. Important exceptions to the 50%-threshold are elections in small municipalities with population smaller than $15,000$ inhabitants and regional elections. In such cases, second round is never held and winner is the one getting largest share of votes in the first round.

Define p_1 as share of votes obtained by a winner and p_2 - share of votes by a runner-up. Then we define a *margin of victory* as difference between p_1 and p_2. At the regional level, there are 85 elections in the 1995-2014 period. 62 among them were decided with a 20% margin, while 15 were decided with a thin 4% margin. At the province level, there were 404 elections: 254 decided with a 20% margin and 52 with a 4% margin. Finally, among 36,516 municipality elections, 20,190 were decided with a 20% margin and 4,819 with a 4% margin. In the analysis, we experiment with various definitions of marginal elections depending on

[5]Major reform concerning province-level elections got enacted around 2014. The reform in essence removed province-level elections.The Budget Law for 2012 (L214/2011: Disposizioni urgenti per la crescita, l'equitáe il consolidamento dei conti pubblici) has laid the foundations for a provincial reform in Italy, that came to an end in 2014 with the so-called Delrio Law (L56/2014). In the transitory regime, elections in the provinces of in Como, Belluno, Vicenza, Genova, La Spezia, Ancona, Caltanissetta e Ragusa were not held. As a result, in a transition period of 2012-2014, many provinces did not hold scheduled elections. Instead, they extended the mandate of previous politicians. Hence in those cases, we can impute results from the previous elections by extending the results to more than 5 years.

[6]Parties may decide to compete within district or regional lists and this will have an effect on how the seats are allocated. However, in our data we have the information on the allocation of final seats, hence we do not need to work out all these details to determine how many seats a party/coalition is getting.

[7]We cannot define marginal elections for regional elections before 1995 as presidents were not chosen directly and seats were allocated proportionally based on votes for parties.

a margin of victory. However, even with a thin margin of victory of 4% (say, election with 48%-52% outcome), we have more than 72 thousands of RLP politicians during the years of marginal elections for whom we can identify whether they belonged to a marginally winning or losing party (details in the next subsection)[8].

3.1.3 Combining RLP and Elections Data

To sum up, we use RLP and Elections Data to define several variables for majority/winning parties at local level. We also identify marginal elections and parties/coalitions that have won/lost on a thin margin. Next, we combine these variables with the individual-level panel from RLP[9] and determine if a politician belongs to a majority/minority by various definitions at a particular point in time. Since this procedure involves several challenges regarding party identifiers, we describe them in details in the Appendix A.1.3.

We summarize variable definitions and the derived politicians data in Table 1. Data is a panel of all local politicians in the 1993-2014 period.

3.2 Firm-level Data (Cerved)

We use proprietary firm-level data from Cerved administered by the Cerved Group[10] Data provides balance sheet and income statement for all incorporated firms in Italy for the 1993-2014 period. First that are not covered are mainly small firms – sole proprietorship or small household producers.

We make use of standard company accounts variables such as assets, capital stock, revenue, profits. Some treatment of those variables in our data is described below. All nominal variables are deflated with GDP deflator (2014 is the base year). Cerved data does not provide a reliable variable for employment, hence we derive employment variable from the match to INPS (discussed below). We replace with missing the value added if the firm reports negative value added (*valore_aggiunto_operativo*). For tangible fixed assets (*immob_mat*) and intangible fixed assets (*immob_immat*), we impute zeros when possible. In most cases,

[8] And among them, about 20 thousands match to INPS hence providing many cases for our regression discontinuity design that we exploit later on.

[9] Elections data is a panel with time gaps in between of elections. We impute most recent election outcomes (up to 4 years) to fill in those time gaps.

[10] This data is the base of the Italian segment in Amadeus (Aida). The Company Accounts Data System (CADS) is a proprietary database administered by CERVEDGroup Ltd. for credit risk evaluation. It is used by banks for credit decisions and, hence, the data are carefully controlled. See Manaresi and Pierri, 2017 for further details.

Table 1: Data on Local Politicians (RLP + Elections Data)

Variable	*Description*	*Statistics*
Person ID	Individual fiscal code	$2,888,480$ obs; $515,201$ unique
Year		$1993 - 2014$
Position level	Categorical variable for whether politician is a regional, province, or municipality-level politician.	Region $24,439$ Province $74,821$ Municipality $2,789,220$
Position rank	Categorical variable for a position rank (within a position level)	President/Mayor 5.95% Council president/ vice-mayor/president 5.35% Executive councillor 19.60% Council member 69.10% Commissioner 0.01%
Education	Categorical variable for politician's education level	$<$ high school 28.05% $\sim$ high school 44.15% University 27.73% Post-graduate 0.08%
Election dummy	Dummy if election is held in that year $\times$ location	Mean= 0.24
Marginal election tag	Tag for whether election was marginal, and if yes, whether party affiliation of winner is not ambiguous	No 89.21% Yes 5.94% Yes, no ID 4.85%
Marginal election winner	Categorical variable for whether politician belongs to winning/losing/other party in marginal election	Winner 61.06% Loser 18.60% Other 20.34%
Dummy Majority party	Dummy for whether politician belongs to the Top 1 majority party	Mean= 0.73
Dummy Top 5 parliament parties	Dummy for whether politician belongs to the Top 5 majority parties from the parliament	Mean= 0.16

Notes: Table presents variable definitions and summary statistics for the panel data on individual politicians. Data combines Registry of Local Politicians (RLP) – data on universe of local politicians in Italy, with the Elections Data.

Cerved data does not distinguish between missing values and zeros. In particular, observations whose value is less than 1 (in 1000) and observations that are truly missing in the report will both appear as missing. This is the case with tangible and intangible fixed assets variables. We impute with 0.5 (in 1000) value of intangible assets if value of tangible assets is not missing, and vice versa for tangible assets[11].

Summary statistics of these variables are included in the Appendix Table 4.

3.3 Patent Data (PATSTAT)

Our patent data source is the European Patent Office Worldwide Patent Statistical Database (EPO PATSTAT)[12]. PATSTAT provides coverage of all patents published (granted or not) at EPO up to Spring 2016. This amounts to up to 60 million patent applications from 1978 to 2014. We use this data to understand patenting activity of firms in Italy.

We proceed in the following three steps that are described in more detailes in Appendix A.2. First, we identify 71,240 EPO patent families applied by Italian firms. Second, to match patent records with our firm-level datasets, we undertake an effort to combine existing matches with our own company name cleaning routines. We identify 13,904 Italian companies that file for patents. To the best of our knowledge, this is by far the best match of Italian patent records to Italian firms spanning the longest time period.

Third, for all patents, we extract information on their technology classification, application date, grant status, number of claims, and backward and forward citations. This data allows us to construct various measures of firms' patent-based innovation measures. Appendix A.2 provides the details. Here, we summarize our three main measures. First is yearly patent counts filed by firms. The second is citations-adjusted patent counts that weight more heavily the valuable patents receiving more citations from subsequent patents. And the third is family-size-adjusted patent counts. Patent family size can serve as another proxy for patent quality as it may indicate extent of geographical protection an applicant is seeking for. We report summary statistics of these measures in Appendix Table 1. Statistics of derived innovation-related variables at the firm-level are included in Appendix Table 4.

[11] We verify these imputations with another simple imputation of missing values in the panel of firms by just imputing missing value with latest non-missing observation. If such imputation is too off from the initial imputation of 0.5, we revert back to missing value.

[12] "EPO Worldwide Patent Statistical Database – 2016 Spring Edition"

3.4 Social Security Data (INPS)

We access the Italian Social Security Data from the Italian National Institute of Social Security (INPS) within the VisitINPS Scholars program. INPS data covers the universe of private sector workers (whose employers make social security contributions) in Italy. Self-employed, public employees, workers in agriculture, or contractors are not in the data. Part-time workers as well as temporary contracts are observed. To have a consistent time span across datasets, we focus on 1993-2014 period of this data.

On the workers side, SS data provides complete information on their employment history. Among others, we have information on identity of firms they work for, job start and separation dates, gross labor income (including bonuses and overtime), number of months/weeks/days worked in a year, type of contract (for example, full-time or part-time, permanent or temporary), position level (from which we classify white-collar[13] and blue-collar workers), occupation. In addition, data provides individual demographic information, job and residence location (municipality).

On the firms side, we have information on all workers they employ and corresponding characteristics of those workers described above. This lets us construct a reliable variable on firm size, variables on average wages paid, or various work-force composition variables. Importantly, we also have a complete demographic data on the firms – firm industry classification (ATECO and CSC), location, entry and exit dates[14]. For our purposes, this data is essential since this is a firm-level data on universe of private-sector firms and we can study firm entry, exit and turnover over time, location, or industry.

Details on how we construct employment, wages and related variables from INPS are delegated to Appendix A.3.

3.5 Matched Dataset (Politicians Data + INPS + Cerved + PATSTAT)

We match all the datasets described separately in previous sections. We start by combining INPS data with the Politicians Data. Next, we combine this data with firm-level datasets from Cerved and PATSTAT. While we refer a reader to Appendix A.4 for more details, here we list main variable definitions at the firm level and report descriptive statistics for the final

[13] Job is classified as white-collar if classification, *qualifica1*, based on UniEMENS is equal to 2,3,7,9,or P, which entails managers, executives, professionals, office workers.

[14] It is hard to identify establishments using this data, so we will always refer to firms. However, in Italy the average number of establishment per firm is 1.07 (Istat, Census 2011 data).

matched dataset in Tables 2 and Appendix Table 4. Different columns of Appendix Table 4 report statistics on the sample of firms connected at different levels.

At the firm level, we define a firm as being connected at time t with a politician of certain type if at least one politician of that type is working in a firm at time t. Specifically, these are the main variables we use throughout the paper.

$Connection_{it}$ – dummy if at least one politician is working in a firm i at time t.

$Connection\ Province_{it}$ – dummy if at least one province-level politician is working in firm i at time t.

$Connection\ Region_{it}$ – dummy if at least one regional politician is working in firm i at time t.

$Connection\ high-rank_{it}$ – dummy if at least one high-rank politician (mayor, regional or province president, vice-mayor or vice-president, (vice-)president of a council) is working in firm i at time t.

$Connection\ majority_{it}$ – dummy if at least one politician from president's/mayor's party is working in firm i at time t.

Wage premium Politicians earn significant wage premia relative to their co-workers in the same firm. Appendix Table 5 illustrates politicians' within-firm wage premium by type of job – white-collar or blue collar, and gender. Premium is calculated relative to co-workers that do not hold political positions. While municipality-level politicians secure on average about 7% wage premium over their co-workers, province-level and regional politicians earn premia that are much higher and, on average, go up to staggering 100% for white-collar male regional politicians. Likewise, high-rank politicians (mayors/vice-mayors, province/region presidents/ vice-presidents) exert a significant wage premia going up to 23%. This all indicates that firms value their worker-politicians beyond usual observable worker characteristics and incur significant cost for being connected with them.

Table 2: Summary of the Matched Data

	Sample A (full sample)	Sample B (& nonzero empl)	Sample C (& balance sheet data)
Years	1993-2014	1993-2014	1993-2014
Observations	32,776,800	27,982,454	7,371,357
Distinct firms	4,457,672	3,939,897	1,028,063
Share of total employment (comparing to 2011 Census)	1.10	1.10	0.73
Average firm size	7.22	8.46	19.81
Years per firm in sample	7.35	7.10	7.17
Number of distinct firms connected (= ever connected)	118,445	112,333	64,612
Number of firms × year connected	469,263	449,236	270,843
Number of firms × year connected by a regional politician	2,568	2,496	914
Number of firms × year connected by a regional politician	13,122	12,703	6,070
Number of firms × year connected w president/mayor/∼vice	52,181	50,224	27,488
Number of firms × year connected w president/mayor/∼vice/assessore	141,976	136,654	81,165
Number of firms × year connected w pres/mayor-party politician	258,856	248,601	148,759
Number of firms × year connected w majority-level politician	285,337	273,821	164,877
Number of firms × year connected w top 5 parliament-party politician	80,109	77,206	45,492

Notes: Table reports summary of the matched INPS data at the firm level. The first column provides statistics for the full sample of INPS firms. The second column limits observations to firms with positive employment in a year. The third column considers matched INPS-Cerved sample.

4 Empirical Analysis

This section documents a number of empirical regularities on firm-level political connections and firm dynamics in Italy. The results can be summarized as follows:

1. Firm-level connections are widespread, especially among large firms.
2. Industries with higher share of politically connected firms have lower share of young firms and show lower average firm growth and productivity.
3. More connected industries also face lower firm entry, but conditional on entry, entrants are more likely to be connected than in other industries.
4. Market leaders are most politically connected but show lowest innovation effort.
5. Politically connected firms are less likely to exit.
6. At the firm level, political connections are associated with higher employment and sales growth *but* lower productivity growth. Regression discontinuity analysis illustrates that this relationship is also causal from acquiring connections to growth.

4.1 Firm-level Political Connections in the Data

Fact 1. *Firm-level connections are widespread, especially among large firms.*

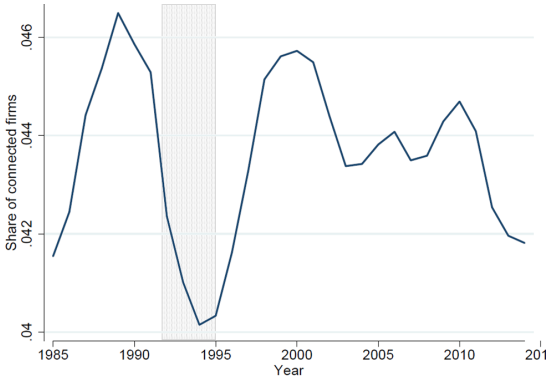
Firm-level connections are widespread. While average share of connected firms by industries is around 4%, connected firms account for 32% of employment across industries. Reminiscent of this observation, connections are particularly common among large firms – 44% of large firms with more than 100 workers are connected with politicians. Most connected industries in the data are pharma, water supply, utilities/ waste disposal, telecommunications, airlines, and finance industries. Industries that have lowest share of connected firms are related to personal services, sanitary/veterinary services, repair/restoration, food-related industries.

Share of connected firms across industries has been more or less stable over the whole time period from 1985 to 2014 as Panel (a) of Figure 4 documents. However, interesting observation is a sharp drop in connections in the early 90's. This corresponds to a famous historical episode of so called *mani pulite* (operation "clean hands"), a period of huge political scandals and nationwide judicial investigations of large corruption cases in Italy. As a

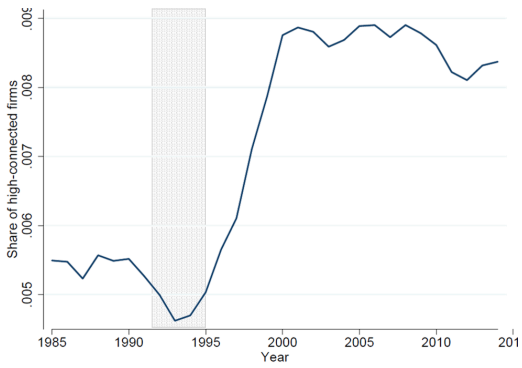
results of these operations, many political parties ceased to exist and many politicians got convicted. Disruption in political connections visible from the data could be a result of firms' precautionary behavior or just of time required to rebuild connections after the dissolution of incumbent parties[15]. Whatever the reason, it clearly took very little time for firms to get back to their pre-crisis level of connections as seen from Panel (a).

Figure 4: Connections over Time

(a) Share of Connected Firms



(b) Share of High-Rank Connected Firms



Notes: Figure plots average share of firms that are politically connected across industries over time. Panel (a) counts firms that are connected with any politician, while Panel (b) counts firms that are connected with high-rank politicians (mayors, vice-mayors, province/region presidents and vice-presidents).

More interesting is however Panel (b) that shows a permanent shift in degree of high-rank connections across industries. We interpret this picture as a smoking gun for a regime shift from a more "under the table" relationship between firms and politicians involving corruption and bribes[16], towards more formal "moonlighting" relationship. This shift also corresponds to the period in which high-rank politicians like mayors, presidents, vice-mayors or vice-presidents acquired higher decision power, hence they were considered more valuable for firms. In fact, since the 1990s, a few reforms were enacted to shift towards a federal government that culminated in the reform of Title V of the Italian Constitution in 2001. The purpose of all these reforms was to give the Italian state a more "federalist" role in which spending and decision-making centers would move from the highest levels, the central state to the more local ones, "getting closer" to the citizens. Over the years, regions have

[15]More than 400 city and town councils were dissolved because of corruption charges (source: Wikipedia).

[16]The estimated value of bribes paid annually in the 80's by Italian and foreign companies bidding for large government contracts reached 4 billion dollars (6.5 trillion lire).

gained more and more power (the most important is healthcare management) and this shift has increased their autonomy. With the 2001 reform in particular, the regions were given financial autonomy to decide freely how to spend their money and organizational autonomy to decide how many councilors and to have and how much to pay them.

4.2 Connections and Industry Dynamics

In this section, we provide evidence on relationship between connections at the industry level and various industry characteristics. We begin by exploring whether industries that are more politically connected grow faster or are more productive. At the industry (88 2-digit Ateco codes) × region × year level, we construct share of connected firms, average employment growth and labor productivity series. We first run regressions of average growth and productivity on share of connected firms controlling for year, industry and region fixed effects. Figure 5 plots scatterplots and linear fit from these regressions. Each point represents industry× region × year-level growth or productivity adjusted for fixed effects. For visibility, we plot binscatters dividing the x-axis into 20 equally sized bins. The figure shows that industries that are more politically connected on average grow slower and are less productive. Results are similar if we look at 6-digit industry × year regressions or use lagged values of connections. Likewise, as Appendix Figure 13 illustrates, results are similar if on the x-axis we look at the share of high-rank connected firms. This result may not come as a surprise if we recall that large firms are more likely to be connected and if they tend to grow slower or be less productive. In line with this argument, Appendix Figure 14 shows that if we in addition control for size of top 5 firms in each industry, negative relationship no longer holds.

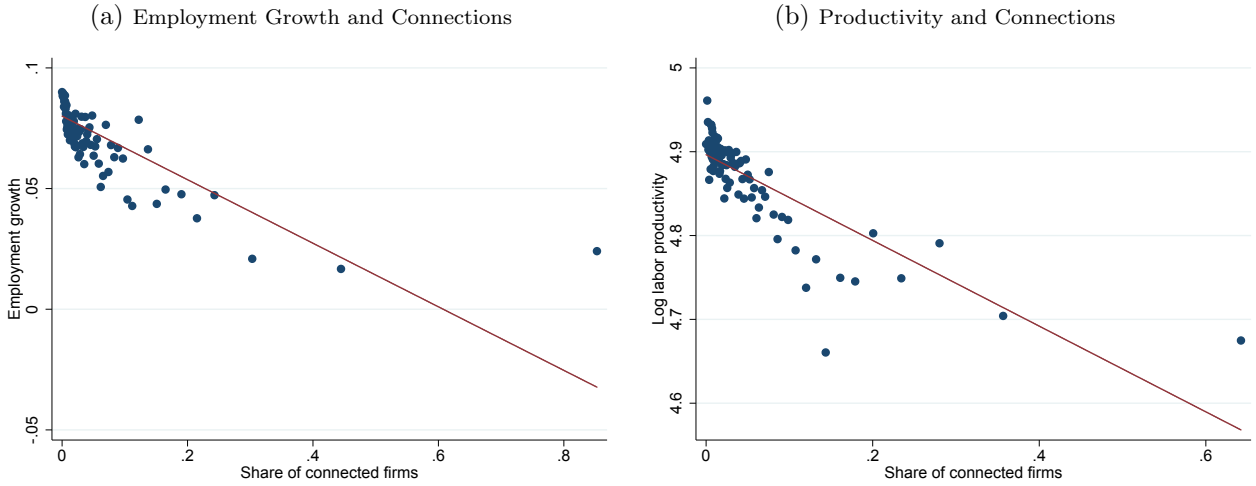
Hence we conclude that:

Fact 2. *Industries with higher share of politically connected firms have lower share of young firms and show lower average firm growth and productivity.*

Next, we explore whether industries with higher share of connected firms face lower entry by new firms. Similar to the above regressions, we regress entry rate at the industry × region × year level on share of connected firms and industry, year, and region fixed effects. Panel (a) of Figure 6 plots binscatters from these regressions, where each dot represents entry rate adjusted for fixed effects. There is a strong negative association between connections and entry.

Interestingly, conditional on entry, in those industries that are more populated by connected firms, new firms tend to start off with connections. Panel (b) of Figure 6 illustrates

Figure 5: Connections and Industry Performance



Notes: Each outcome variable at the industry × region × year level is regressed on share of connected firms controlling for industry, year, and region fixed effects. Each dot represents the adjusted outcome variable, namely the outcome from which we subtract all fixed effects times their estimated coefficients. Regression lines are depicted in each panel. X axis is divided into 20 equally sized bins and each dot represents average value within that bin. In Panel (a), the outcome is average employment growth rate. Panel (b) considers average log labor productivity.

this. It may indicate that in those industries, in order to compete with incumbents, entrants need to seek for protection. However, we can not also exclude that other factors at the industry level that led incumbents to seek for political connections and that are not time-invariant could as well make entrants to resort to rent-seeking.

These observations are strongly preserved even if we control for size of top firms in each industry as seen in the Appendix Figure 15. In line with these observations, Appendix Figure 15 shows that industries that are more politically connected have lower share of young firms.

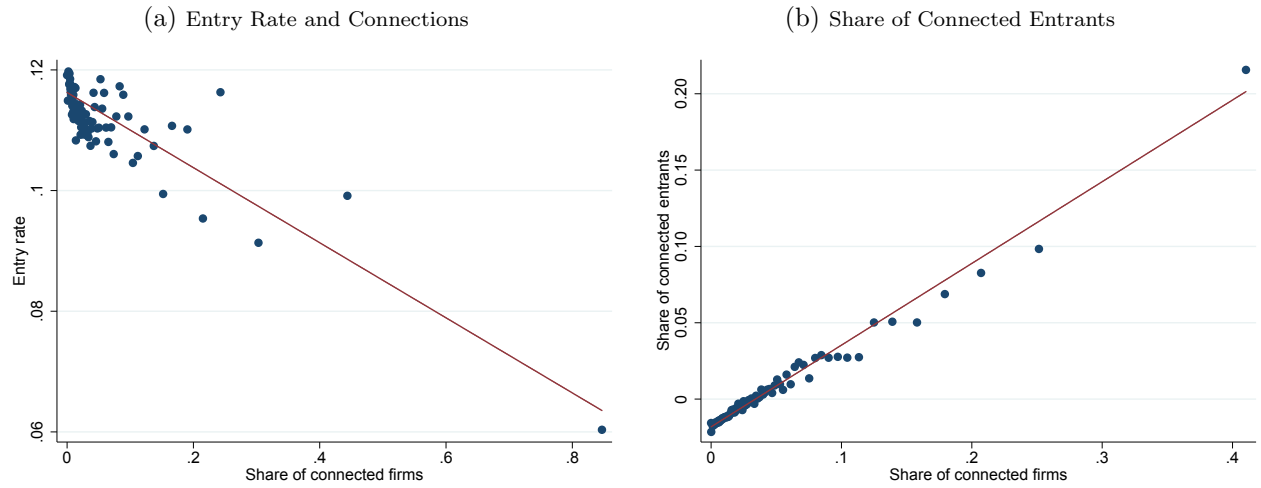
These findings establish our next fact:

Fact 3. *More connected industries also face lower firm entry, but conditional on entry, entrants are more likely to be connected than in other industries.*

4.3 Rent-Seeking vs Innovation

While connections may play positive role if they help to overcome regulations, bureaucracy or other market frictions, they may as well imply dynamic negative effects if connected firms are hard to replace and if they do not have incentives to innovate and increase productivity.

Figure 6: Connections and Industry Entry



Notes: Each outcome variable at the industry × region × year level is regressed on share of connected firms controlling for industry, year, and region fixed effects. Each dot represents the adjusted outcome variable, namely the outcome from which we subtract all covariates (except share of connected firms) times their estimated coefficients. Regression lines are depicted in each panel. X axis is divided into 20 equally sized bins and each dot represents average value within that bin. In Panel (a), the outcome is entry rate of new firms. Panel (b) considers share of connected entrants.

We try to shed light on this argument by trying to understand how aligned connections and innovation incentives across firms are.

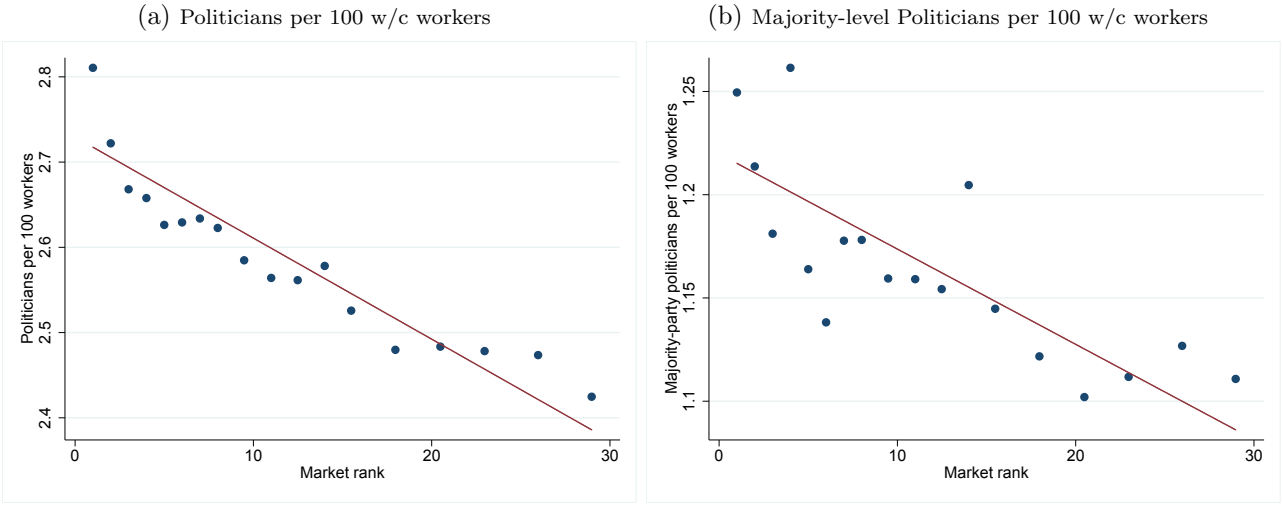
A striking feature of the data is a strong positive relationship between market leadership and connections on the one hand, but a strong negative relationship between market leadership and innovation, on the other hand. In the main text, we provide evidence by zooming in into top 30 firms across markets, however we provide additional evidence on a larger scale in the Appendix B.

We identify largest top 30 firms within the same industry and region over time[17] and based on employment shares assign market rank to each firm. We then plot various measures of political connections in Figure 7 and of innovation in Figure 8 over firm's market rank. Measures of connection in Figure 7 are connection dummy (Panel (a)), connection with a majority-member politician dummy (Panel (b)), politicians per white-collar workers (Panel (c)) and majority-member politicians per white-collar workers (Panel (d)). Like in previous figures, plots here represent binscatters from regressions that adjust outcome variables with industry, region and year fixed effects. Consistently over all measures, we observe that

[17]Defining market by industry, excluding regional dimension, leads to similar results.

market leaders are more likely to be politically connected. This relationship persists in a more general regression of same outcome variables on firm's market share as illustrated in the Appendix Figure 17. Panels (b) and (d) also control for firm size, indicating that even conditional on size, market leadership is significantly correlated with political connections. Appendix Figure 18 also shows that market leaders hire politicians with relatively higher rank than their competitors.

Figure 7: Connections over Market Leadership

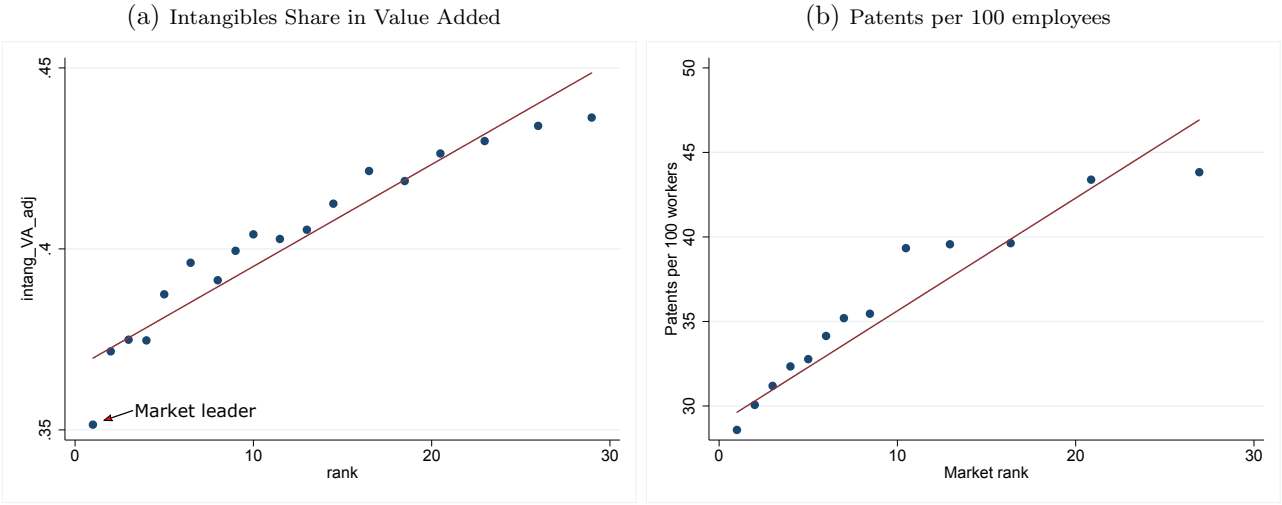


Notes: Figure plots average outcome variable over firms' size rank for top 30 firms in the markets. Market is defined at (6-digit) industry × region × year level. Markets in which top 1 firm holds less than 10% share are dropped. Outcome variables are demeaned with industry, year and region fixed effects. In Panel (a), the outcome is connection dummy. In Panel (b), the outcome is majority-member politician dummy. In Panel (c) the outcome is politicians per white-collar workers. Panel (d) considers majority-member politicians per white-collar workers. Market leaders are more politically connected relative to their competitors.

Interestingly, a completely opposite picture appears when focusing on innovation incentives against market leadership as shown in Figure 8. Different panels plot various measures of firms' innovation over firm's market rank. Panel (a) considers intangible assets over value added, Panel (b) considers patent counts per employees, Panels (c) and (d) consider quality-adjusted patent counts per employees. Market leaders show lowest incentives to innovate relative to their competitors. Figures 19 and 20 extend this relationship to all firms controlling for firms' market share and for firm size in panels (b) and (d). Figures also show similar relationship for labor productivity as another measure that is related to firm's innovation.

Fact 4. *Market leaders are most politically connected but show lowest innovation effort.*

Figure 8: Innovation over Market Leadership



Notes: Figure plots average outcome variable over firms' size rank for top 30 firms in the markets. Market is defined at (6-digit) industry × region × year level. Markets in which top 1 firm holds less than 10% share are dropped. Outcome variables are demeaned with industry, year and region fixed effects. In Panel (a), the outcome is intangible assets over value added. In Panel (b), the outcome is patents per 100 workers. In Panel (c) the outcome is patent family size-adjusted patent counts per 100 workers. Panel (d) considers citations-adjusted patent counts per 100 workers. Market leaders are less innovative relative to their competitors.

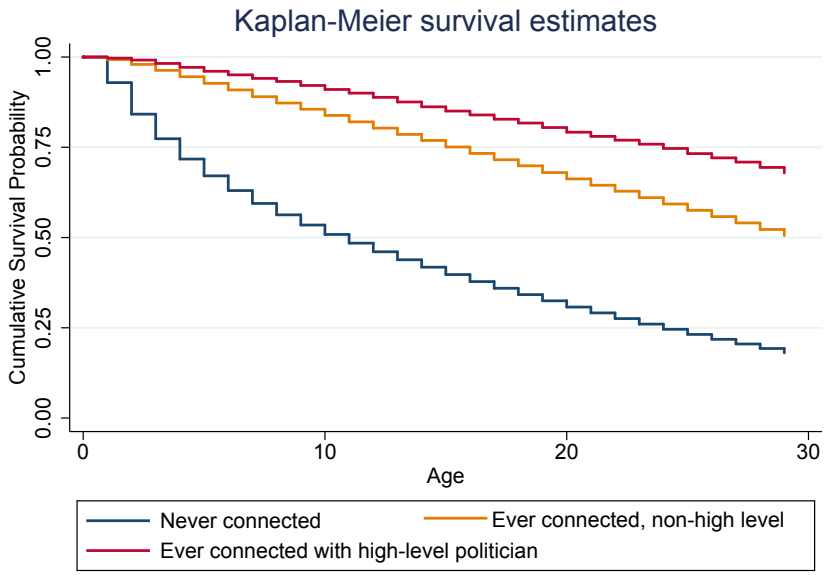
4.4 Connections and Firm Survival

In the data, differences in survival probabilities of firms with different connection statuses are large. To illustrate this, Figure 9 presents Kaplan-Meyer survival estimates splitting sample of firms based on connection status over their lifecycle. Blue curve represents firms that have never been connected, orange curve represents firms that have been connected but never at the high-level, and red curve bundles the firms that have ever been connected with a high-level politician. These unconditional estimates show that existence of connections and strength of connections both are positively associated with firm's survival. Clearly, large part of this should be driven by the fact that connected firms are also larger. In addition, firms that survive longer have higher chance of being observed as connected. To address these issues, we conduct Cox survival analysis for the universe of firms in our data, reported in the Appendix Table 6. Main explanatory variables are connection dummy and high-rank connection dummy. Regressions also control for firm size, firm's market share and year dummies.

We find that conditional on observables, firms that are connected have lower hazard and

therefore a longer survivor time. Survival time increases even further if a firm is connected with a high-rank politician. Relative to non-connected firms, firms that are connected with high-rank politicians experience 0.243 decline in log hazard rate.

Figure 9: Kaplan-Meyer Survival Estimates by Connection Status



Notes: Kaplan-Meyer Survival Estimates by maximum level of connections over the lifetime. Blue curve represents firms that have never been connected, orange curve represents firms that have been connected but never at the high-level, and red curve bundles the firms that have ever been connected with a high-level politician.

Fact 5. *Politically connected firms are less likely to exit.*

4.5 Connections and Firm Growth

Do firms that get connected experience higher growth? Since finding and retaining connections should be costly (recall that firms provide significant wage premium to worker-politicians, especially those in high-level positions), we would expect that connected firms acquire benefits by expanding in size or sales. Indeed, we find that connections are associated with large gains in employment and value added growth to the next period. Table 3 reports regressions of employment growth (columns 1 and 2) and value added growth (columns 3 and 4) on connection and majority-level connection dummies. Regressions in addition control for firm's assets, size, age, as well as year, region and industry fixed effects in columns 1 and 3; and for year dummies and firm fixed effects in columns 2 and 4. Connection dummy adds

6 pp growth in employment and 1 pp to 4 pp growth in value added to firms. Connection with majority-level politicians adds an additional 1 pp of growth.

These results indicate that firms that are getting connected expand in terms of size and sales. However, is this growth accompanied by a corresponding growth in firms' productivities? We find a negative answer to this question. Table 4 shows similar regressions to Table 3 but for labor productivity growth (columns 1 and 2) and TFP growth (columns 3 and 4). We see that connections are associated with weak decline in productivity growth, while connections with majority-level politicians are not significant.

Appendix Tables 7 and 8 show that results are similar if instead of majority-level connections we use high-rank connections as a control.

While we usually think of resources being reallocated towards firms that become more productive these results indicate that in the presence of rent-seeking, the opposite may actually be happening. To explore whether part of this relationship is causal and not just driven by endogeneity, in the next section, we proceed with the regression discontinuity analysis.

Fact 6. *At the firm level, political connections are associated with higher employment and sales growth but lower productivity growth.*

4.6 Causal Inference using Regression Discontinuity Design

We exploit a quasi-random discontinuity caused by local elections decided on a thin margin to gauge about causality in our previous firm-level results (Lee, 2008). The idea is to compare firms that have been connected right *before* a marginally contested election with a politician from marginally losing versus marginally winning parties. Since outcomes of closely contested elections can be considered as a pure chance (breaking news, weather shock) (Lee, 2008), discontinuity in outcomes between marginally winning and losing firms *after* the election can be attributed to a causal effect of majority-level connections on firms' outcomes. In this sense, firms that are connected with marginal losers serve as a control group for firms that are connected with marginal winners, our treated group.

More formally, denote by T a year of an election that has been decided on a thin margin. As discussed in Section 3.1.2, share of votes for a mayor, president or president at the municipality, province or regional level, respectively, decides identity of a majority party/coalition. Hence, we define *victory margin* as a difference between winning candidate's share of votes and losing candidate's share of votes in a decisive round. y_{iT} is the outcome variable equal

Table 3: Connections and Firm Growth

	(1)	(2)	(3)	(4)
	Empl growth	Empl growth	VA growth	VA growth
Connection	0.068***	0.062***	0.039***	0.014***
	(48.58)	(33.87)	(24.33)	(6.65)
Connection major	0.011***	0.009***	0.010***	0.002
	(6.42)	(4.02)	(4.87)	(0.99)
Log Assets	0.083***	0.232***	0.036***	-0.091***
	(280.33)	(264.03)	(118.75)	(-89.75)
Log Size	-0.136***	-0.566***	-0.080***	-0.235***
	(-348.95)	(-525.51)	(-217.56)	(-251.16)
Age	-0.004***	-0.010***	-0.004***	-0.005***
	(-174.18)	(-119.98)	(-145.67)	(-44.34)
Year FE	YES	YES	YES	YES
Region FE	YES	NO	YES	NO
Industry FE	YES	NO	YES	NO
Firm FE	NO	YES	NO	YES
Observations	6545131	6585740	5684519	5710338

Notes: Firm-level OLS regressions. Dependent variable is columns 1 and 2 is employment growth from time t to time $t+1$ as defined in equation 2. Dependent variable is columns 3 and 4 is value added growth from time t to time $t+1$. Main variables of interest are *Connection* – a dummy variable equal to one if firm is connected with a politician, and *Connection major* – a dummy equal to one if a firm is connected with a majority-member politician at time t. Regressions in addition control for firm's assets, size, age, as well as year, region and industry fixed effects in columns 1 and 3; and for year dummies and firm fixed effects in columns 2 and 4. Robust standard errors clustered at firm level reported in parentheses. $^{*}p < 0.1,^{**}p < 0.05,^{***}p < 0.01$.

Table 4: Connections and Firm Productivity Growth

	(1) LP growth	(2) LP growth	(3) TFP growth	(4) TFP growth
Connection	-0.014***	-0.028***	-0.008***	-0.019***
	(-8.22)	(-12.48)	(-6.03)	(-10.65)
Connection major	-0.001	-0.004	0.000	-0.003
	(-0.27)	(-1.55)	(0.15)	(-1.30)
Log Assets	-0.028***	-0.274***	-0.001***	-0.106***
	(-83.23)	(-236.12)	(-4.86)	(-116.33)
Log Size	0.021***	0.274***	-0.006***	0.125***
	(55.72)	(255.00)	(-18.20)	(145.41)
Age	-0.001***	-0.002***	-0.001***	-0.003***
	(-47.83)	(-17.48)	(-46.37)	(-31.58)
Year FE	YES	YES	YES	YES
Region FE	YES	NO	YES	NO
Industry FE	YES	NO	YES	NO
Firm FE	NO	YES	NO	YES
Observations	5598367	5623077	5271002	5291979

Notes: Firm-level OLS regressions. Dependent variable in columns 1 and 2 is labor productivity (value added per labor) growth from time t to time $t+1$. Dependent variable in columns 3 and 4 is TFP growth from time t to time $t+1$. TFP is calculated using Cobb-Douglas specification where capital is measured as total assets, labor is given by employment level from INPS and labor share is taken equal to average industry-level labor share from the data. Main variables of interest are *Connection* – a dummy variable equal to one if firm is connected with a politician, and *Connection major* – a dummy equal to one if a firm is connected with a majority-member politician at time t. Regressions in addition control for firm's assets, size, age, as well as year, region and industry fixed effects in columns 1 and 3; and for year dummies and firm fixed effects in columns 2 and 4. Robust standard errors clustered at firm level reported in parentheses. $^{*}p < 0.1,^{**}p < 0.05,^{***}p < 0.01$.

to firm i's employment or labor productivity growth from t to $t+1$. Win_{iT-1} is a dummy equal to one if a firm i at time $T-1$ employs a politician from a party that marginally wins in the election at time T.

We estimate a relationship

$$y_{iT} = \alpha + \beta Win_{iT-1} + f(margin) + \delta_1 X_{iT} + \delta_2 X_T + \nu_{iT} \quad (1)$$

where $f(margin)$ is a third order polynomial function estimated on both sides of the threshold. X_{iT} includes firm-level controls: firm's age, province dummy and size of a firm at time T. X_T includes election year dummies and ν_{iT} is error term. When the assignment of treatment is random, our coefficient of interest β – the effect of winning at the margin, should be invariant to inclusion of additional controls X_{iT} and X_T since they should be orthogonal to treatment. We validate this assumption below and show results estimating this equation with or without additional controls.

More than 37 thousand local elections have been held in Italy during the period of 1993-2014. Among them, more than 11 thousand elections got decided on a 10% margin, while up to 5 thousand elections had a thin margin of victory of 4%[18]. Appendix Figure 21 shows that marginal elections have been geographically scattered all over Italy and there does not seem to be a particular local concentration.

If in anticipation of closely contested elections firms hire politicians from both competing parties, our identification of treated and control groups in RD would be noisy. We check if this is the case by looking at party composition of politicians within a firm. Indeed, by focusing on firms that hire at least one politician from a marginally winning or losing party, we see that only 4% of firms simultaneously hire politicians from both competing parties. Appendix Figure 22 shows the full distribution of share of winners across firms. As seen, firms usually "bet" on one side of an election.

Graphical Analysis. We begin with a graphical analysis of RD when the outcome variable is firm-level employment growth – Panels (a) and (b) in Figure 10. We plot firm's growth from T to $T+1$ against margin of victory at time T. Positive margins of victory denote firms that have been connected at time $T-1$ with a politician from a party that won an election at time T with a corresponding margin of victory. Likewise, negative margins of victory depict firms that are connected with losing politicians. Panel (a) focuses on all the election that were decided with no more than 10% margin. For visibility, we divide X-axis

[18] As discussed in Section 3.1.2, up to half of municipality-level elections dropped from the sample because of ambiguous winner identifiers.

into 0.01-wide intervals of the margin of victory at time T and each point denotes average growth of firms in that interval. The solid lines represent predicted third order polynomial fits from a regression that includes third-order polynomial in margin of victory, a dummy Win_{it-1} and an interaction of the dummy with the polynomial (a regression in equation 1 that excludes additional controls). Dashed line represents a running-mean smoothing fit. As a robustness check, we repeat same plot for elections within 5% victory margin in Panel (b).

If the regression discontinuity design is valid and has generated random assignment of who wins in T, a gap in the outcome when margin of victory is equal to zero represents a credible estimate of the effect of majority-level connections on the outcome. As seen from Panels (a) and (b), there is indeed a large positive gap in employment growth at the zero victory margin threshold. This confirms that direction of causality in previous firm-level regressions does (also) run from connections to growth. Interesting observation is that for firms further away from the zero threshold, difference in growth rates is not sizable. This may indicate that firms connected with fierce competitors of barely winning candidates are performing worst.

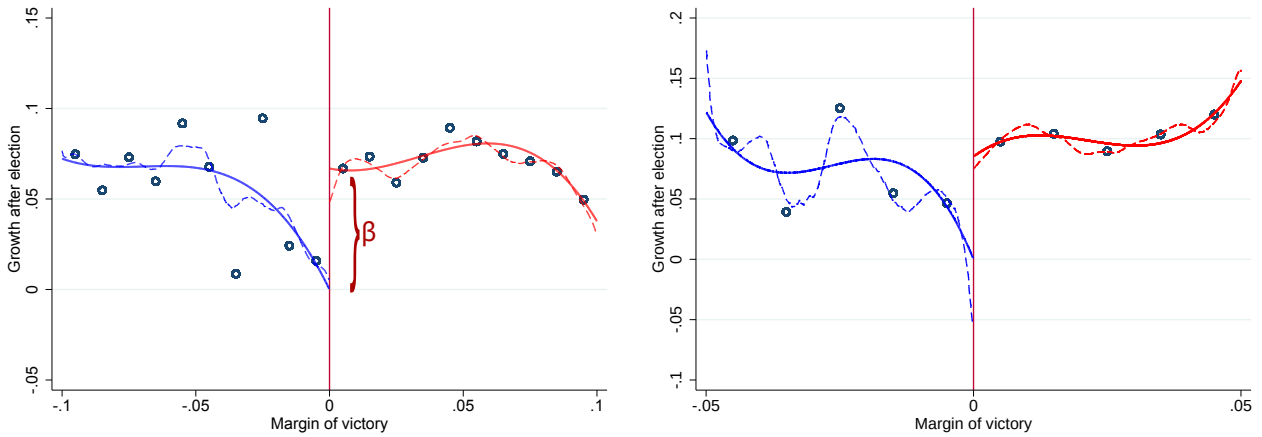
RD plots also confirm causal interpretation of firm-level results on labor productivity growth. Panels (c) and (d) of Figure 10 show negative effects of connections on productivity growth.

We quantify these figures in Table 5 more precisely. We restrict attention to elections within 10% margin of victory and focus on employment and labor productivity growth as outcome variables. Columns 1 and 3 correspond to the above RD plots: regressions include win dummy, Win_{iT-1}, and $f(Victory\ Margin)$ – third order polynomial in victory margin interacted with win dummy. Coefficient on Win dummy is large and significant for employment growth while it is negative and significant at 10% significance level for LP growth. Main assumption of the RD setup is that there is no systematic difference in pre-determined covariates between firms on the two sides of the threshold. This means that inclusion of additional covariates should not change the main effect of treatment. Indeed, after including additional controls such as year and firm province fixed effects, log size and age in columns 2 and 4, we see that the magnitude of the main coefficients did not change much.

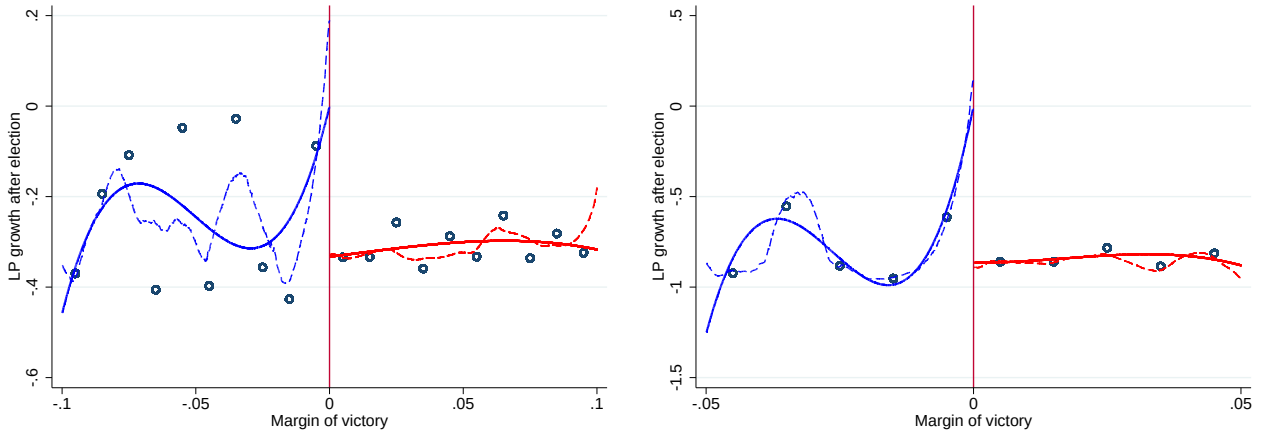
Tests for Quasi-Random Assignment. Our identification strategy relies on the assumption of random assignment of the winner in marginally contested elections at T. This implies that firms closer to the zero-margin threshold are very comparable and do not show systematic differences in pre-determined covariates. We begin by examining pre-trends:

Figure 10: Employment and LP Growth after Election, RD

(a) Employment growth after election$_{(T \to T+1)}$ (b) Employment growth after election$_{(T \to T+1)}$



(c) LP growth after election$_{(T \to T+1)}$ (d) LP growth after election$_{(T \to T+1)}$



Notes: Figure plots firm's growth from T to $T+1$ against margin of victory at time T. Positive margins of victory denote firms that have been connected at time $T-1$ with a politician from a party that won an election at time T with a corresponding margin of victory. Likewise, negative margins of victory depict firms that are connected with losing politicians. For visibility, we divide X-axis into 0.01-wide intervals of the margin of victory at time T and each point denotes average outcome of firms in that interval. The solid lines represent predicted third order polynomial fits from a regression that includes third-order polynomial in margin of victory, a dummy Win_{it-1} and an interaction of the dummy with the polynomial (a regression in equation 1 that excludes additional controls). Dashed line represents a running-mean smoothing fit. Outcome variable in Panels (a) and (b) are employment growth, while Panels (c) and (d) depict labor productivity growth. Panels (a) and (c) focus on all the election that were decided with no more than 10% margin, while Panels (b) and (d) plot elections within 5% victory margin. Figures are normalized such that outcome variables for marginal losers at the threshold are equal to zero.

Table 5: Employment and LP Growth after Election, RD

	Empl Growth	Empl Growth	LP Growth	LP Growth
Win dummy	0.089**	0.079**	-0.378*	-0.433*
	(2.25)	(2.07)	(-1.65)	(-1.88)
Age		0.000		-0.001
		(0.02)		(-0.74)
Log Size		0.004**		0.018
		(2.02)		(1.54)
f(Victory Margin)	YES	YES	YES	YES
Year FE	NO	YES	NO	YES
Province FE	NO	YES	NO	YES
Observations	11118	11076	6064	6055

Notes: OLS regressions of employment growth (columns 1 and 2) and labor productivity growth (columns 3 and 4) on Win dummy in an election at time T. Growth rates are defines from T to $T+1$. We restrict attention to elections within 10% margin of victory. In the columns 1 and 3, regressions include win dummy, Win_{iT-1}, and $f(Victory\ Margin)$ – third order polynomial in victory margin interacted with win dummy. Columns 2 and 4 include additional controls such as year and firm province fixed effects, log size and age. Regressions drop those firms that hire politicians from both of the two competing parties.

Figure 11 illustrates RD plots similar to the above plots but for the employment growth and labor productivity growth at $T-1$, right before the marginal elections. Panels (a) and (b) show results for employment growth, while Panels (c) and (d) show results for productivity growth. We see no significant difference in before-elections growth rates at the threshold. The only sizable difference is In Panel (d) though it is not statistically significant.

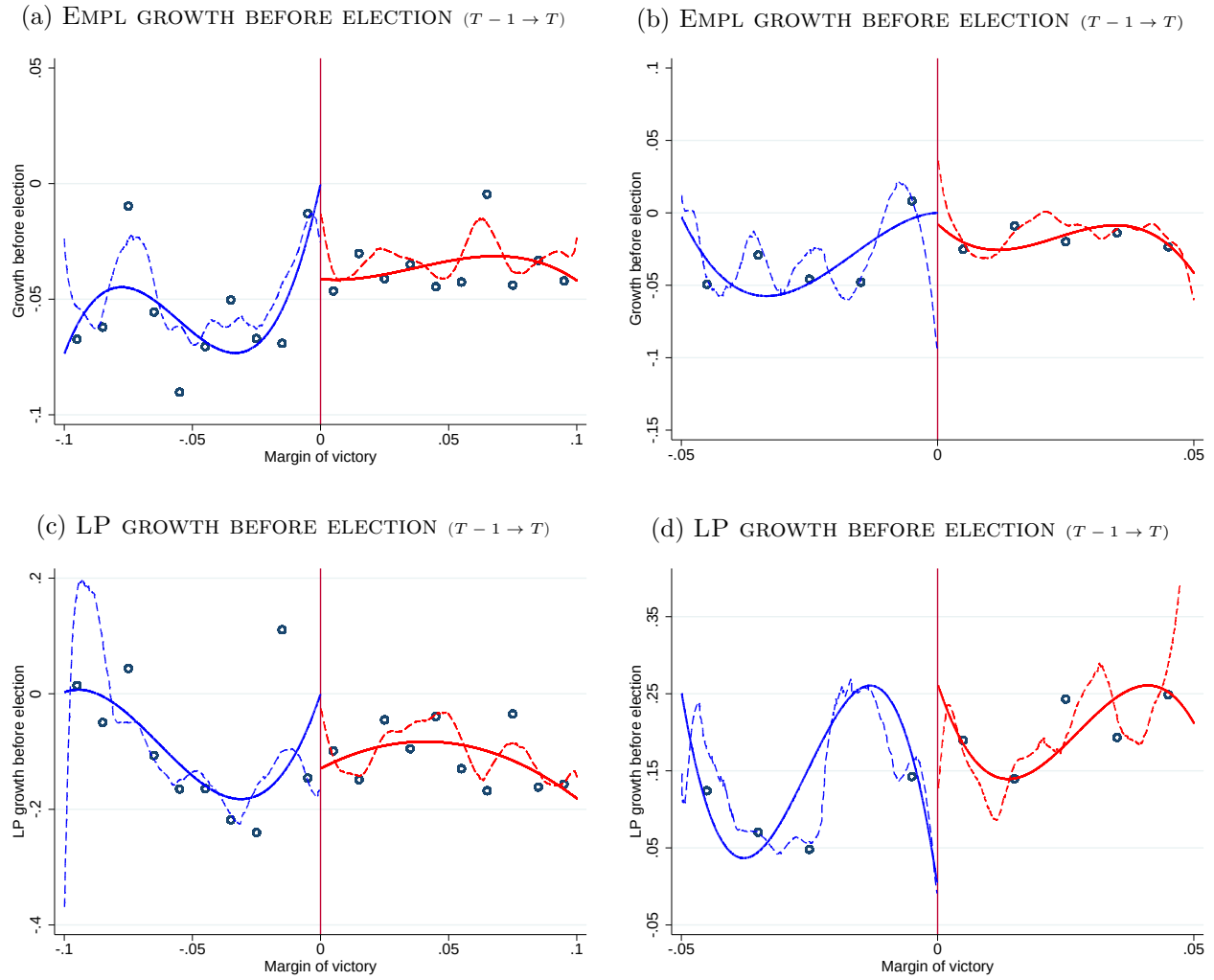
Next, we show balancing tests for other firm-level covariates in Table 6. Our covariates are firm size, firm value added, labor productivity, age, dummy for being in the Center, East or West of Italy, and average level of politicians' position (ranging from 1 at the municipality, to 3 at the regional level). The table reports differences between covariates of marginally winning and marginally losing firms and standard errors of the differences in parentheses. As we look at the first column including all the elections within 20% victory margin, we see sizable differences in literally all covariates between firms. However, as we move towards thinner margins of victory in the next columns and hence compare firms that "by chance" won or lost, we see that difference in covariates disappears reassuring us in comparability of treatment and control groups around the threshold.

Table 6: Differences in Pre-determined Firm Characteristics between Marginally Losing and Winning Firms

	20% Margin	10% Margin	5% Margin	2% Margin
Log Size	-.514	-.513	-.174	.084
	(.037)	(.05)	(.069)	(.111)
Log Value Added	-.244	-.254	-.116	.069
	(.043)	(.058)	(.086)	(.146)
Log LP	-.043	-.029	-.034	-.057
	(.017)	(.023)	(.035)	(.065)
Age	-1.632	-1.718	-1.513	-1.283
	(.205)	(.269)	(.398)	(.644)
Center	.006	.01	-.002	-.043
	(.007)	(.01)	(.015)	(.025)
East	.004	-.001	.012	.009
	(.005)	(.007)	(.01)	(.018)
West	-.023	-.017	.001	.026
	(.006)	(.007)	(.011)	(.017)
Politicians	-.047	-.051	-.043	-.025
level	(.006)	(.008)	(.012)	(.018)
Observations	25134	14611	7037	2598

Notes: Table reports differences in pre-determined firm characteristics (at time $T-1$) between firms that are connected with politicians from a winning party and those connected with losing party. Standard errors are in parentheses. The covariates are firm size, firm value added, labor productivity, age, dummy for being in the Center, East or West of Italy, and average level of politicians' position (ranging from 1-municipality, to 3-region). Each column corresponds to the sample of firms whose politicians participated in elections within corresponding margins of victory. Hence, the last column compares firms that are just around the threshold and thus should be very similar.

Figure 11: Pre-Trend: Employment and LP Growth before Election, RD



Notes: Figure plots firm's growth from $T-1$ to T against margin of victory at time T. Positive margins of victory denote firms that have been connected at time $T-1$ with a politician from a party that won an election at time T with a corresponding margin of victory. Likewise, negative margins of victory depict firms that are connected with losing politicians. For visibility, we divide X-axis into 0.01-wide intervals of the margin of victory at time T and each point denotes average outcome of firms in that interval. The solid lines represent predicted third order polynomial fits from a regression that includes third-order polynomial in margin of victory, a dummy Win_{it-1} and an interaction of the dummy with the polynomial (a regression in equation 1 that excludes additional controls). Dashed line represents a running-mean smoothing fit. Outcome variable in panels (a) and (b) are employment growth, while panels (c) and (d) depict labor productivity growth. Panels (a) and (c) focus on all the election that were decided with no more than 10% margin, while panels (b) and (d) plot elections within 5% victory margin. Figures are normalized such that outcome variables for marginal losers at the threshold are equal to zero.

5 Final Remarks

In this paper, we studied the link between political connection and firm dynamics in Italy. We showed that hiring a politician is a common practice, especially among large market leaders. We also showed the politically connected firms grow in employment and sales, survive longer in the market, yet have lower labor productivity growth. This finding is consistent with the view that hiring politicians helps firms block competition as opposed to help them push the productivity and technology frontier. Our analysis also showed that firms lower their innovation efforts and increase their political connections as they become the market leader.

A growing literature has argued that factor reallocation from low productivity incumbents to high productivity entrants is an important source of economic growth. Our results suggest that political connections might be an important impediment to factor reallocation and productivity growth. While these connections might alleviate regulatory barriers, its detrimental impact on market competition and new firm entry might reverse its static benefits. Future work should incorporate these opposing effects that have been highlighted in our model and assess their quantitative importance on aggregate growth and welfare.

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Appendix

A Data Construction

This section provides more details on the steps undertaken during the data construction. Each subsection is an extension of a corresponding subsection in the main text.

A.1 Politicians Data (RLP and Elections Data)

A.1.1 Registry of Local Politicians (RLP)

The following are the steps undertaken to clean and utilize RLP data.

Step 1. First, to link individual politicians to Social Security data on private-sector employees, we need to assign fiscal codes (similar to social security numbers in the U.S.) to politicians. In Italy, assignment of fiscal code follows a specific rule that deterministically assigns a fiscal code using individuals demographic information, like name, surname, date of birth, place of birth, gender. We develop an algorithm following this rule and use a detailed demographic information from RLP to assign fiscal codes to each politician.

Step 3. We determine whether a politician belongs to political majority or minority using reported political affiliations in RLP. Data provides either party, list or a coalition to which a politician is affiliated to. For example, a typical example of the variable would be an entry "A | B" meaning that politician belongs to a list/coalition of two parties A and B participating in an election in that area. To define majorities, we first clean individual party names and then define major parties at local level.

- *Cleaning party names:*

First tedious task is to clean political party/coalition names in the data. Common problem is misspellings and abbreviations of party names. Second problem is that political parties sometimes change their names, merge, split, form coalitions, etc. We tackle these problems by developing name cleaning algorithm that is based on information from extensive online searches and manual checks.

More specifically, in the example above with the "A | B" entry, we parse this entry into two names, "A" and "B", clean each of those names separately, and then combine those names again. To clean names, we first compile a list of full names and abbreviations of parties/coalitions at all levels municipality, province, regional or national from Wikipedia. This represents a basic dictionary that helps to spot multiple forms of the same name in the data. Next, we develop a name cleaning algorithm where we standardize commonly used words and special characters, correct for word misspellings and shortcuts. Using this name standardization and dictionary approach gets us a long way in cleaning the data. Furthermore, we iteratively improve the algorithm by manually verifying and updating special cases.

- *Defining majority parties in RLP:* Next, we define parties/coalitions that represent majorities at the regional/province/municipality level in a given year. We define several variants of majority party variable at the location-year level. First definition uses political affiliation of a president/mayor. Second definition uses most frequent political affiliation of all politicians found in RLP[19].

[19]In effect, president's/mayor's elections determine party composition in the councils. Hence, to determine a majority - party that has the largest representation, one needs to look at party affiliations of council members. Councilmen represent majority of politicians in RLP. However, about 15% of politicians in RLP are not elected. To define majorities, we could use both samples, however we prefer defining majority using sample of councilmen only.

Specifically, we define following variables at j-location and t-year level:

Main party $(RLP)_{jt}$ party (coalition) of a regional president/province president/mayor in year t in a j region/province/municipality, respectively[20].

#1 *Party* $(RLP)_{jt}$ most frequent party (coalition) affiliation of politicians in a region/province/municipality.

Since a winning candidate is generally also assured majority of seats, the first and second definitions should be equivalent. However, there is one main reason for why in many cases those definitions provide different information in RLP. Consider this example. Suppose, a winning candidate belonged to a part "B" and was supported by a coalition consisting of parties "A", "B", and "C". In such a case, RLP could report the candidates party affiliation as either "A | B | C", "B", or "Z", where "Z" is a new name of a coalition[21]. Often, the third variant appears. Similarly, other politicians may have an affiliation reported in one of those ways (often, the second variant appears for an ordinary council member). Hence, we make use of both variables – affiliation reported by a president/mayor (*Main party* $(RLP)_{jt}$) and most frequent affiliation reported by all politicians (#1 *Party* $(RLP)_{jt}$). Importantly, we will complement these definitions with yet another information coming from the Elections data, which we discuss below.

Using this data on majority parties we can define whether individual belongs to majority or minority. We delegate its discussion after we describe the Elections data below.

[20]If affiliation is missing (in less than 3% of cases), we use an affiliation of council president. If those are still missing, we use affiliation of a vice-president/vice-mayor or a council vice-president.

[21]Often, for example, coalition may be listed as "Centro Destra" (center-right), or "Lista Civica" (civil list), or using other official name of a coalition, like "Polo per le Liberta" instead of listing its members "Forza Italia", "Alleanza Nazionale" or others.

Step 2. We define following variables using information on education and position attributes.

Position level$_{it}$ categorical variable for whether a politician is a regional, province, or municipality-level politician[22].

Position rank$_{it}$ categorical variable for a position type (within a *Position level*$_{it}$). Categories are: i) president/mayor; ii) vice-president/vice-mayor/president of a council/vice-president of a council/secretary of a council ; iii) assessore (town councillor, and executive position similar to local minister); iv) council member; v) questore/commissario (a superintendent or commissioner).

Education$_i$ categorical variable for politician's education. Categories are i) below high school; ii) high-school or equivalent professional certification; iii) university degree; iv) post-graduate degree.

Finally, we complement RLP data on local politicians with data on parties in the Italian parliament from BPR (Bibliografia del Parlamento italiano e degli studi elettorali) and from Wikipedia. We later use it to define top five parties at the national level each year, and to determine a link of local politicians with national parties.

A.1.2 Elections Data

Defining majority parties in the Elections data:

For each election, we define coalitions as set of parties supporting same candidate (it may be just one party or multiple). We define a coalition that gets most seats and a coalition that supports a winning candidate (mayor or president). Because of the majority premium

[22]In few cases, when a politician has multiple observations in RLP at different position levels within a year, we keep the observation with the highest position level in that year.

described above, these two definitions should be equivalent. Indeed, definitions are the same in all instances except for rare cases ($<< 1\%$). Hence, we define a variable:

Main party $(Elections)_{jt}$ party/coalition that gets most seats in the election in region/province/municipality j at time t. It is equivalent to a party/coalition of a president, president, or a mayor at regional, province, or municipality level, respectively.

A.1.3 Combining RLP and Elections Data

We used RLP and Elections Data to define several variables for majority/winning parties at local level. We also identified marginal elections and parties/coalitions that have won/lost on a small margin. Next, we combine these variables with the individual-level panel from RLP[23] and determine if a politician belongs to a majority/minority by various definitions at a particular point in time.

There are two challenges when defining majority affiliations for individual politicians.

First challenge has been already mentioned in the part on *Defining majority parties in RLP*. Because in RLP politicians may report an affiliation with just one party (in our previous example, "B"), or a coalition ("A | B | C"), or a coalition name "Z", there may be a noise in defining majorities just based on this data. In those cases, when, for example, mayor reports "Z", we would not be able to classify politicians reporting "A", "B" or "C" as belonging to mayor's coalition. Hence, it is very useful to complement this data with information from the Elections data. Advantage of the Elections data is that we observe all party names ("A", "B", and "C") that form a coalition, and we also often observe an official coalition name

[23]Elections data is a panel with time gaps in between of elections. We impute most recent election outcomes (up to 4 years) to fill in those time gaps.

("Z"), if any. Hence, when defining majority affiliation at the individual level, we compare individual affiliation with both majority definitions from RLP and majority definition from the Elections data. This gives us confidence that majority affiliations can be defined as clean as possible. Extensive manual checks confirm that this definition significantly improves upon the definition based on RLP only.

Second challenge concerns politicians at the municipality level. At the municipality level, especially for small municipalities, many politicians are affiliated with local political lists/coalitions (so called, civil lists, "lista civica") that may combine various party members. As an example, in an election held in the municipality of Cecima, there were two coalitions "Lista Civica con Voi per Voi" and "Lista Civica per Cecima", however both of them were reported as "Lista Civica" for short. If then both of those lists got at least one seat after the elections, it would not be possible to understand whether "Lista Civica" affiliation reported in RLP is of a winning list or not. We call such cases (elections that have multiple lista civica that got at least one seat in council) elections with ambiguous Lista Civica names. Such cases are prevalent and represent half of the elections at municipality level. In these ambiguous cases, if a winning party is Lista Civica and a politician reports Lista Civica, we treat individual majority affiliation as missing. This results in more than 600K missing values from up to 3 million observations at the municipality level. Though it is a significant share of missing values, as we will see, we leverage on other position-type information (which is never missing) to define additional measures of politicians influence.

Notice that same treatment applies when we identify if a politician belongs to a marginally winning/losing party when elections are marginally contested. In half of the municipality-level marginal elections we cannot identify winning and losing parties because both of them

are Lista Civica, so we ignore those elections (and we label them below as marginal elections with "no ID").

A.2 Patent Data (PATSTAT)

First, we identify sample of EPO patents applied for by Italian firms. Focusing on the period of 1990-2014, we identify 84,085 EPO patent applications filed by Italian companies. Some of those applications represent variants of the same patent and belong to same patent families. Hence, relevant count is a count of unique patent families. (In what follows, when it does not incur ambiguity, we will refer to patent families as jus patents.) We have 71,240 EPO patent families.

Second, we need to match patent records with our firm-level datasets. Unfortunately, patent data does not provide firm fiscal codes which we could use to directly match PATSTAT records to Cerved data. Hence, we turn to company name cleaning routines to help to standardize company names in PATSTAT and then match those names to fiscal codes. We proceed in the following three steps. We start by using an extensive patent-firm fiscal code match conducted by Unioncamere-Dintec. The name cleaning by Unioncamere is very precise and it combined standard name cleaning routines with extensive manual checks to maximize patent matches for the period of 2000-2016. We extend Unioncamere match backward by applying a Unioncamere "dictionary" from 2000-2016 to 1990-1999. Combined, this procedure results in up to 90% of patent matches. We further increase the matching rate (especially for the 90's) by using name cleaning routines from Lotti and Marin (2013) and matched sample of patents from Thoma, et al. (2010). Final match results in 93% matching rate of all EPO patents for the period of 1990-2014. We identify 13,904 companies who file

for patents. To the best of our knowledge, this is by far the best match of Italian patent records to Italian firms spanning the longest time period.

Third, for all patents, we extract information on their technology classification (IPC international patent classification), application date, grant status, number of claims, and backward and forward citations. To avoid double-counting, we focus on patent families. Applicants may seek for protection for their inventions in multiple national offices resulting in multiple applications that effectively represent same invention. We treat members of this kind of patent family as one patent. We will refer to the earliest application date of family members as a family's application date.

Data allows us to construct various measures of firms' patenting activity considering different measures of patent qualities.

1. Clearly, whether patent is granted or not is one type of patent quality measure. Hence, for each year, we construct a simple count of all patents and all granted patents of a firm in a year.

2. Number of claims is another quality measure often used in the literature to proxy for patent breadth (Lerner 1994; Lanjouw and Schankerman 2004). For each year, we construct claims-weighted patent counts of a firm.

3. We also consider patent family size as another proxy for patent quality as it may indicate extent of geographical protection applicant is seeking for. Hence, another measure of firms inventive activity in a year is family-size-weighted patent counts in a year.

4. Patent citations received have traditionally been used as measures of the economic

and technological significance of a patent (see Pakes 1986; Schankerman and Pakes 1986; Trajtenberg 1990; Harhoff et al. 1999; Hall, Jaffe, and Trajtenberg 2001; Bessen 2008; Kogan et al. 2012; Moser, Ohmstedt, and Rhode 2015; Abrams, Akcigit, and Popadak 2013). Our main measure of firm's inventive activity is citations-weighted patent counts. We consider different variations when constructing this measure. First, citations received clearly suffer from truncation problem – the fact that latest patents have less time to accumulate citations in the data. To reduce this problem, we also consider 5-year citations measure number of citations received by patent within 5 years from its application date. Second, our data allows us to see whether citation reported in a patent application originated from the applicant or it was introduced during the prior art search at the time of application, or it was introduced by an examiner. In the data, about third of citations made originate from applicants. Since this may be a closer proxy for the impact of a patent, we also consider citations measure that just counts citations made by applicants. In all these cases, we construct family-to-family citations and for this exercise we make use of the full (not just Italian) EPO citations data.

Appendix Table A.2 presents correlation matrix for different quality measures defined at patent level. Though all measures are positively correlated, in many cases correlation is not very strong, indicating that these measures entail information on different aspects of patent quality. We also show summary statistics of those measures in Appendix Table 1. Statistics of derived innovation-related variables at the firm-level are included in Appendix Table 4.

Appendix Table 1: Summary Statistics for Italian Patents (1990-2014)

Variable	Average
Patent family size	5.43
Grant dummy	0.54
Number of claims	10.43
Citations received	4.94
Citations received in 5 yrs	2.00
Applicant citations	1.71
Applicant citations in 5 yrs	0.63

Notes: Table provides summary statistics for the universe of EPO patents applied by Italian firms in the 1990-2014 time period. Observation is a patent family – one or more patent applications that are variants of the same patent. Sample contains 66,176 patent families.

Appendix Table 2: Cross-correlations of Various Patent Quality Measures

Variables	Grant	Fam. size	Claims	Cits	5-yr cits	Cits, applicant
Grant	1.000					
Fam. size	0.410	1.000				
Claims	0.313	0.106	1.000			
Cits	0.207	0.362	0.163	1.000		
5-yr cits	0.151	0.293	0.154	0.750	1.000	
Cits, applicant	0.144	0.305	0.121	0.878	0.593	1.000
5-yr cits, applicant	0.097	0.251	0.122	0.592	0.813	0.637

Notes: Table presents correlation matrix of different measures of patent qualities. Grant- dummy for whether patent has been granted; Fam. size – number of different patent applications within one patent family ID; Claims – number of patent claims; Cits – number of citations received; 5-yr cits – number of citations received

within 5 years from application date; Cits, applicant – number of citations received excluding non-applicant citations (made by examiners or else); 5-yr cits, applicant – number of applicant-citations received within 5 years from application date.

A.3 Social Security Data (INPS)

To construct yearly firm employment, we count number of workers present in a firm in March[24]. We define employment growth at time t as employment growth to the next period, so

$$g_{it} = \frac{L_{it+1} - L_{it}}{L_{it}}$$

where, g_{it} stands for growth rate and L_{it} for employment.

Alternative measure for growth rate often used in the literature is a measure by Davis, Haltiwanger and Schuh (1996), henceforth DHS, which is bounded between -2 and 2 and reduces impact of outliers. We denote this growth rate by g_{it}^{DHS} and it is defined as:

$$g_{it}^{DHS} = 2\frac{L_{it+1} - L_{it}}{L_{it+1} + L_{it}} \tag{2}$$

We calculate weekly gross labor income (including bonuses and overtime) as total yearly labor income divided by number of weeks worked. At the firm level, *Pay per worker*, refers to average weekly pay (in 1000 of 2014 Euros) of workers present in March.

[24]This is consistent with data construction by Haltiwanger (2013) using the U.S. Census data. Alternatively, one can look at average yearly employment, but the measures are very similar.

A.4 Matched Dataset (Politicians Data + INPS + Cerved + PATSTAT)

A.4.1 Matching INPS with Politicians Data (RLP + Elections)

We merge Politicians Data with INPS worker records using individual fiscal codes and years. This allows us to identify those local politicians that are employed in private firms while holding office. Appendix Table 3 shows summary statistics for the matched politicians-workers sample. It is similar to Table 1 but on a sample of moonlighting politicians. By comparing two tables, we see that among all local politicians about third has ever taken a private job while in office. Clearly, overwhelming majority of connections are through politicians at the municipality level. This is both because majority of politicians are municipality politicians and because proportionally municipality-level politicians work in private sector more than other politicians. In terms of education, worker-politicians on average have lower education (relatively more high-school graduates than university graduates relative to the whole sample). Share of politicians belonging to majority (by various definitions) is slightly higher among worker-politicians. In addition, by comparing to other workers, politicians are employed more on white-collar jobs and have significantly higher wages (about 40% higher).

A.4.2 Matching INPS with Firm-level Data (Cerved + PATSTAT)

We match INPS with Cerved using firm identifiers. Many observations in INPS data do not match to Cerved as can be seen from Table 2 – these are mainly small or short-lived firms not filing balance sheet information, sole-proprietorships or household producers. On the other hand, for about 16% of observations from Cerved, firm fiscal codes were not possible to match to INPS. This means those firms did not make any INPS social security contributions for

their workers, they could be employing only contractors or workers in agriculture. Finally, we merge this data with firms' patenting information using data described in Section 3.3. Only about 4% of patents did not get matched with INPS firms. In the data, over 11K firms patent at least once.

Descriptive statistics for the final matched dataset are provided in Tables 2 and Appendix Table 4. Different columns of Appendix Table 4 report statistics on the sample of firms connected at different levels.

Appendix Table 3: Descriptive Statistics for Politicians Matched to Firms

Variable		*Statistics*
Person ID		825,111obs; 162,417 unique
Year		1993 − 2014
Position level	Region	3,301
	Province	17,425
	Municipality	804,385
Position type	President/Mayor	4.26%
	Council presid./ ∼ vice	4.37%
	Assessore	17.79%
	Council member	73.58%
	Questore/ Commisario	0.00%
Education	< high school	28.57%
	∼ high school	53.09%
	University	18.29%
	Post-graduate	0.05%
Dummy main party		Mean= 0.69
Dummy Top 1 party		Mean= 0.77
Dummy Top1-2 parties		Mean= 0.91
Dummy Top 5 parliament parties		Mean= 0.15
Dummy for white collar		Mean= 0.58
Average weekly pay		Mean= 545

Notes: Summary statistics for the sample of politicians who work in private sector while holding office. The table is similar to Table 1 but on a sample of politicians who match to INPS.

Appendix Table 4: Data Summary by Connection Status

	Full sample	Connected – any politician	Connected – majority politician	Connected – province/region politician	Connected – president/mayor/ ∼vice politician
Age	11.48	17.60	18.00	20.05	19.97
Employment	19.81	196.09	278.86	1,387.04	711.34
Share full-time	0.81	0.89	0.89	0.86	0.90
Share white-collar	0.42	0.42	0.42	0.53	0.47
Pay per worker	0.44	0.54	0.55	0.60	0.60
Pay per white-collar	0.51	0.64	0.65	0.68	0.70
Value added (VA)	1,096.07	9,283.82	11,907.07	27,248.47	21,563.45
Total assets	4,495.36	37,798.28	48,437.93	115,993.73	91,668.19
K stock	1,893.92	17,360.71	22,734.66	55,627.36	43,706.67
Net K stock	1,661.33	14,946.66	19,543.19	47,640.52	37,235.31
Intangible assets	168.78	1,461.95	1,871.23	4,808.41	3,708.07
Intangibles share	0.20	0.31	0.32	0.42	0.40
Profits	111.59	1,088.77	1,389.61	3,125.92	2,609.66
Profitability	-0.01	0.01	0.02	0.01	0.01
K/L ratio	363.25	388.01	396.04	599.06	525.26
LP (VA/empl)	64.47	72.88	74.51	91.57	85.28
KP (VA/tot assets)	0.48	0.48	0.48	0.49	0.44
TFP	12.45	13.69	13.88	15.41	14.72
Growth (VA)	0.17	0.11	0.11	0.11	0.10
Growth (profits)	-0.37	-0.23	-0.19	-0.12	-0.20
Growth (empl)	0.10	0.08	0.08	0.09	0.07
Growth (empl),DHS	-0.03	-0.01	0.00	-0.01	-0.01
Growth (empl), med	0.00	0.00	0.00	0.00	0.00
Number of obs					
innovating firms	106,001	23,118	14,292	928	4,185
Patent stock	5.26	13.04	16.71	44.42	32.36
Cit-patent stock	34.44	98.62	129.93	369.41	259.92

Notes: Table presents summary statistics for main variables at the firm level from the matched INPS-Cerved sample. All nominal variables are deflated to 2014. Capital stock (K stock) is calculated using perpetual inventory method. Intangible assets share is equal to intangible capital stock divided by the sum of tangible and intangible capital stock. Profitability is defined as profits divided by total assets. Labor productivity (LP) is equal to value added divided by labor; capital productivity (KP) is value added per total assets. TFP is defined using Cobb-Douglas assumption with net assets as capital input, K, and total labor compensation from Cerved as labor input, L; output Y is value added. Labor share in Cobb-Douglas is taken as median labor share of firms in the corresponding 2-digits industry classification.

Appendix Table 5: Politicians' Within-Firm Wage Premium

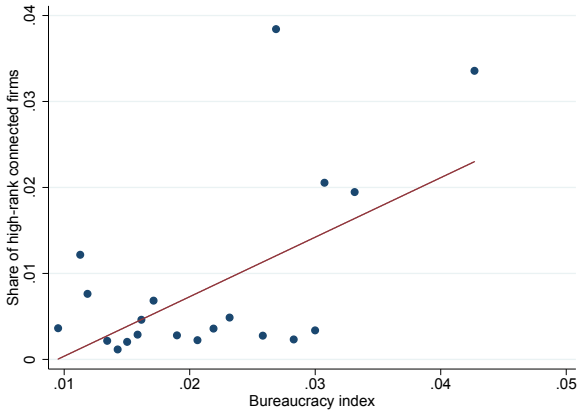
	Municipality level politicians		Province level politicians	
	Female	**Male**	**Female**	**Male**
Blue-collar	1.04	1.07	1.15	1.03
White-collar	1.09	1.07	1.17	1.16
	Regional level politicians		High-rank politicians	
	Female	**Male**	**Female**	**Male**
Blue-collar	.	.	1.06	1.07
White-collar	1.46	2.00	1.23	1.15

Notes: Table shows politicians' within-firm wage premium by type of job and gender. Premium in each cell is defined as average wage paid to politicians divided by average wage paid to non-politicians within same firm conditional on same type of job and gender. Four different panels present wage premia calculated for politicians at the municipality level, province level, regional level and high-rank politicians, respectively. Cells are empty if number of observations in that cell are less than 100.

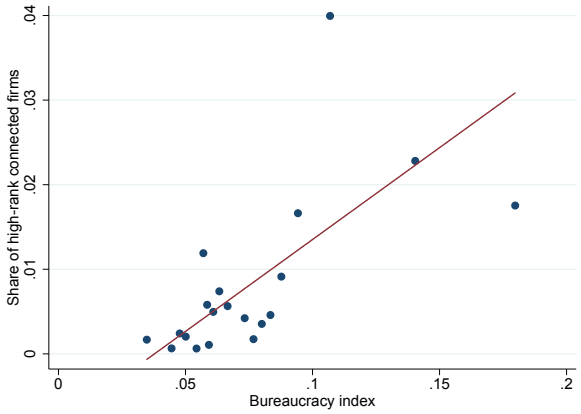
B Empirical Results

Figure 12: Bureaucracy and Connections across Industries

(a) Bureaucracy, index 1, and high-rank connections

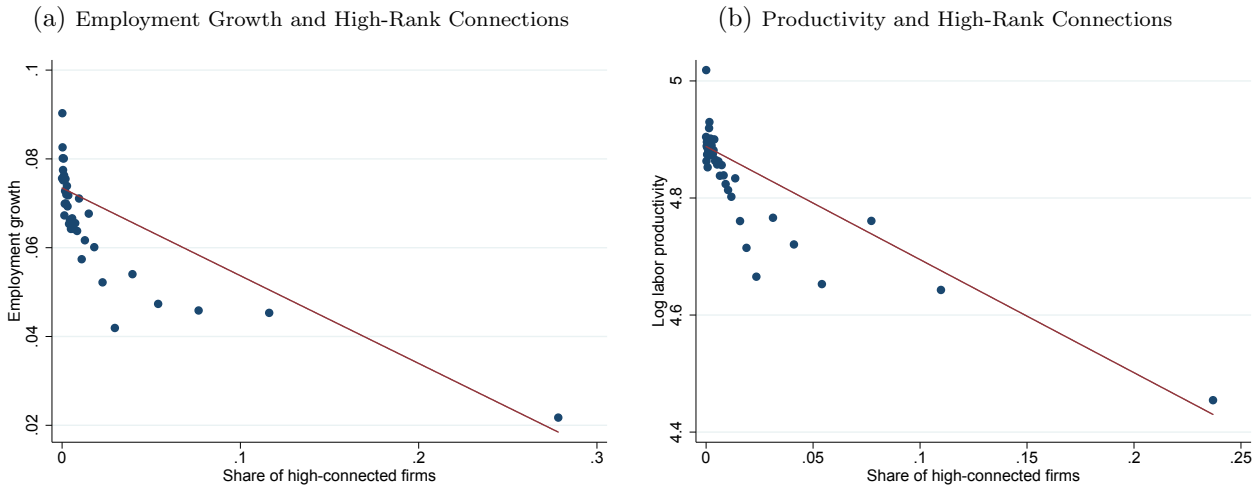


(b) Bureaucracy, index 2, and high-rank connections



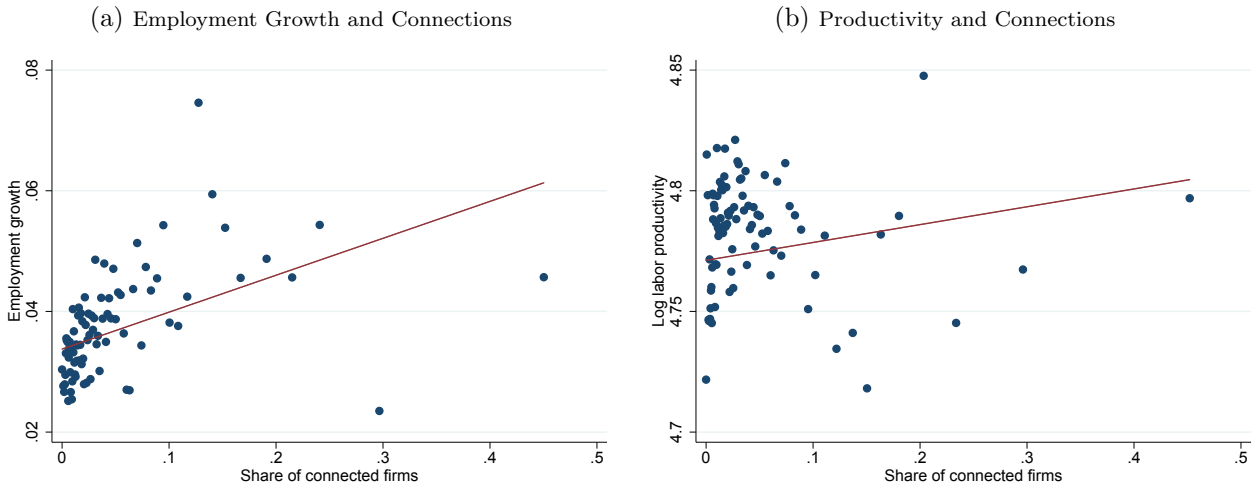
Notes: Binscatter plots (split into 20 quantiles) and linear fits between bureaucracy indices and share of connected firms across 52 industries. Sector-level bureaucracy index 1(2) is defined as share of newspaper articles about a sector from Factiva News search that have government regulation or bureaucracy-related words as listed in the List 1(2) in the main text. Panel (a) uses index 1, while panel (b) uses index 2. Y axis is share of firms connected with high-rank politicians across industries.

Figure 13: High-Rank Connections and Industry Performance



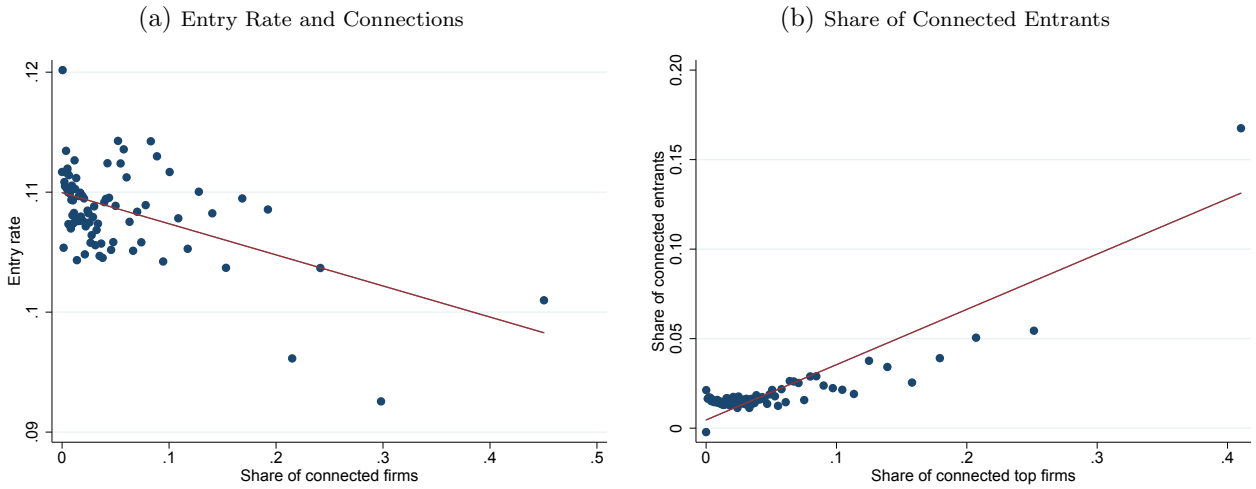
Notes: Each outcome variable at the industry × region × year level is regressed on share of connected firms with high-rank politicians controlling for industry, year, and region fixed effects. Each dot represents the adjusted outcome variable, namely the outcome from which we subtract all fixed effects times their estimated coefficients. Regression lines are depicted in each panel. X axis is divided into 20 equally sized bins and each dot represents average value within that bin. In Panel (a), the outcome is average employment growth rate. Panel (b) considers average log labor productivity.

Figure 14: Connections and Industry Performance Conditional on Size of Top firms



Notes: Each outcome variable at the industry × region × year level is regressed on share of connected firms controlling for size of top 5 firms, industry, year, and region fixed effects. Each dot represents the adjusted outcome variable, namely the outcome from which we subtract all covariates (except share of connected firms) times their estimated coefficients. Regression lines are depicted in each panel. X axis is divided into 20 equally sized bins and each dot represents average value within that bin. In Panel (a), the outcome is average employment growth rate. Panel (b) considers average log labor productivity.

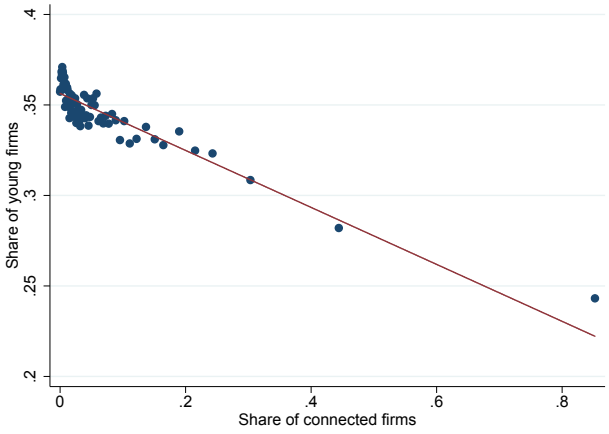
Figure 15: Connections and Industry Entry Conditional on Size of Top firms



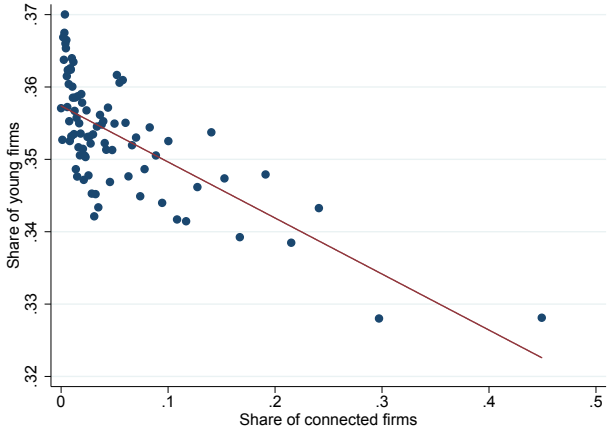
Notes: Each outcome variable at the industry × region × year level is regressed on share of connected firms controlling for average size of top 5 firms, industry, year, and region fixed effects. Each dot represents the adjusted outcome variable, namely the outcome from which we subtract all covariates (except share of connected firms) times their estimated coefficients. Regression lines are depicted in each panel. X axis is divided into 20 equally sized bins and each dot represents average value within that bin. In Panel (a), the outcome is entry rate of new firms. Panel (b) considers share of connected entrants.

Figure 16: Connections and Industry's Share of Young Firms

(a) Share of Young Firms and Connections



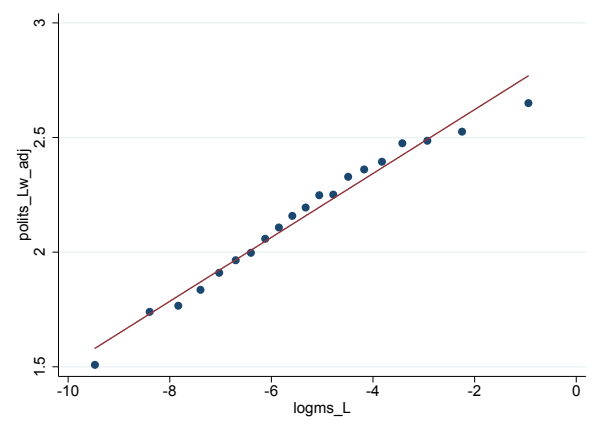
(b) Share of Young Firms and Connections, conditional on size of top firms



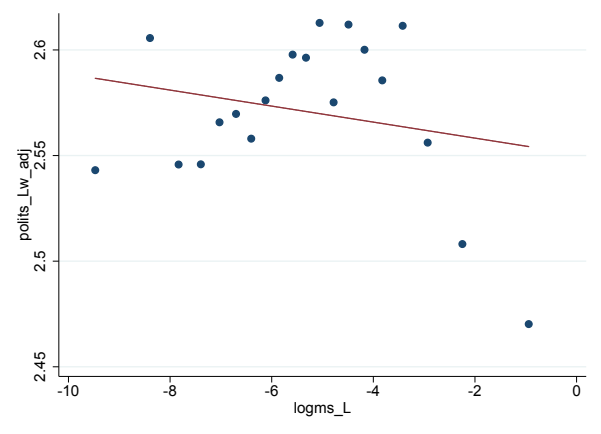
Notes: Each outcome variable at the industry × region × year level is regressed on share of connected firms controlling for industry, year, and region fixed effects and average size of top 5 firm for Panel (b) . Each dot represents the adjusted outcome variable, namely the outcome from which we subtract all covariates (except share of connected firms) times their estimated coefficients. Regression lines are depicted in each panel. X axis is divided into 20 equally sized bins and each dot represents average value within that bin. In both panels the outcome is share of firms that are younger than 5 years.

Figure 17: Connections over Market Share

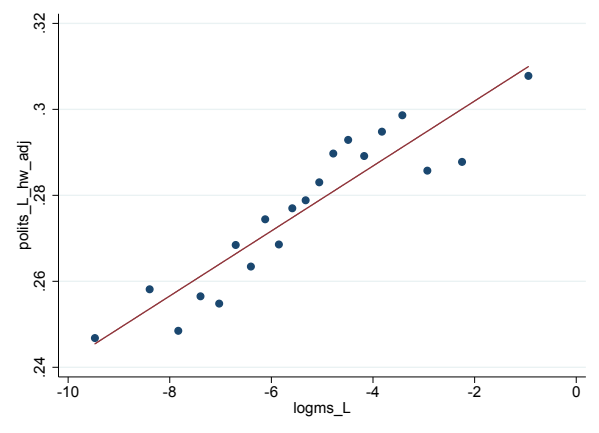
(a) Politicians per 100 w/c workers



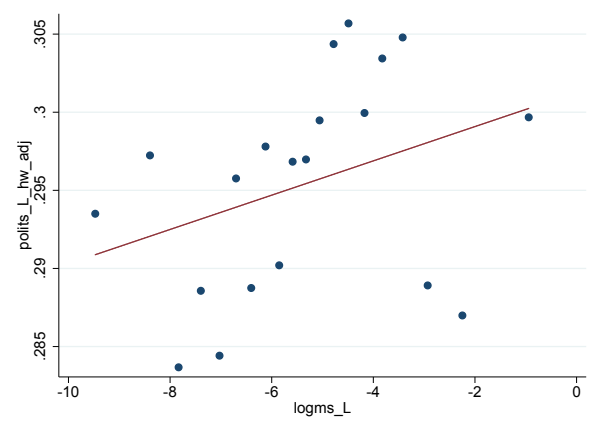
(b) Politicians per 100 w/c workers, control for logL



(c) High-rank Politicians per 100 w/c workers

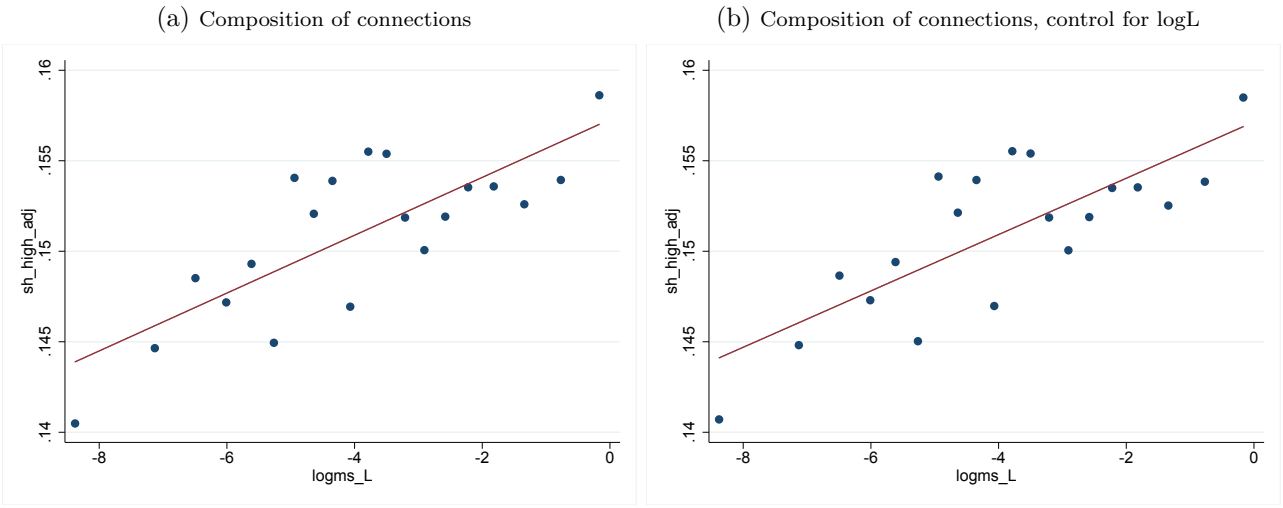


(d) High-rank Politicians per 100 w/c workers, control for logL



Notes: Each outcome variable at the firm level is regressed on log market share controlling for industry, year, and region fixed effects and also for log size in Panels (b) and (d). Market is defined at (6-digit) industry × region × year level. Each dot represents the adjusted outcome variable, namely the outcome from which we subtract all covariates (except log market share) times their estimated coefficients. Regression lines are depicted in each panel. X-axis is divided into 20 equally sized bins and each dot represents average value within that bin. In Panels (a) and (b), the outcome is politicians per 100 white-collar workers. In Panels (c) and (d), the outcome is high-rank politicians per 100 white-collar workers.

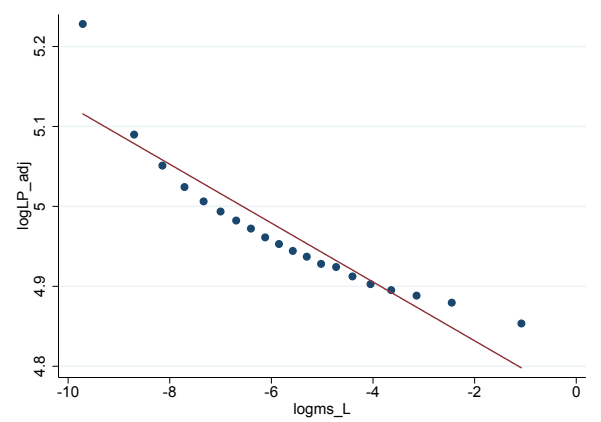
Figure 18: Composition of Connections over Market Share



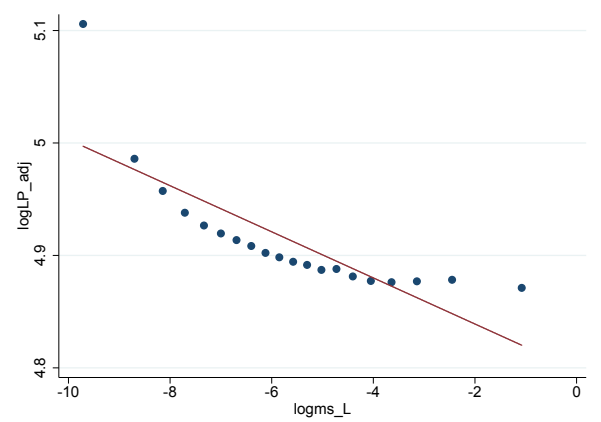
Notes: Share of high-rank connections among all connections at the firm level is regressed on log market share controlling for industry, year, and region fixed effects and also for log size in Panel (b). Market is defined at (6-digit) industry × region × year level. Each dot represents the adjusted outcome variable, namely the outcome from which we subtract all covariates (except log market share) times their estimated coefficients. Regression lines are depicted in each panel. X-axis is divided into 20 equally sized bins and each dot represents average value within that bin.

Figure 19: Innovation over Market Share

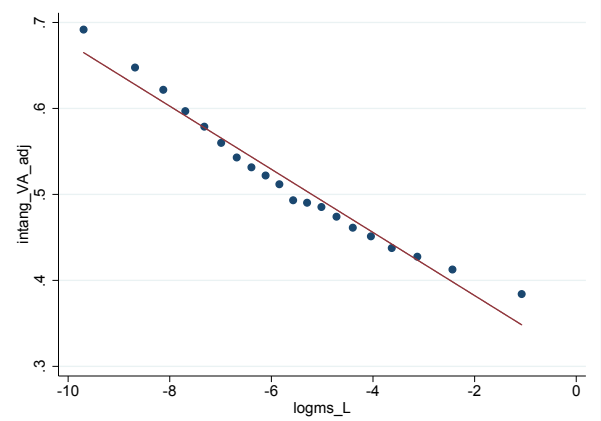
(a) Labor Productivity



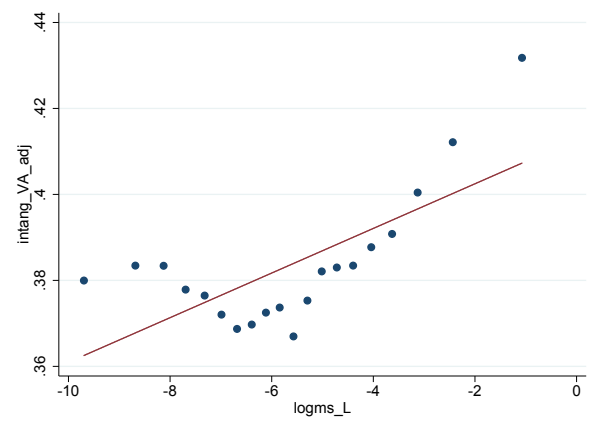
(b) Labor Productivity, control for logL



(c) Intangibles Share in Value Added



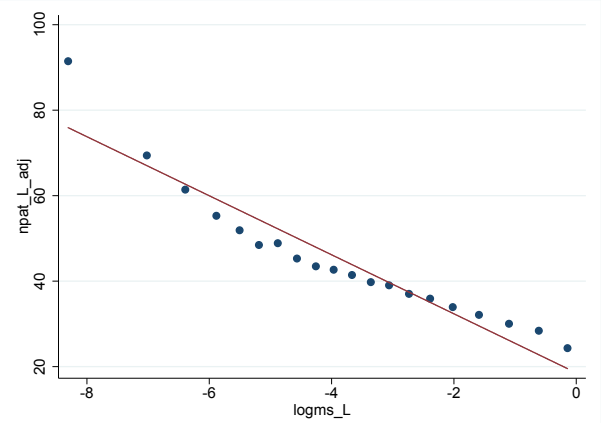
(d) Intangibles Share in Value Added, control for logL



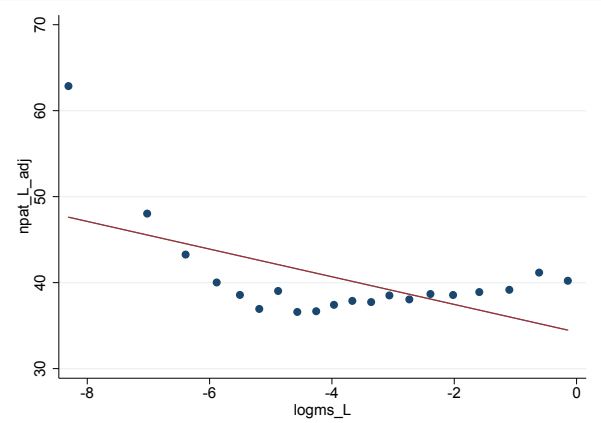
Notes: Each outcome variable at the firm level is regressed on log market share controlling for industry, year, and region fixed effects and also for log size in Panels (b) and (d). Market is defined at (6-digit) industry × region × year level. Each dot represents the adjusted outcome variable, namely the outcome from which we subtract all covariates (except log market share) times their estimated coefficients. Regression lines are depicted in each panel. X-axis is divided into 20 equally sized bins and each dot represents average value within that bin. In Panels (a) and (b), the outcome is labor productivity (value added per labor). In Panels (c) and (d), the outcome is intangible assets over value added.

Figure 20: Innovation over Market Share

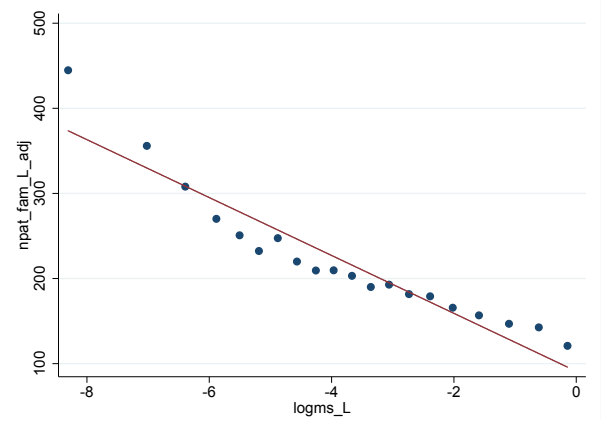
(a) Patents Per Labor



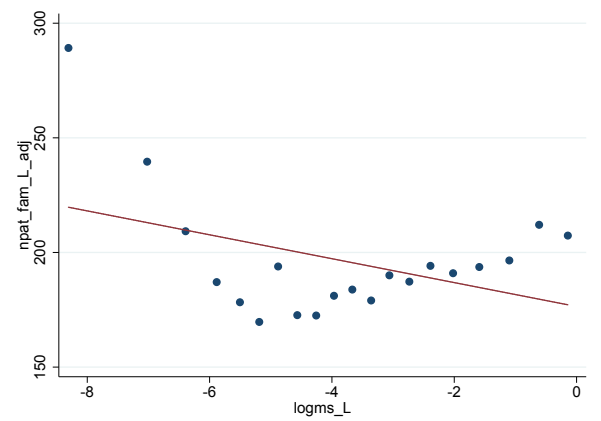
(b) Patents per Labor, control for logL



(c) Family size-adjusted Patents Per Labor



(d) Family size-adjusted Patents per Labor, control for logL



Notes: Each outcome variable at the firm level is regressed on log market share controlling for industry, year, and region fixed effects and also for log size in Panels (b) and (d). Market is defined at (6-digit) industry $\times$ region $\times$ year level. Each dot represents the adjusted outcome variable, namely the outcome from which we subtract all covariates (except log market share) times their estimated coefficients. Regression lines are depicted in each panel. X-axis is divided into 20 equally sized bins and each dot represents average value within that bin. In Panels (a) and (b), the outcome is patent counts per labor. In Panels (c) and (d), the outcome is patent family size-adjusted patent counts per labor.

Appendix Table 6: Cox Survival Analysis

	(1)	(2)
	_t	_t
Connection	-0.083***	-0.074***
	(-9.94)	(-8.88)
Connection high	-0.180***	-0.168***
	(-6.24)	(-5.80)
Log Size	-0.383***	-0.381***
	(-471.25)	(-463.87)
Market share		-2.744***
		(-21.14)
Year FE	YES	YES
Observations	34914391	34912916

Notes: Cox proportional hazard model of firm survival as a function of connection status. *Connection* – dummy equal to one if a firm is hiring a politician within a year, *Connection high* – dummy equal to one if a firm is hiring a high-rank politician within a year. Other controls are *Log Size*, *Market Share* defined as share of firm's employment in industry × region × year, and year dummies. Sample is the universe of firms in the period of 1985-2014. Efron method for tied failures is used. $^{*}p < 0.1,^{**}p < 0.05,^{***}p < 0.01$

Appendix Table 7: Connections and Firm Growth

	(1)	(2)	(3)	(4)
	Empl growth	Empl growth	VA growth	VA growth
Connection	0.074***	0.066***	0.043***	0.015***
	(70.60)	(43.79)	(37.21)	(9.51)
Connection high	0.010***	0.016***	0.011***	-0.005
	(3.42)	(3.56)	(3.41)	(-1.04)
Log Assets	0.083***	0.232***	0.036***	-0.091***
	(280.34)	(264.02)	(118.76)	(-89.75)
Log Size	-0.136***	-0.566***	-0.080***	-0.235***
	(-348.91)	(-525.55)	(-217.54)	(-251.15)
Age	-0.004***	-0.010***	-0.004***	-0.005***
	(-174.20)	(-120.00)	(-145.69)	(-44.33)
Year FE	YES	YES	YES	YES
Region FE	YES	NO	YES	NO
Industry FE	YES	NO	YES	NO
Firm FE	NO	YES	NO	YES
Observations	6545131	6585740	5684519	5710338

Notes: Firm-level OLS regressions. Dependent variable is columns 1 and 2 is employment growth from time t to time $t+1$ as defined in equation 2. Dependent variable is columns 3 and 4 is value added growth from time t to time $t+1$. Main variables of interest are *Connection* – a dummy variable equal to one if firm is connected with a politician, and *Connection high* – a dummy equal to one if a firm is connected with a high-rank politician at time t. Regressions in addition control for firm's assets, size, age, as well as year, region and industry fixed effects in columns 1 and 3; and for year dummies and firm fixed effects in columns 2 and 4. Robust standard errors clustered at firm level reported in parentheses. $^{*}p < 0.1,^{**}p < 0.05,^{***}p < 0.01$.

Appendix Table 8: Connections and Firm Productivity Growth

	(1)	(2)	(3)	(4)
	LP growth	LP growth	TFP growth	TFP growth
Connection	-0.015***	-0.030***	-0.009***	-0.020***
	(-12.14)	(-16.91)	(-8.68)	(-14.48)
Connection high	0.005	-0.011*	0.004	-0.008
	(1.49)	(-2.24)	(1.38)	(-1.90)
Log Assets	-0.028***	-0.274***	-0.001***	-0.106***
	(-83.24)	(-236.12)	(-4.87)	(-116.33)
Log Size	0.021***	0.274***	-0.006***	0.125***
	(55.70)	(255.01)	(-18.21)	(145.41)
Age	-0.001***	-0.002***	-0.001***	-0.003***
	(-47.83)	(-17.47)	(-46.37)	(-31.56)
Year FE	YES	YES	YES	YES
Region FE	YES	NO	YES	NO
Industry FE	YES	NO	YES	NO
Firm FE	NO	YES	NO	YES
Observations	5598367	5623077	5271002	5291979

Notes: Firm-level OLS regressions. Dependent variable in columns 1 and 2 is labor productivity (value added per labor) growth from time t to time $t+1$. Dependent variable in columns 3 and 4 is TFP growth from time t to time $t+1$. TFP is calculated using Cobb-Douglas specification where capital is measured as total assets, labor is given by employment level from INPS and labor share is taken equal to average industry-level labor share from the data. Main variables of interest are *Connection* – a dummy variable equal to one if firm is connected with a politician, and *Connection major* – a dummy equal to one if a firm is connected with a majority-member politician at time t. Regressions in addition control for firm's assets, size, age, as well as year, region and industry fixed effects in columns 1 and 3; and for year dummies and firm fixed effects in columns 2 and 4. Robust standard errors clustered at firm level reported in parentheses. $^{*}p < 0.1,^{**}p < 0.05,^{***}p < 0.01$.

Figure 21: Marginal Election Counts by Provinces
(municipality & province elections)

(a) 2% VICTORY MARGIN

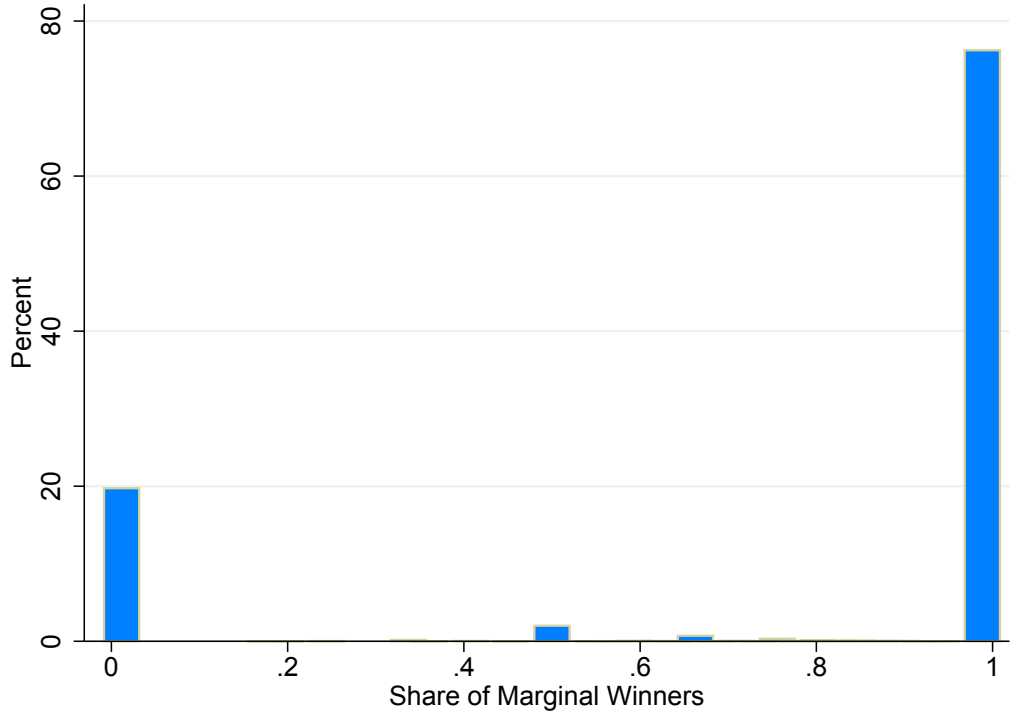


(b) 5% VICTORY MARGIN



Notes: Panel (a) plots number of municipality and province-level marginal elections decided within a 2% victory margin by provinces. Each circle depicts location of the main city in a province and number of total marginal elections in 1993-2014 in a corresponding province in that circle. Panel (b) plot is similar but counts marginal elections within a wider 5% victory margin. Victory margin is defined as difference between share of votes of a winning candidate and share of votes of the closest competitor.

Figure 22: Distribution of Share of Marginal Winners across Firms



Notes: Sample consists of firms that have at least one politician from a marginally winning or losing party in elections within 10% victory margin. We compute *share of marginal winners* of a firm as a ratio of number of politicians from a marginally winning party divided by number of politicians from a marginally winning *or* losing party. The figure plots a distribution of *share of marginal winners* across firms. We see that firms usually "bet" on one side of an election and share of firms hiring politicians from competing parties is very low.