Econometrica Supplementary Material

SUPPLEMENT TO “CONNECTING TO POWER: POLITICAL CONNECTIONS, INNOVATION, AND FIRM DYNAMICS”

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APPENDIX A: MODEL

TABLE A.I summarizes model variables and their meaning.

Model Extension: Endogenizing Politician's Compensation

Our benchmark model in the main text has focused on the static gains and dynamic losses. To keep these aspects tractable, we kept the determination of the politician's compensation exogenous. However, it is fairly straightforward to incorporate a Nash bargaining framework that would provide some additional insights. To this end, let us assume that politicians have different political powers $\phi \in (0, 1)$, in line with their hierarchies. A politician with a political power ϕ is able to remove red tape by the same fraction ϕ; thus, the firm has to pay $(1 + (1 - \phi)\tau)wl$ for hiring l workers (our benchmark model corresponds to $\phi = 1$). This implies that a firm with a politician with power ϕ earns the

APPENDIX TABLE A.I

MODEL VARIABLE DEFINITIONS.

(Static Environment Description)		(Dynamic Environment Description)	
Variable	Meaning	Variable	Meaning
Y	Aggregate output	s	State variable for political network access
q	Quality level	q^d	Dynamic cutoff for political connections
p	Price		
w	Wage	$V_{-1}(q)$	Value function of incumbent with $q < q^d$
π^p/π^n	Profit of connected/unconnected firm	$V_0(q)$	Value function of incumbent with $q > q^d$ & $s = 0$
q^s	Static cutoff for political connections	$V_1(q)$	Value function of incumbent with $q > q^d$ & $s = 1$

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following gross profit:

$$\frac{\pi q}{1+(1-\phi)\tau}. \tag{S1}$$

Denote the bargaining power of the politician by γ and assume his/her outside value is simply $\eta(\phi)$, where $\eta'(\phi) > 0$. For simplicity, we also assume that the firm's outside option is to operate without a politician; hence, it is $V_{-1}(q)$. Once the firm and the politician decide to match together, they stay together until the firm is replaced by another firm. It is convenient to formulate the problem in terms of the lump-sum compensation of the politician, which we denote by $\bar{w}^p$. We denote the dynamic value of being connected with a ϕ-power politician (including politician's compensation) by V_1^ϕ and of not being connected by V_{-1}. Then the Nash bargaining problem is simply

$$\begin{aligned}\bar{w}^p(\phi) &\equiv \arg\max_{\bar{w}^p(\phi)}\left[V_1^\phi(q) - V_{-1}(q) - \bar{w}^p(\phi)\right]^{1-\gamma}\left[\bar{w}^p(\phi) - \eta(\phi)\right]^\gamma \\ &= \gamma\pi q\left(\frac{1}{[1+(1-\phi)\tau][r+\tilde{p}(\phi)]} - \frac{1}{[1+\tau][r+p]}\right) + (1-\gamma)\eta(\phi),\end{aligned} \tag{S2}$$

where $\tilde{p}(\phi)$ is creative destruction rate faced by a firm connected with ϕ-power politician, while p is creative destruction rate faced by a non-connected firm. Note that by connecting to a politician with ϕ, the incumbent manages to generate a cost advantage equal to $\phi\tau$. Hence, the quality threshold for the creative destruction to take place becomes $\lambda^*(\phi) = \phi\tau$.

This time, the rate at which a connected incumbent gets replaced is

$$\tilde{p}(\phi) = p\left[\alpha + (1-\alpha)\Pr(\lambda > \phi\tau)\right], \tag{S3}$$

which implies $\tilde{p}'(\phi) < 0$. This implies that a firm that is connected with a more powerful politician is more likely to survive.

Next, we interpret the compensation of the politician as a function of its political power. The compensation $\bar{w}^p(\phi)$ increases in ϕ through three channels evident from equation (S2). First, a more powerful (large ϕ) politician brings higher static profits due to lower wedges ($(1-\phi)\tau$) that the firm is required to pay. Second, a more powerful politician leads to lower replacement rate of the incumbent ($\tilde{p}(\phi)$). Finally, a more powerful politician has a better outside option, which allows him/her to extract a bigger fraction of the joint surplus. We conclude this section with the following implication. Politician's compensation $\bar{w}^p(\phi)$ increases in his/her political power ϕ.

APPENDIX B: DATA CONSTRUCTION

This section provides more details on the steps undertaken during the data and variables construction.

Data Set #1: Social Security Data (INPS). The Italian SS data contain rich information on the universe of private-sector firms and their workers making Social Security contributions at INPS. At the individual level, we calculate an individual *weekly wage*—weekly gross labor income (including bonuses and overtime) as total yearly labor income, divided by number of weeks worked. We classify a worker as a *white-collar* if s/he is a manager, executive, professional, or an office worker (*qualifica1* variable from UniEMENS equal to 2, 3, 7, 9, or P). At the firm level, we describe a construction of three variables from INPS—employment, average weekly pay, and age. To construct yearly employment at the firm level[S1]—a variable firm *Size*—we count the number of workers present in a firm in March.[S2] Some observations may be zeros, especially when firm is just starting or before it exits the business. We define employment growth at time t as employment growth to the next period:

$$gL_{it} = 2\frac{L_{it+1} - L_{it}}{L_{it+1} + L_{it}}, \tag{S4}$$

where gL_{it} stands for growth rate and L_{it} for employment. This measure follows Davis, Haltiwanger, and Schuh (1998) and is bounded between -2 and 2 and reduces impact of outliers, which is especially important at the entry and exit of a firm. At the firm level, *Average weekly pay* refers to the average weekly pay (in thousands of 2014 Euros) of workers who are present in March.

Data Set #2: Firm Financials Data (Cerved). We use the following main company accounts variables from Cerved: a firm's total assets, intangible assets, value added, and profits. In addition, we compute labor productivity, *LP*, and total factor productivity, *TFP*.

VA is the yearly value added of a firm—revenue less the cost of intermediates. We replace with missing any negative value added (*valore_aggiunto_operativo*). *Profits* is value added less operating expenses, depreciation, and financial costs. *Assets* (*attivo*) is the total assets of a firm. *Intangibles* is intangible fixed assets. For tangible assets (*immob_mat*) and intangible fixed assets (*immob_immat*), we replace missings with zeros when possible. In most cases, Cerved data do not distinguish between missing values and zeros: 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) the value of intangible assets if value of tangible assets is not missing, and vice versa for tangible assets. We verify these imputations with another simple imputation of missing values in the panel of firms—by simply imputing the missing value with latest non-missing observation. If such an imputation is too far off from the initial imputation of 0.5, we revert back to the missing value.

LP—labor productivity—is defined as value added per employee. We calculate a firm's total factor productivity, *TFP*, using a standard Cobb–Douglas specification: $Y = zK^{\alpha}L^{1-\alpha}$. Output ($Y$) is measured as value added, capital (K) is measured as total assets, labor (L) is employment, and labor share ($1-\alpha$) is the average industry-level labor share from the data. This gives us z—our TFP measure.

Corresponding growth rates of the above variables at time t are calculated as a growth from t to $t+1$. All nominal variables are deflated with GDP deflator (2014 is the base year). In the analysis, we winsorize all these variables at top and bottom 1 percent.

[S1]Note that firm-level employment variable in Cerved data is of very poor quality, so INPS data are crucial to construct a complete firm-level data set.

[S2]This is consistent with data construction by Haltiwanger, Jarmin, and Miranda (2013) using the U.S. Census data. Alternatively, one can look at average monthly employment in a year, but the measures are very similar.

Data Set #3: Patent Data (PATSTAT). We use EPO PATSTAT to obtain information on patenting activities of Italian firms. This section describes the matching procedure of EPO PATSTAT to our firm-level data, as well as the construction of our patent-based innovation measures.

First, we identify the 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 the same patent family. Applicants may seek for protection for their inventions in multiple national offices, resulting in multiple applications that effectively represent the same invention. Hence, the relevant count is a count of unique patent families: we have 71,240 EPO patent families. In what follows, when it does not incur ambiguity, we will refer to patent families as just patents.

Second, we need to match patent records with our firm-level data sets. Unfortunately, patent data do 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, as it combines standard name cleaning routines with extensive manual checks to maximize patent matches for the period of 2000–2016. We extend the Unioncamere matches backwards by applying the Unioncamere "dictionary" from 2000 to 2016 to the period 1990–1999. Combined, this procedure results in up to 90% of patent matches. We further increase the matching rate (especially for the 1990s) by using name cleaning routines from Lotti and Marin (2013) and the matched sample of patents from Thoma et al. (2010). Final matches result in a 93% matching rate of all EPO patents for the period of 1990–2014. We identify 13,904 unique companies who file for patents. To the best of our knowledge, this is by far the most comprehensive 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. We take the application date of a patent to be the earliest application date of all patents in the same patent family. These data allow us to construct various measures of a firm's patenting activity considering different measures of patent qualities.

1. Clearly, whether a 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 of all granted patents of a firm in a year.
2. The number of claims is another quality measure often used in the literature to proxy for patent breadth (Lerner (1994) and 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 indicates the extent of the geographical protection that an applicant is seeking. Hence, another measure of firm's inventive activity in a year is family-size-weighted patent counts in a year.
4. The number of citations a patent receives has traditionally been used as a measure of the economic and technological significance of a patent (see Pakes (1986), Trajtenberg (1990), Hall, Jaffe, and Trajtenberg (2001), Kogan et al. (2012), Abrams, Akcigit, and Popadak (2013), Moser, Ohmstedt, and Rhode (2015). Our main measure of a firm's inventive activity is citations-weighted patent counts. We consider different variations when constructing this measure. First, citations received clearly suffer

APPENDIX TABLE B.I

CROSS-CORRELATIONS OF VARIOUS PATENT QUALITY MEASURES.

Variables	Grant	Fam. size	Claims	Cits	5-yr cits	Cits, applicant
Grant	1.000					
Family size	0.410	1.000				
Claims	0.313	0.106	1.000			
Citations	0.207	0.362	0.163	1.000		
5-yr citations	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

Note: Table presents a correlation matrix of different measures of patent qualities. Grant—dummy for whether patent has been granted; Family size—number of different patent applications within one patent family ID; Claims—number of patent claims; Citations—number of citations received; 5-yr citations—number of citations received within 5 years from the 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.

from a truncation problem—the fact that later patents have less time to get cited. To reduce this problem, we also consider a 5-year citations measure—the number of citations received by patent within 5 years from its application date. Second, our data allow us to see whether citations reported in a patent application originate from the applicant, were introduced during the prior art search at the time of application, or were introduced by an examiner. In the data, about one third of all citations made originate from the applicants themselves. Since this may be a closer proxy for the impact of a patent, we also consider a citations measure that just counts citations made by applicants. In all these cases, we construct family-to-family citations and we also count citations originating not only from the Italian, but all EPO patents.

Appendix Table B.I in this supplement presents the correlation matrix for different quality measures defined at the patent level. Though all measures are positively correlated, in many cases, the correlation is not very strong, indicating that these measures entail information on different aspects of patent quality. We show summary statistics of those measures in Appendix Table B.II.

Data Set #4: Registry of Local Politicians (RLP). The following are the steps undertaken to clean and make use of RLP data.

APPENDIX TABLE B.II

STATISTICS ON PATENT QUALITY 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

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

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

Step 2. We determine which parties are the majority or minority based on political affiliations of politicians in RLP. The data provide either the party or coalition to which a politician is affiliated. For example, a typical example of an observation would be an entry "A | B" meaning that politician belongs to a list/coalition consisting of two parties A and B, which together participate 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: Cleaning political party/coalition names in the data turned out to be a tedious task. The first challenge is misspellings and abbreviations of party names. The second is that political parties sometimes change their names, merge, split, form coalitions, etc. We tackle these issues by developing a name cleaning algorithm, 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 separate party 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—municipal, provincial, regional, or national—from Wikipedia articles. This represents a basic dictionary that helps to spot multiple forms of the same party/coalition name in the data. Next, we develop a name cleaning algorithm, where we standardize commonly used words and special characters, and correct for word misspellings and shortcuts. Using this name standardization and dictionary-based 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/coalitions in RLP: Next, we define parties/coalitions that represent majorities at the regional/provincial/municipal level in a given year. We start by defining two variants of majority party variable at the location-year level. The first definition uses the political affiliation of a president/mayor. The second definition uses most frequent political affiliation of all politicians found in RLP.[S3] Specifically, we define following variables at j-location and t-year level: *Main party* $(\text{RLP})_{jt}$—party (coalition) of a regional president/provincial president/mayor in year t in j region/province/municipality, respectively.[S4] #1 *Party* $(\text{RLP})_{jt}$—most frequent party (coalition) affiliation of politicians in a region/province/municipality.

Since the winning candidate is generally also assured the 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 belongs to a party "B" and is supported by a coalition consisting of parties "A," "B," and "C." In such a case, RLP could report the candidate's party affiliation as either "A | B | C." "B," or "Z," where "Z" is some name of a coali-

[S3]For the benchmark definition, we prefer defining majority using sample of councilmen only. 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. Indeed, councilmen represent majority of politicians in RLP and about 15% of politicians in RLP are not elected.

[S4]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.

tion.[S5] 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 combine information from both variables—an affiliation reported by a president/mayor (*Main party* $(\mathrm{RLP})_{jt}$) and most frequent affiliation reported by all politicians (#1 *Party* $(\mathrm{RLP})_{jt}$) to define the majority party/coalition in the most accurate fashion. Importantly, we will complement these definitions with further information from the Elections data, which we discuss below. Using these data on majority parties, we can define whether an individual belongs to the majority or the minority. We postpone further discussion until after we describe the Elections data below.

Step 3. We define the following variables using political position attributes in RLP.

Regional $Rank_{it}$—a categorical variable for whether a politician i is a regional, provincial, or municipal politician at time t. In a 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 held in that year.

Hierarchical $Rank_{it}$—a categorical variable for the position level (within *Regional* $Rank_{it}$) of a politician i at time t. In the first category, we group together the key positions of a municipality's mayor or vice mayor; provincial/regional president or a vice/president; as well as the important positions of president/vice-president of the local councils. The second category includes so-called "assessore" that represent town councilors—executive position holders similar to local ministers. The third category is for regular council members.[S6]

Our newly constructed, detailed data set on local elections at the regional, provincial, and municipal levels serves two purposes. First, using information on vote shares in the election, we identify marginally contested elections. The details are described in Section 5.3. Second, we use these data to construct another variable on majority parties at the local level, and combine it with the RLP definitions of majority parties (*Main party* $(\mathrm{RLP})_{jt}$ and #1 *Party* $(\mathrm{RLP})_{jt}$ explained above). This gives us confidence in the accuracy of our definition of local majorities as it taps the information from multiple sources.

Defining majority parties/coalitions in the Elections data: For each election, we define a coalition as a set of parties supporting the same candidate (it may be just one party or multiple). Then, we define a coalition that gets most seats and define a coalition that supports a winning candidate (mayor or president). Because of the existence of a majority premium for the winning candidate, these two definitions should be equivalent. Indeed, these definitions are the same in all instances except for the rare cases, which account for well under 1% of observations. Hence, we define a variable: *Main party* $(Elections)_{jt}$—the party or coalition that gets the most seats in an election in region/province/municipality j at time t. It is equivalent to a party/coalition of a winning regional president/province president/municipality mayor in j at time t.

Combining Data Set #4 and Data Set #5 and Defining Individual Majority Affiliation. Next, we describe construction of *Majority Affiliation* for each politician from RLP. For that, we combine information on local majority parties/coalitions derived

[S5]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 Libertá" instead of listing its members "Forza Italia," "Alleanza Nazionale," or others.

[S6]Data also include other positions of "questore/commissario"—a superintendent or commissioner. But these are temporary positions that appear on rare occasions, hence we do not report statistics on them.

from RLP—*Main party* $(\text{RLP})_{jt}$ and #1 *Party* $(\text{RLP})_{jt}$, and from the Elections data—*Main party* $(\textit{Elections})_{jt}$.[S7] There are two challenges when defining majority affiliation for individual politicians. The first challenge has been already mentioned above. Since, for any politician, RLP 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 some noise in defining majorities just based on these 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 these data with information from the Elections data. The main advantage of the Elections data is that we observe all party names ("A," "B," and "C" separately) that form a coalition, and we also often observe an official coalition name ("Z"), if this exists. 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 cleanly as possible. Extensive manual checks confirm that this definition significantly improves upon the definition based on RLP only. The second challenge concerns politicians at the municipal level: in small municipalities, many politicians are affiliated with local political lists/coalitions—so-called civil lists, "lista civica." that may unite 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, in RLP, both of them were reported as "Lista Civica" for short. If then both of those lists got at least one seat after the election, it would not be possible to understand whether the "Lista Civica" affiliation reported for a politician in RLP was that of the winning list or not. We call such cases (elections that have multiple "Lista Civica" coalitions that got at least one seat in the council) elections with ambiguous "Lista Civica" names. Such cases are quite prevalent and represent half of all elections at the municipal 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 600 thousand missing values from up to 3 million individual-level observations at the municipal level. For some of those missing cases, however, we can be certain that individuals belong to local majorities. This happens for individuals holding key positions (the highest *Hierarchical rank*). This decreases the number of missing observations in the *Majority affiliation*.

Matching INPS With Politicians Data (Combining Data Set #1 with Data Sets #4 and #5). We merge Politicians Data with INPS worker records using individual fiscal codes over time. This allows us to identify those local politicians that are employed in private firms, while also holding political office. Appendix Table B.III of this supplement shows summary statistics for the matched politician-workers sample (in the years when they are both employed in a firm and work as politicians). We see that, among all local politicians, about one third (162,417) have ever taken a private job while also in office. Clearly, the overwhelming majority of connections are through politicians at the municipal 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. It is also interesting to look at their education levels (this is a self-reported education level from RLP). Relative to the full sample of politicians, worker-politicians, on average,

[S7] Notice that the Elections data are unbalanced panel data with time gaps in between elections. We impute most recent election outcomes (up to 4 years) to fill in those time gaps.

APPENDIX TABLE B.III

STATISTICS ON LOCAL POLITICIANS EMPLOYED IN THE PRIVATE SECTOR.

VARIABLES		
Observations	825,105	
Distinct politicians	162,417	
Years	1993–2014	
Job in the firm:	Top management	2.86%
	Middle management	6.66%
	Other white-collar job	55.45%
	Blue collar job	35.03%
	Trainee	1.25%
Education:	<High school	28.57%
	Hhigh school	53.09%
	University	18.29%
	Post-graduate	0.05%
Average weekly pay		829
POLITICAL VARIABLES		
Regional Rank:	Region	0.40%
	Province	2.11%
	Municipality	97.49%
Hierarchical Rank:	Mayor, President, Vice-mayor, Vice-president	8.63%
	Executive councilor	17.79%
	Council member	73.58%
Majority Affiliation:	Majority	77.97%

Note: Summary statistics for the sample of politicians who work in the private sector while holding office. The table is an extended version of Table III but on a sample of politicians who match to INPS. Nominal variables are deflated with GDP deflator with a base year in 2014.

have slightly lower education levels (relatively more high-school graduates than university graduates, when compared to the whole sample). The share of politicians with majority affiliation is just slightly higher among worker-politicians than among all politicians. As Table B.IV shows, politician-workers are distinct along many dimensions from other

APPENDIX TABLE B.IV

CHARACTERISTICS OF POLITICIAN AND NON-POLITICIAN EMPLOYEES.

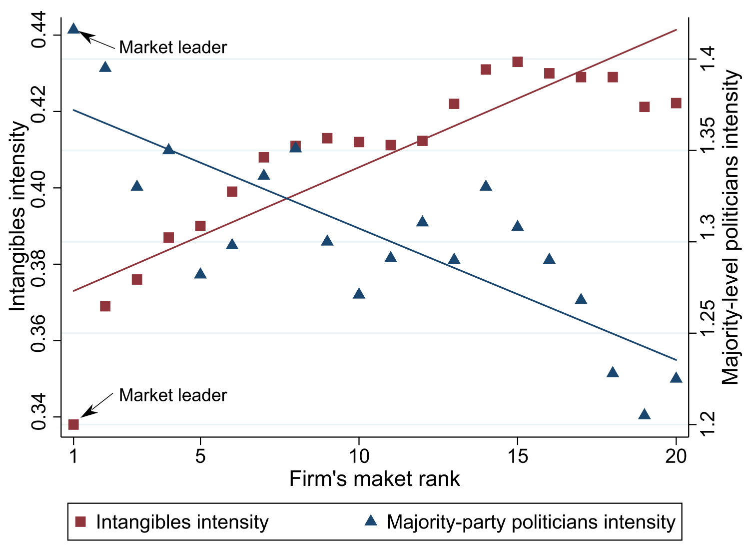
Variables	Politicians	Non-politicians
White-collar	0.65	0.52
Manager	0.09	0.07
Temporary contract	0.29	0.35
Full-time	0.90	0.85
Wages (weekly)	0.67	0.62
Work experience	11.36	9.83
Job tenure	6.46	5.59
Age	41.56	39.97
Female	0.17	0.37
Observations	825,054	94,369,600

Note: Characteristics of politician and non-politician employees. The sample includes all employees of the firms that employ at least one politician in 1993–2014.

workers in the private sector: they are older, more likely to be males, have longer tenure, are paid more, have more secure permanent contracts, and perform more white-collar or managerial jobs.

Matching INPS With the Firm Financials and Patent Data (Combining Data Set #1 with Data Sets #2 and #3. We match firm-level data from INPS with Cerved using firms' fiscal codes. Many firm observations in INPS data do not match to Cerved, as can be seen from Table IV; 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 might be employing only contractors or workers in agriculture. Finally, we merge these data with firms' patenting information from Data Set #3. Only about 4% of patents did not get matched with INPS firms. In the data, over 12 thousand firms filed a patent at least once.

APPENDIX C: ROBUSTNESS AND ADDITIONAL EMPIRICAL RESULTS



APPENDIX FIGURE C.1.—Leadership paradox; alternative innovation and connection measures.

APPENDIX TABLE C.I

MARKET RANK, INNOVATION, AND POLITICAL CONNECTION.

	(1) Politicians intensity	(2) Majority politicians intensity	(3) Intangibles intensity	(4) Patents intensity
Rank 1	0.298	0.126	−0.036	−18.74
	(0.0181)	(0.0129)	(0.0042)	(0.797)
Rank 2	0.236	0.112	−0.024	−16.87
	(0.0191)	(0.0136)	(0.0044)	(0.973)
Rank 3	0.203	0.078	−0.0129	−15.42
	(0.0202)	(0.0143)	(0.0046)	(1.081)
Rank 4	0.194	0.086	−0.022	−13.15
	(0.0212)	(0.0150)	(0.0049)	(1.232)
Rank 5	0.168	0.052	−0.013	−14.36
	(0.0221)	(0.0157)	(0.0050)	(1.385)
Log age	0.038	0.025	−0.0653	−7.184
	(0.0033)	(0.0024)	(0.0007)	(0.302)
pt *N*	5,441,271	5,441,271	4,962,755	23,409

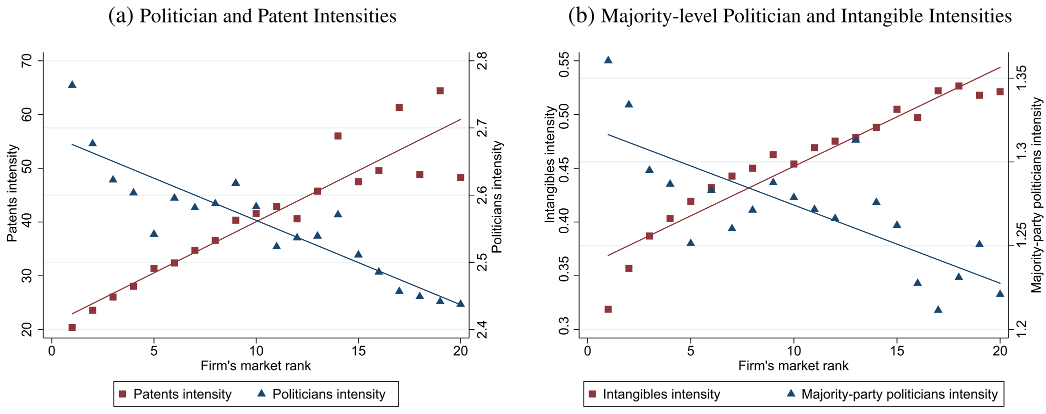
Note: Firm-level OLS regressions of political connection and innovation intensity over firm's market rank. Market is defined at (6-digit) industry × region × year level. *Rank n* is a dummy equal to 1 if a firm is ranked *n*th in the market in that year based on its employment level. Omitted group pools firms that are ranked 6 and above. Dependent variables: column 1—*Politicians intensity* is the number of politicians employed over 100 white-collar workers; columns 2—*Majority politicians intensity* is the number of majority-party politicians employed over 100 white-collar workers; column 3—*Intangibles intensity* is intangibles over firm value added; column 4—*Patents intensity* is the number of patents (conditional on patenting) over 100 white-collar workers. All regressions include year, region, and industry fixed effects. Similarly to Figures 3 and C.1, this table shows that the largest market leaders are more politician-intensive but less innovation-intensive. In addition, age has a strong effect for both connections and innovation intensities.

APPENDIX TABLE C.II

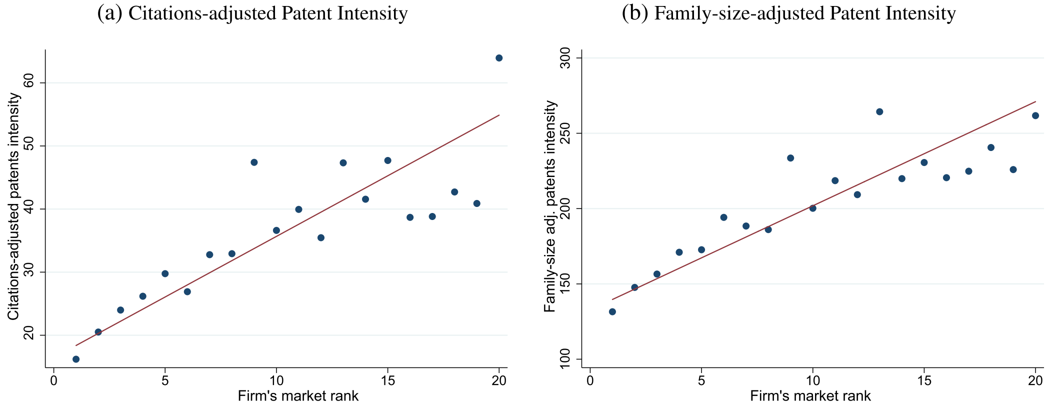
POLITICAL CONNECTIONS AND GROWTH IN SIZE VERSUS PRODUCTIVITY. OTHER OUTCOMES.

Dependent variable— *Growth in*:	Profits	Employment, white-collar	Intangibles	Patents
Connection	0.0284	0.0312	−0.0510	−0.0042
	(0.0135)	(0.106)	(0.0112)	(0.0038)
Age, Size, Assets	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Observations	5,983,604	5,237,358	5,538,995	73,180

Note: Firm-level regressions described in equation (10). Table shows a positive association of firm-level political connections with the next-period growth in profits and white-collar employment and a negative association of connections with the next-period growth in intangible assets and patent stock. Since patenting is a slow-moving process, we use the average (annualized) 3-year patent stock growth of firms. The data cover the years 1993–2014. Average length of political connections within firms is 4.2 years. Robust standard errors clustered at firm level reported in parentheses.



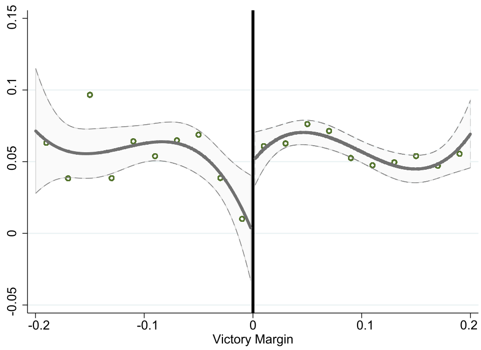
APPENDIX FIGURE C.2.—Leadership paradox; alternative definition of market rank.



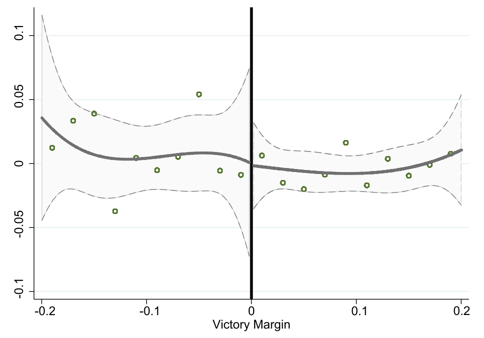
APPENDIX FIGURE C.3.—Market rank and innovation; quality-adjusted patent intensity.

RDD Analysis

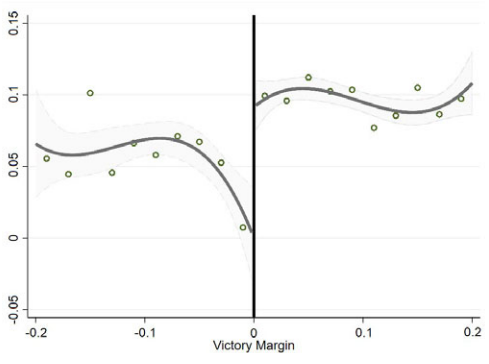
(a) EMPLOYMENT GROWTH AFTER ELECTION $(T \to T+1)$



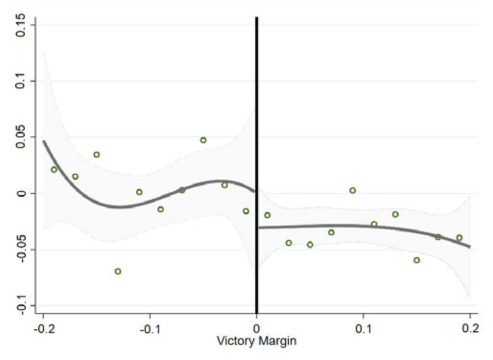
(b) LP GROWTH AFTER ELECTION $(T \to T+1)$



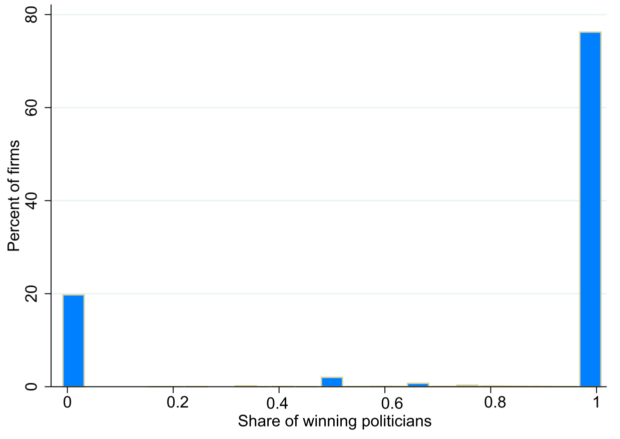
(c) EMPLOYMENT GROWTH AFTER ELECTION $(T \to T+1)$
DROPPING POLITICIANS EXITING BY $T+1$



(d) LP GROWTH AFTER ELECTION $(T \to T+1)$
DROPPING POLITICIANS EXITING BY $T+1$



APPENDIX FIGURE C.4.—Employment and labor productivity growth after election. 20% margin of victory sample. Notes: Figures plot a firm's growth from T to $T+1$ against margin of victory at time T for the sample of elections within a 20% margin of victory. Positive margins of victory denote firms that were connected at time $T-1$ with a politician from a party that won an election at time T with the corresponding margin of victory. Likewise, negative margins of victory depict firms that are connected with losing politicians. For visibility, we divide the 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 the regression that includes third-order polynomial in margin of victory, a dummy Win_{it-1}, and an interaction of the dummy with the polynomial. The dashed line represents 90% confidence intervals. Outcome variable in Panel (a) is employment growth, while in Panel (b) it is labor productivity growth. Panels (c) and (d) repeat the figures dropping firms whose winning politicians do not stay until $T+1$. Figures are normalized such that outcome variables for marginal losers at the threshold are equal to zero.



APPENDIX FIGURE C.5.—Distribution of the share of winning politicians across firms, conditional on getting any seat. Notes: Figure shows distribution of firms over *share of winning politicians* for elections within 10% victory margin. *Share of winning politicians* in a firm is the number of employees at $t-1$ who win elections at t, divided by the total number of employees at $t-1$ winning or losing at t. These shares are *conditional* on these politicians getting any seats. We cannot identify individuals on a party list who did not get any seats since these individuals would not be considered as politicians in RLP. Because of the majority premium, the count of politicians from the majority party is always higher than the count of politicians from the minority party (after *any* election, including the ones with a thin margin). Then, recall from our summary statistics that 76% of politicians in RLP are from majority parties. This means that if every firm had employed only one randomly-chosen politician, by construction, we would have observed about 76% of the firms at 1. This is indeed very close to the actual distribution the Figure shows (75% of firms at 1).

APPENDIX TABLE C.III

EMPLOYMENT AND PRODUCTIVITY GROWTH AFTER ELECTION. RDD ESTIMATES; DROPPING POLITICIANS EXITING BY $T+1$.

	(1) Empl Growth	(2) Empl Growth	(3) LP Growth	(4) LP Growth
Win dummy	0.0788	0.0796	−0.0371	−0.0392
	(0.0220)	(0.0211)	(0.0426)	(0.0416)
Age		−0.0001		−0.0000
		(0.0003)		(0.0007)
Log Size		−0.0000		−0.0064
		(0.0038)		(0.0090)
f(Victory margin)	YES	YES	YES	YES
Year FE	NO	YES	NO	YES
Province FE	NO	YES	NO	YES
Observations	11,642	11,600	6362	6352

Note: RD estimates for employment growth (columns 1 and 2) and labor productivity growth (columns 3 and 4) based on regression specification (11). Growth rates are defined from T to $T+1$. The sample excludes firms whose winning politicians do not stay until $T+1$. In columns 1 and 3, regressions include win dummy, Win_{iT-1}, and f(*Victory margin*)—a linear polynomial interacted with win dummy. Columns 2 and 4 also include additional controls such as year and firm province fixed effects, log size, and age. The local linear regressions are estimated on the optimal Imbens and Kalyanaraman (2012) bandwidth and are weighted using a triangular kernel function. Robust standard errors reported in parentheses.

APPENDIX TABLE C.IV

RDD ESTIMATES FOR OTHER OUTCOMES.

	(1) VA Growth$_t$	(2) VA Growth$_{t+1}$	(3) TFP Growth$_t$	(4) External finance dependence$_t$	(5) Investment Growth$_t$
Win dummy	−0.0020	0.0468	−0.0132	2.256	−0.130
	(0.0272)	(0.0263)	(0.0229)	(0.908)	(0.0621)
f(Victory margin)	Yes	Yes	Yes	Yes	Yes
Log size, age	Yes	Yes	Yes	Yes	Yes
Province, Year FE	Yes	Yes	Yes	Yes	Yes
Observations	10,444	5987	10,256	10,063	10,766

Note: RD estimates for various outcome variables based on regression specification (11). Growth rates are defined from T to $T+1$, where T denotes election year. The local linear regressions are estimated on the optimal Imbens and Kalyanaraman (2012) bandwidth and are weighted using a triangular kernel function. Robust standard errors are in parentheses. The effect of winning on value added growth is not statistically significant from t to $t+1$; however, the effect is positive and significant in the subsequent year. The effect on TFP growth is negative and insignificant. The financial conditions of the firms on the winning side improve significantly after the election. External finance dependence, measured as capital expenditures minus cash flow, divided by cash flow, increases after firm's politician gets into majority party or a coalition. Finally, we see a decline in investment growth right after the elections, consistent with our facts on declining productivity and innovation-enhancing activities with political connections.

APPENDIX TABLE C.V

EMPLOYMENT GROWTH AFTER ELECTION. RDD FOR NEWLY ELECTED AND EXISTING POLITICIANS.

	Newly-elected politicians		Existing politicians	
Win dummy	0.0554	0.0624	0.0333	0.0310
	(0.0249)	(0.0236)	(0.0197)	(0.0184)
Age		−0.0002		0.0003
		(0.0004)		(0.0003)
Log Size		0.0029		−0.0034
		(0.0048)		(0.0045)
f(Victory margin)	Yes	Yes	Yes	Yes
Year, province FE	No	Yes	No	Yes
Observations	9264	9222	11,025	10,961

Note: RD estimates for employment growth based on regression specification (11). Growth rates are defined from T to $T+1$, where T denotes the election year. *Newly-elected politicians* denotes a sample of firms with employee-politicians elected to office for the first time at T. Hence, these firms go from unconnected to the connected status at T. *Existing politicians* denotes a sample of firms with employee-politicians who already held office at $T-1$. In columns 1 and 3, regressions include win dummy, Win_{iT-1}, and $f(\textit{Victory margin})$—a linear polynomial interacted with win dummy. Columns 2 and 4 also include additional controls such as year and firm province fixed effects, log size, and age. The local linear regressions are estimated on the optimal Imbens and Kalyanaraman (2012) bandwidth and are weighted using a triangular kernel function. Robust standard errors are in parentheses.

Industry Dynamics

Cross-Border Effects. In the spirit of Wilson (2009), we investigate if the high presence of political connections in the neighboring areas is associated with an increase in entry locally. To identify cross-border entry spillovers from political connections, we focus on provinces as our geographic unit since regional aggregation, previously used in our regressions, is too coarse to identify any neighboring effects. Hence, we consider province-industry-level data and use the following two specifications to identify cross-border effects

APPENDIX TABLE C.VI

POLITICAL CONNECTIONS AND INDUSTRY DYNAMICS. TRADABLE VERSUS NON-TRADABLE.

	(1) Growth	(2) Log LP	(3) Share young	(4) Share small	(5) Entry rate	(6) Share conn. entry
Share of conn.	−0.106	−0.405	−0.273	−0.728	−0.0495	0.182
firms	(0.0455)	(0.214)	(0.0256)	(0.0415)	(0.0131)	(0.0395)
Share of conn.	0.0203	−1.840	−0.0455	−0.678	0.0469	0.123
firms × Trad.	(0.0566)	(0.247)	(0.0405)	(0.0497)	(0.0211)	(0.0386)
Observations	34,214	33,569	36,049	36,049	35,857	30,411

Note: Table reports coefficients from OLS regressions of various outcomes at the market level (industry × region × year) on the share of connected firms (share of connected incumbents in the case of columns 5 and 6), distinguishing between tradable and non-tradable industries. We define a sector as (non-)tradable if its share of export over total production is (below) above the median. Columns list various outcome variables: (1) market-level employment growth; (2) market-level labor productivity (total value added over total employment); (3) share of firms younger than 5 years; (4) share of small firms (<5 workers); (5) entry rate of new firms; and (6) share of connected firms among entrants. Regressions include year, region, and industry fixed effects. Regressions are weighted by the number of firms in each industry × region × year to weight more representative markets more heavily. Standard errors are in parentheses.

at the extensive and intensive margins. The first, extensive-margin analysis, estimates

$$\begin{aligned} \textit{Entry rate}_{jpt} = {} & \beta \textit{Conn. own}_{jpt-1} \\ & + \gamma D\{\textit{Conn. neighb}_{jpt-1} > \textit{Conn. own}_{jpt-1}\} + FE + \varepsilon_{jpt}, \end{aligned} \tag{S5}$$

where $\textit{Conn. own}_{jpt-1}$ is the share of connected firms in a province p in industry j and time $t-1$. $\textit{Conn. neighb}_{jpt-1}$ is the average or the maximum share of connected firms across all neighboring provinces of p in industry j at time $t-1$. Operator D returns 1 if neighbors' connection share is higher than own connection share, and zero otherwise. FE denote province, industry, and year fixed effects. If the cross-border effects are present at the extensive margin, entry in a focal province should be higher if firms are more connected in neighboring provinces than in the focal province. Hence, we should expect $\gamma > 0$.

APPENDIX TABLE C.VII

POLITICAL CONNECTIONS AND INDUSTRY DYNAMICS. MANUFACTURING VERSUS NON-MANUFACTURING.

	(1) Growth	(2) Log LP	(3) Share young	(4) Share small	(5) Entry rate	(6) Share conn. entry
Share of conn.	−0.115	−0.585	−0.276	−0.746	−0.0526	0.177
firms	(0.0424)	(0.196)	(0.023)	(0.0383)	(0.0127)	(0.0356)
Share of conn.	0.0509	−1.742	−0.0451	−0.763	0.0677	0.163
firms × Mnfg.	(0.0556)	(0.244)	(0.0434)	(0.0510)	(0.0215)	(0.0365)
Observations	34,214	33,569	36,049	36,049	35,857	30,411

Note: Table reports coefficients from OLS regressions of various outcomes at the market level (industry × region × year) on the share of connected firms (share of connected incumbents in the case of columns 5 and 6), distinguishing between manufacturing and non-manufacturing industries. Columns list various outcome variables: (1) market-level employment growth; (2) market-level labor productivity (total value added over total employment); (3) share of firms younger than 5 years; (4) share of small firms (<5 workers); (5) entry rate of new firms; and (6) share of connected firms among entrants. Regressions include year, region, and industry fixed effects. Regressions are weighted by the number of firms in each industry × region × year to weight more representative markets more heavily. Standard errors are in parentheses.

APPENDIX TABLE C.VIII

CONNECTIONS AND ENTRY. CROSS-BORDER ANALYSIS.

	(1)	(2)	(3)	(4)
			Conn. neighb > Conn. own	
	Panel A. Entry Rate			
$Conn.\ own_{t-1}$	−0.0183	−0.0072	−0.177	−0.188
	(0.0067)	(0.0073)	(0.0145)	(0.0162)
$D\{Conn.\ neighb_{t-1} > Conn.\ own_{t-1}\}$		0.0019		
		(0.0004)		
$Conn.\ neighb_{t-1}$			0.0136	0.0284
			(0.0055)	(0.0156)
Observations	171,678	171,678	86,335	84,842
	Panel B. Non-Connected Entry Rate			
$Conn.\ own_{t-1}$	−0.0282	−0.0173	−0.183	−0.191
	(0.0066)	(0.0072)	(0.0144)	(0.0161)
$D\{Conn.\ neighb_{t-1} > Conn.\ own_{t-1}\}$		0.0019		
		(0.0004)		
$Conn.\ neighb_{t-1}$			0.0128	0.0249
			(0.0055)	(0.0154)
Observations	171,678	171,678	86,335	84,842

Note: Table reports province × industry × year-level regressions of entry rate of new firms (Panel A) and entry rate of non-connected firms (Panel B). Column (2) estimates specification (S5), and columns (3) and (4) estimate specification (S6). $Conn.\ own_{t-1}$ is the share of connected firms in a province × industry in the previous year. $Conn.\ neighb_{t-1}$ is the maximum and the weighted (by the number of firms in the neighboring province × industry) average share of connected firms across all neighboring province × industries in the previous year in column (3) and column (4), respectively. $D\{Conn.\ neighb_{t-1} > Conn.\ own_{t-1}\}$ is a dummy equal to 1 if the neighbors' average connection share is higher than own connection share. All regressions include year, province, and industry fixed effects. Regressions are weighted by the number of firms in each industry × province × year to weight more representative markets more heavily. Standard errors are in parentheses.

In addition, we check for intensive margin of the cross-border effects. In the following specification, we check if the share of connections in neighboring provinces, conditional on it being higher than in the focal province, is associated with higher entry. Hence, we check if $\zeta > 0$ in specification (S6):

$$\begin{aligned} Entry\ rate_{jpt} &= \beta Conn.\ own_{jpt-1} \\ &\quad + \zeta Conn.\ neighb_{jpt-1} + FE + \varepsilon_{jpt}|_{Conn.\ neighb_{jpt-1} > Conn.\ own_{jpt-1}}. \end{aligned} \tag{S6}$$

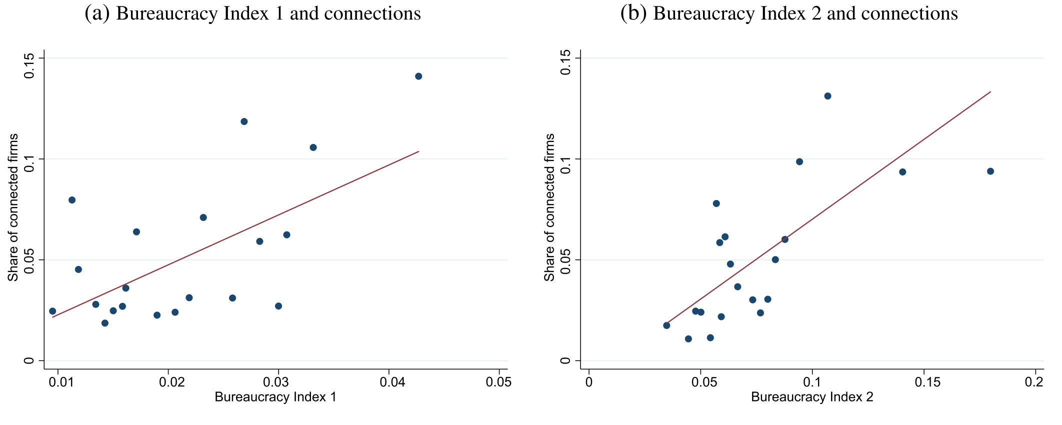
Table C.VIII presents results for entry rate in Panel A and entry rate of non-connected firms in Panel B. The first column repeats our benchmark entry regressions and confirms that there is a negative relationship between entry and the share of connected firms at industry × province level, too. Column 2 estimates the regression specification in (S5) and shows that the cross-border effects at the extensive margin are positive, however small in magnitude. We further estimate the intensive-margin regressions from (S6) in columns 3 and 4 using the maximum and the weighted average share of connections in neighboring provinces to measure *Conn. neighb*. We see some support for the positive cross-border spillovers at the intensive margin; however, the coefficients are much smaller in magnitude than the coefficients on own connections. Taken together, our results suggest that although there is some evidence for cross-border spillovers, a decline in entry at local level is not fully offset by the reallocation of entry to other places.

APPENDIX D: BUREAUCRACY AND REGULATION CHANNEL

Bureaucracy and Institutional Deficiency Indexes. We build on Pellegrino and Zingales (2014) and develop our industry-level "*Bureaucracy Index*" that measures the level of regulatory or bureaucratic burden based on newspaper articles from *Factiva*—an online search engine that searches newspaper articles. We look at newspaper articles from four large news providers and count the number of articles that contain keywords that proxy for government intervention or bureaucracy level that sectors are facing.[S8] Factiva groups newspaper articles into 58 sectors that roughly correspond to 2-digit NACE Rev 2 industry classification. We focus on articles starting from 1991 and experiment with alternative lists of keywords. List 1 consists of "regulation*", "regulated", "regulator*", "bureaucracy", "bureaucratic", "deregulation*", "deregulated", "paperwork*", "red tape", "license*", and plural forms of these words. List 2 adds additional words: "authority", "authorities", "liberaliz*", "reform*", "Agency", "Agencies", "Commission", "Commissions", "policy maker*", "policymaker*", "government", "official form*", "official procedure*." The * character shows that variations of these words were also included. We calculate the *Bureaucracy Index 1 (2)* of sector i as

$$\begin{aligned}&\textit{Bureaucracy Index } 1(2)_i\\&\quad= \frac{[\text{All articles related to } i] \ \cap \ [\text{All articles with keywords from List } 1(2)]}{\text{All articles related to } i}. \qquad \text{(S7)}\end{aligned}$$

This measure is simply the share of newspaper articles in a sector that have certain keywords related to bureaucracy or regulation. Figure D.1 shows a strong and positive relationship between industry's Bureaucracy Indexes and the share of firms that are politically connected.[S9] Table D.I reports Bureaucracy Indexes and connection intensities for all sectors available in Factiva.[S10]



APPENDIX FIGURE D.1.—Bureaucracy and connections across industries.

[S8] These news providers are Bloomberg, Dow Jones Adviser, Financial Times, and The Wall Street Journal. Using international newspapers alleviates concerns of endogeneity and reverse causality, as opposed to looking at Italian news.

[S9] For this exercise, we aggregate industry classification from INPS (ATECO 2007) to the 58 sectors reported in Factiva.

[S10] These correlations are stronger if we consider majority-level or high-rank connections instead.

APPENDIX TABLE D.I

POLITICAL CONNECTIONS AND BUREAUCRACY INDEX ACROSS INDUSTRIES.

Code	Industry description	Connection intensity	High-rank connection intensity	Bureaucracy Index 1	Bureaucracy Index 2
E36	Water Utilities	0.254	0.065	0.046	0.159
K64	Banking/Credit or Investment/Securities	0.222	0.075	0.027	0.110
D	Electricity/Gas Utilities	0.155	0.032	0.033	0.191
C12	Tobacco Products	0.146	0.005	0.028	0.092
C21	Pharmaceuticals	0.139	0.024	0.031	0.087
C24	Primary Metals	0.119	0.026	0.011	0.057
J61	Telecommunication Services	0.114	0.040	0.031	0.095
B	Mining/Quarrying	0.101	0.008	0.011	0.057
C29	Motor Vehicles or Motor Vehicle Parts	0.099	0.008	0.017	0.062
C11	Beverages/Drinks	0.083	0.005	0.023	0.059
C19	Downstream Operations	0.080	0.015	0.012	0.071
E38	Waste Treatment/Disposal	0.060	0.005	0.013	0.085
C26	Computer Hardware/Consumer Electronics	0.059	0.005	0.023	0.060
C22	Rubber Products or Plastics Products	0.057	0.009	0.018	0.058
C20	Chemicals	0.057	0.006	0.026	0.081
C28	Machinery	0.051	0.005	0.015	0.051
A	Agriculture	0.049	0.009	0.011	0.063
C27	Batteries/Electric Lighting Eqpm/Electrical Components	0.047	0.005	0.021	0.064
F42	Heavy Construction Not Sewer Construction	0.041	0.005	0.022	0.104
N	Rental/Leasing/Recruitment Services/Admin/Support Serv	0.040	0.004	0.016	0.082
J58	Publishing	0.039	0.007	0.031	0.076
C17	Paper/Pulp	0.039	0.004	0.022	0.047
H	Transportation/Logistics or Postal Service	0.036	0.005	0.020	0.096
C23	Building Materials/Products or Glass/Glass Products	0.036	0.003	0.017	0.059
J62	Computer Services	0.034	0.004	0.016	0.071
E37	Sewer Construction or Wastewater Treatment	0.033	0.003	0.016	0.169
C30	Aerospace/Defense or Shipbuilding or Railroads	0.032	0.005	0.016	0.079
C33	Machinery Re-pair/Maintenance/Aircraft Maintenance Serv	0.028	0.002	0.040	0.076
C13	Textiles	0.026	0.002	0.030	0.061
R	Theaters/Entertainment Venues/Libraries/Archives	0.024	0.003	0.035	0.090
F41	Building Construction	0.022	0.001	0.014	0.059
J59	TV Program/Sound/Music Recording/Publishing	0.022	0.001	0.021	0.059

(*Continues*)

APPENDIX TABLE D.I

Continued.

Code	Industry description	Connection intensity	High-rank connection intensity	Bureaucracy Index 1	Bureaucracy Index 2
J63	Online Service Providers	0.019	0.002	0.025	0.077
C15	Leather Goods	0.018	0.002	0.011	0.028
C31	Furniture	0.018	0.001	0.015	0.037
J60	Broadcasting	0.018	0.001	0.029	0.086
I55	Lodgings	0.017	0.001	0.027	0.073
C16	Wood Products	0.016	0.001	0.014	0.044
C25	Metal Products	0.016	0.001	0.008	0.048
C32	Jewelry/Musical Instruments/Sport Goods/Games	0.016	0.001	0.030	0.065
C18	Printing	0.015	0.002	0.014	0.039
M	Legal and Professional	0.015	0.002	0.027	0.145
C10	Food Products	0.014	0.001	0.022	0.064
G46	Wholesalers Non-Auto/Auto Part Wholesale	0.014	0.001	0.016	0.055
C14	Clothing	0.013	0.002	0.028	0.057
K	Financial Services	0.011	0.001	0.031	0.118
L68	Real Estate	0.011	0.000	0.011	0.048
G45	Motor Vehicle Dealing/ Repair/Maintenance/Auto Stores	0.009	0.000	0.018	0.053
F43	Special Trade Contractors or Building Refurbishment	0.009	0.000	0.010	0.044
G47	Retail Non-Auto Parts/Tire Stores Not Auto Dealing	0.007	0.000	0.013	0.046
I56	Bars/Public Houses or Restaurants/Cafes	0.005	0.000	0.015	0.051
E39	Waste Management/Recycling Services	0.003	0.000	0.020	0.080

Note: Table reports measures of connections and the bureaucracy indexes across industries. Industry codes are based on classifications from the Factiva News search and the codes correspond to NACE Rev 2 classification. Column 3 reports the average share of connected firms in an industry. Column 4 reports the average share of high-rank connected firms in an industry. Columns 5 and 6 report Bureaucracy Index 1 and Index 2, respectively. The indexes show the average share of newspaper articles about a sector from Factiva News search that mention government regulation- or bureaucracy-related words. Industry-level Bureaucracy Index 1 is our benchmark index defined in Section 3, while Bureaucracy Index 2 is defined in Section C.

We measure local business environment faced by firms by bringing in data on the Institutional Quality Index (IQI) across Italian regions for the period 2004–2019 (Nifo and Vecchione (2015)). We consider two indicators evaluating regional control of corruption (*IQI Corru*) and the regulatory quality (*IQI regu*). We define the Institutional Deficiency Indexes (IDI), where IDI $= 1 -$ IQI. IDI indexes range from zero to 1, with 1 indicating the worst institutional quality. To arrive at our final index, we interact our Bureaucracy Index[S11] at the industry level with the average institutional quality indexes at the regional level. Now, the interacted indexes *Bur* $\times$ IDI *Corru* and *Bur* $\times$ IDI *Regu* vary over regions and industries. For our analysis in Table D.II, we define *High Bur*, *High* (*Bur* $\times$ IDI *Corru*),

[S11] Both indexes lead to the same results, so we chose the Bureaucracy Index 1.

APPENDIX TABLE D.II

POLITICAL CONNECTIONS AND INDUSTRY DYNAMICS. BUREAUCRACY, REGULATION, AND INSTITUTIONAL DEFICIENCY INDEXES.

	Growth, Empl	Entry Rate	Share Connected Entrants
	Panel A. Bureaucracy Index		
Share of connected firms	−0.0531	0.0024	0.232
	(0.0383)	(0.0152)	(0.0103)
Share of connected firms	−0.143	−0.102	0.0588
× High Bur	(0.0749)	(0.0295)	(0.0203)
Observations	30,427	31,895	31,914
	Panel B. Bureaucracy × IDI Corruption Index		
Share of connected firms	−0.0558	−0.0137	0.247
	(0.0356)	(0.0141)	(0.0096)
Share of connected firms	−0.202	−0.0405	−0.0202
× High (Bur × IDI Corru)	(0.0594)	(0.0233)	(0.0158)
High (Bur × IDI Corru)	0.0019	−0.0025	0.0005
	(0.0021)	(0.0009)	(0.0006)
Observations	30,337	31,790	27,108
	Panel C. Bureaucracy × IDI Regulation Index		
Share of connected firms	−0.0614	−0.0107	0.242
	(0.0357)	(0.0142)	(0.0096)
Share of connected firms	−0.196	−0.0733	0.0125
× High (Bur × IDI Regu)	(0.0659)	(0.0259)	(0.0178)
High (Bur × IDI Regu)	−0.0022	−0.0000	−0.0002
	(0.0021)	(0.0009)	(0.0006)
Observations	30,337	31,790	27,108

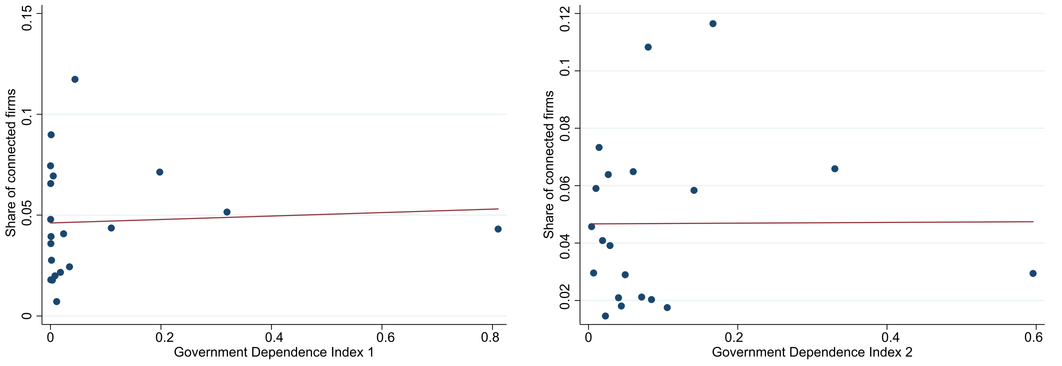
Note: Table reports the coefficients from OLS regressions at the industry × region × year level of various outcomes on the share of connected firms (share of connected incumbents in the case of columns 2 and 3) and its interaction with *High Bur*, *High (Bur × IDI Corru)*, and *High (Bur × IDI Regu)*. These indexes are defined as dummies equal to 1 if an industry or an industry × region is in the top quartile of the respective index distribution. Outcome variables: (1) aggregate industry × region employment growth; (2) firm entry rate; and (3) the share of connected firms among entrants. All regressions include year, region, and industry fixed effects. Regressions are weighted by the number of firms in each industry × region × year to weight more representative markets more heavily. Standard errors are in parentheses.

and *High* (*Bur* × IDI *Regu*) as dummies equal to 1 if an industry or an industry × region is in the top quartile of the respective index distribution.

Government Dependence Index and Political Connections. We define industry-level indexes of government dependence to proxy for the importance of government demand and procurement contracts for the firms. For this purpose, we use a 2-digit input-output table issued by the Italian National Statistical Institute (Istat) in 2010. Denote by Y_j total output of an industry j. Then $Y_j = F_j + I_j$, where F_j denotes industry's output used as final consumption, while I_j denotes industry's output used as an intermediate input. Our Government Dependence Indexes then measure the share of industry's output—by type of use—demanded by the public sector, that is, public administration, education, health, and waste management services. Specifically,

$$\begin{aligned} \textit{Government Dependence Index } 1 &= \frac{F_j^P}{F_j}, \\ \textit{Government Dependence Index } 2 &= \frac{I_j^P}{I_j}, \end{aligned} \tag{S8}$$

(a) Government Dependence Index 1 and connections (b) Government Dependence Index 2 and connections



APPENDIX FIGURE D.2.—Government dependence and connections across industries.

where superscript P denotes output demanded by the public sector.

Government Dependence Index 2 is similar to the index defined in Cingano and Pinotti (2013). Figure D.2 shows that none of these measures of government dependence correlate with the share of firms that are politically connected. These correlations are essentially zero also if we look at majority-level or high-rank connections instead.[S12]

APPENDIX E: MODEL-BASED CALCULATIONS OF STATIC GAINS AND DYNAMIC LOSSES

Using our model, we provide back-of the envelope estimates of the static gains and dynamic losses from political connections in Italy. First, we calculate the implied wedge τ. Recall that in Section 5.4, the total rent created from the politicians-firm relationship was estimated at 11,348 Euros. This rent estimate can be mapped to the model as follows:

$$\mathit{Total\ Rent} = \pi^p - \pi^{np} + w^p = \pi^{np}\big((1+\tau)^{\frac{1-\beta}{\beta}} - 1\big). \tag{S9}$$

In Table E.I, we present calculations for different values of β. In our example in the paper, we fixed $\beta = 0.5$ (which would also correspond to the parameter values considered in Hsieh and Klenow (2009) and Garicano, Lelarge, and van Reenen (2016)); however, we also consider the value of $\beta = 0.2$ following estimates from Guner, Ventura, and Xu (2008) and Akcigit et al. (2022). In addition, given that markups in the model are equal to $\frac{1}{1-\beta}$, the markup value of 1.2 in Italy (Ciapanna et al. (2021)) implies a similar estimate of β. Given the average profit of 300,000 Euros in the sample, the implied wedge is equivalent to 0.9% to 3.8% tax rate on labor. Since the total labor remuneration in Italy is 300 billion (Istat, National Accounts (2014)), the total cost of wedges paid in the economy ranges from 2.8 to 11 billion Euros, which amounts to 0.2–0.7% of GDP. It is worth putting the estimated wedge in perspective. First, we compare it to Garicano, Lelarge, and van Reenen (2016), who estimated a labor wedge caused by labor regulations in France.

[S12]If we jointly regress the share of connected firms in an industry on the Bureaucracy and Government Dependence Indexes, we find that a one-standard-deviation increase in the Bureaucracy Index is associated with 44% increase in the share of connected firms from the mean. However, the coefficient on the Government Dependence Index is statistically indistinguishable from zero.

APPENDIX TABLE E.I

BACK-OF-THE-ENVELOPE CALCULATIONS FROM THE MODEL.

	$\beta = 0.2$	$\beta = 0.5$
Wedge, τ	0.0093	0.0378
Total (labor) cost of wedges	2.8 billion	11 billion
Total cost of wedges % of GDP	0.175	0.71
Output loss from wedges, $Y^{\tau,np}/Y$	0.96	0.96
Static gain from connections, $Y^{\tau,p}/Y^{\tau,np}$	1.012	1.012
Dynamic loss from connections	0.97	0.97
Net effect of connections, $\frac{PV\ Y^{\tau,p}}{PV\ Y^{\tau,np}}$	0.982	0.982

Note: The table summarizes the back-of-the-envelope inference of bureaucracy and regulation wedges and the resulting static gains and dynamic losses from political connections in Italy. Y is an output in the economy with no regulation and bureaucracy. $Y^{\tau,np}$ denotes aggregate output in the economy where all the firms face regulation and bureaucracy wedges. $Y^{\tau,p}$ denotes output in the benchmark economy with wedges and political connections as in Italy.

τ in their case is 2.3% and 5.9% for the β choices presented in our calculations. Although Garicano, Lelarge, and van Reenen (2016) found twice larger tax rates, these regulatory wedges kick in only for the firms above 50 employees; hence, the average wedge applied to all firms is lower. Second, it is important to note that the magnitude of wedges we identify is a lower bound on the aggregate amount of bureaucratic and regulatory costs in the Italian economy. In the model, the firm with political connections faces zero wedges. Hence, we should interpret the implied τ as that part of the regulatory and bureaucratic costs that connections with local politicians can alleviate. Next, we calculate the implied output loss from the bureaucracy and regulation wedges. Using expressions for the equilibrium value of output of unconnected and connected firms, y^n and y^p, and substituting into aggregate production function (Eq. (1)), we can calculate $Y^{\tau,np}/Y$, where $Y^{\tau,np}$ denotes aggregate output in the economy where all the firms face regulation and bureaucracy wedges, while Y is an output in the economy with no regulation and bureaucracy: $Y^{\tau,np}/Y = (1+\tau)^{\frac{\beta-1}{\beta}}$. This implies that the economy facing regulations and bureaucracy has 4% lower output than the economy without.[S13] Some of these output losses are recovered by static gains from the presence of political connections that remove wedges for the connected firms. We estimate aggregate static gains obtained from political connections by calculating $\frac{Y^{\tau,p}}{Y^{\tau,np}} = \frac{s^{np}\times Y^{\tau,np}+s^{p}\times Y}{Y^{\tau,np}}$, where $Y^{\tau,p}$ denotes output in the benchmark economy with wedges and political connections as in Italy; and s^{np} and s^p are the shares of output accounted for by unconnected and connected firms, respectively. These shares are 67% and 33% in the data, respectively. The implied static gain is 1.2% of output. Hence, the third of output loss is recovered with existing political connections. Finally, we provide a back-of-the-envelope estimate for dynamic output losses from political connections. For that, we need to compare growth rate in the economy with no political connections ($g^{\tau,np}$) with the growth rate in the economy with political connections as in Italy ($g^{\tau,p}$). We take a steady-state growth rate of 1%, so that $g^{\tau,np} = 0.01$.[S14] Next, we estimate the reduction in productivity growth from lowered creative destruction. Note that the estimates from column 5 of Table X imply the reduction in entry rate by 0.014 from political connections.[S15]

[S13]Notice that this calculation is unaffected by our choice of β since $(1+\tau)^{\frac{\beta-1}{\beta}} = 1/1.0378$ from equation (S9).

[S14]Italy's growth in 1993–2014 was 0.62%.

[S15]The coefficient -0.031 multiplied by the average share of connected firms among large incumbents (45%) is -0.014.

This constitutes a 38% reduction in entry rate relative to the economy with no political connections. Given that entrants' contribution to productivity growth is 33% (Citino et al. (2022)), this implies that the reduction in growth rate due to lower creative destruction is $0.33 \times 0.38 = 0.12\%$, hence ($g^{\tau,p} = 0.0088$). We can now calculate the ratio of the discounted present value of output in the economy with and without political connections as

$$\frac{PV\ Y^{\tau,p}}{PV\ Y^{\tau,np}} = \frac{Y^{\tau,p}\dfrac{1+r}{r-g^{\tau,p}}}{Y^{\tau,np}\dfrac{1+r}{r-g^{\tau,np}}} = \underbrace{\frac{Y^{\tau,p}}{Y^{\tau,np}}}_{=1.012,\text{ static gain}} \times \underbrace{\frac{r-g^{\tau,np}}{r-g^{\tau,p}}}_{=0.97,\text{ dynamic loss}} = 0.982,$$

where we took interest rate of $r = 0.05$. We obtain that political connections imply 3% output loss through the dynamic channel, outweighing static gains and resulting in the net loss of 1.8% of output from political connections. Therefore, our calculations show that the presence of political connections is likely to exacerbate the economic losses already created by the burden of bureaucracy and regulations.

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