The Local Innovation Spillovers of Listed Firms *

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Abstract

This paper provides evidence of local innovation spillovers, i.e. innovation by one firm fostering innovation by neighboring firms. First, I document that exogenous shocks to innovation by listed firms affect innovation by private firms in the same geographical area and that such local innovation spillovers decline rapidly with distance. Second, these local innovation spillovers stem from knowledge diffusing locally through two channels: learning across local firms and inventors moving from their employer to both existing firms and newly started spin-outs. Finally, I study the two-way relationship between innovation spillovers and the availability of capital. I find that local innovation spillovers cause venture capital funds from outside the area to invest more in the local area, and that capital availability amplifies local innovation spillovers.

JEL codes: K41, L24, O31, O34

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1 Introduction

The success of innovation clusters such as Silicon Valley is often explained by local networks of innovative firms helping to diffuse knowledge across firms. It has motivated large investments by governments to promote such clusters. Often, particular emphasis is put on developing ecosystems of large and small firms, such as the recent American "Regional Cluster Initiative" funded by the Economic Development and Small Business administrations.[1] Supporters of such policies stress that knowledge produced by large firms will benefit neighboring smaller firms, as exemplified by Seattle's innovation cluster that began developing after Microsoft relocated its headquarters to the area.

The spatial concentration of innovative activities is expected to foster innovation because, as for economic spillovers in general, agglomeration allows local firms to share inputs, workers and ideas more efficiently.[2] However, while strong evidence exists that agglomeration and innovation are correlated, causal identification remains elusive as innovation trends for all firms located in the same area are likely driven by the same underlying local factors such as leading research universities, benign weather conditions and tax advantages (Carlino and Kerr, 2015).

To disentangle innovation spillovers from the effects of local conditions, I exploit a shock on the research labs of listed firms in a given geographical area produced by a regulatory change coming from a different state. The shock is caused by the staggered adoption by individual states of business combination (BC) laws, preventing acquirers from using the target's assets to pay down acquisition debt. The laws made it more difficult to complete hostile takeovers of listed firms incorporated in the adopting state. The lower takeover threat has been shown to have weakened external governance, allowing management to enjoy "the quiet life" (Bertrand and Mullainathan, 2003), resulting in a decrease in innovation by listed firms, even in areas outside their state of incorporation (Atanassov, 2013).

BC laws provide an appealing shock to identify innovation spillovers because they cause local areas to experience variation in activities of listed firms' research labs driven by out-of-state shocks, while not having a direct effect on the innovation of local private firms. My hypothesis is that changes in listed firms' innovation in a given area directly affects innovation by private firms in the same area. I limit the concerns that local private firms may be affected by other changes in the state correlated with the adoption of business combination laws by focusing on the innovation activity of listed firms outside their state of incorporation and by controlling for important economic characteristics at the local area level.

1. In a similar initiative, the French government has invested nearly $2 billion to create "competitiveness clusters" ("pôles de compétitivité").

2. Surveys about the link between knowledge and agglomeration include Audretsch and Feldman (2004), Moretti (2004b), Feldman and Kogler (2010) and Carlino and Kerr (2015).

I study innovation by US firms over the period 1975–2000.[3] I use the NBER patent and inventor database containing information about patent inventors, including addresses and employers. Inventor addresses allow me to allocate innovations to different commuting zones, i.e. local geographic areas encompassing all metropolitan and non-metropolitan areas in the US. I consider that a firm is active in a commuting zone if it files patents in that area. The dataset covers both listed and private firms, a classification my identification strategy exploits. In the data, both sets of firms account for a similar fraction of patents filed: around 60% for listed firms and 40% for private firms. However, as one would expect, they differ in the degree of geographical concentration of their patenting activity. On average, listed firms produce patents in 12 different commuting zones relative to 1.5 for private firms. Moreover, listed firms produce less than 20% of their patents in their state of incorporation.

The activity of listed firms' research labs in a specific area will be driven by out-of-state shocks at different points in time, which depends on when a given state adopts a BC law. Moreover, the same shock affects different areas with different intensities, depending on how many listed firms active in an area are incorporated in the adopting state. This allows me to employ a difference-in-differences strategy that studies how innovation by private firms reacts to the change in innovation of listed firms' research labs in the same area, triggered by the adoption of out-of-state BC laws.

In the first part of the paper, I study both how large these spillovers are and how local they are. I find that the out-of-state shocks on listed firms generate negative and economically significant spillovers onto private firms in the same area and that this result is robust to the inclusion of controls for commuting zone-level innovation capacities and labor characteristics as well as to sample restrictions, such as excluding the most innovative cities or states. I also find these innovation spillovers to be markedly local, i.e. they fade away quickly with distance. Indeed, shocks on listed firms' research labs in a given commuting zone have spillovers mostly for private firms in the same commuting zone. For private firms' innovation in other commuting zones within 100 miles, spillovers are still negative, but small: the elasticity is divided by a factor of three. Beyond 100 miles, spillovers are indistinguishable from zero.

To obtain an economic interpretation of the reduced form shock on listed firms, I predict the number of patents produced by listed firms in the area using the BC shock and estimate an elasticity of 0.2, implying that decreasing innovation produced by listed firms in a given area will reduce innovation made by private firms located in the same area by more than 20% .

Next, I test if the spillovers of listed firms onto private firms can be explained by an overall change in listed firm efficiency or if private firms change their innovation policy specifically in reaction to a change in listed firms' innovation. I find limited support for the

3. The sample stops in 2000 to avoid truncation bias.

overall efficiency hypothesis. In particular, I find no local spillovers onto non-innovative firms and no change in the probability for private innovative firms being acquired. I also find that private firms' innovation displays the same changes whether firms are in the upstream or downstream industries and whether they are or are not suppliers of listed firms. This makes it unlikely that the identified spillovers are driven by a demand channel, whereby in response to BC laws, listed firms would change their demand for technologies which would affect innovation by private firms.

Since the changes in innovation by private firms appears to be driven by a variation in *innovation* by listed firms, rather than a change in other listed firm policies. I explore the two channels specific to these "***innovation spillovers***": a direct competition in the market for ideas and the existence of knowledge spillovers between listed and private firms when they are in the same area. I find limited evidence that changes in private firms' innovation are driven by a change in their incentives to innovate in reaction to variation in *local* competition with listed firms. By contrast, I find that private firms even in very unrelated industries (e.g. computer vs chemical) still strongly benefit from the knowledge created by listed firms, consistent with the fact that innovation can stimulate the production of other new ideas across sectors.[4]

Since knowledge spillovers appear to be the main driver behind the existence of the broader "innovation spillovers", I study in details which pipes knowledge can go through to spread across local firms and focus on two main channels: learning from local firms and inventors moving from their employer to both existing and newly started local firms. First, I find evidence of knowledge diffusion via learning across local firms. Indeed, I document higher local innovation spillovers onto firms that are technologically closer to the listed firms innovating locally (those that file patents in the same technological classes, or tend to cite patents filed by listed firms or by local firms). For each proxy of technological proximity, I find that a one standard deviation of this proxy amplifies local innovation spillovers by about half of the average effect.

Knowledge diffusion through learning across local firms is also likely to depend on the local supply of educated workers, whose ability to incorporate and apply new knowledge may be more important than low-skill workers (e.g. Moretti, 2004). For each commuting zone, I calculate the supply of college graduate workers at the beginning of the period. I find that commuting zones in the 75^{th} percentile of the distribution of educated workers experience local innovation spillovers that are twice as large as those of commuting zones in the 25^{th} percentile. I find similar results using instruments that exploit historical differences in the supply of colleges to predict the fraction of educated workers today.

Second, I find evidence of knowledge diffusion via employees moving across local firms.

4. For instance, Jaffe, Trajtenberg, and Henderson (1993) report that up to 25% of citations occur *across* five broad technological fields. When looking at the 3-digit level approximately 40% of citations are across fields.

In a first test, I exploit variation across states in the enforcement of non-compete clauses that limit worker mobility and I find that commuting zones in states that allow for more mobility experience local innovation spillovers that are twice as large as those in states that do not.

I also study how variation in regulation-induced changes in listed firms' innovation affects the mobility of inventors from listed firms to both existing private firms and newly started spin-outs in the same area. I define a spin-out as a new firm employing, in the first year it files patents, inventors formerly employed by a listed firm active in the same area. For both existing and new firms, I observe more mobility when the stock of patents by listed firms increases.

In the third part of the paper, I investigate the two-way connection between local innovation spillovers and the availability of venture capital. First, I examine whether local innovation spillovers attract capital to the area. To identify non local investors, I use the VentureXpert database, which reports for each venture capital (VC) fund covered its address and the location of all its investments. I find that when listed firms in a commuting zone innovate more, VC funds located outside that commuting zone increase the volume of their investments in that commuting zone. On average, a one standard deviation increase in the stock of patents by listed firms in a commuting zone increases non local VC investments per year by 11%. This is all the more remarkable given that non-local investments are rare in the VC industry.

Second, I test whether conversely, exogenous fluctuations in local capital availability amplify local innovation spillovers by enabling local firms to better finance innovations. To do so, I instrument the amount of VC capital available locally using variation in the size of state pension funds. Because state pension funds invest disproportionably in local investment funds (such as private equity and venture capital funds), local investment funds raise capital more easily when local pension pools are larger (Gonzalez-Uribe, 2014). I find that commuting zones in the 75^{th} percentile in the distribution of (exogenous) VC financing experience local innovation spillovers that are twice as large as those in commuting zones in the 25^{th} percentile.

Taken together, the paper shows that sizeable local innovation spillovers exist, which are at least partly driven by knowledge diffusion via learning across local firms as well as employees and inventors moving across local firms. Furthermore, these spillovers attract capital to the area which in turn amplifies the spillovers. These findings point to several policy implications. If the clustering of innovation were mostly due to attractive local attributes (universities, etc.), local public policies aimed at fostering innovation clusters should focus on providing those. However, if instead, innovation clusters stem from innovation spillovers, then subsidies can be justified.[5] My findings also suggest that local

5. The existence of spillovers constitutes a rationale for location-based policies but does not imply these to improve aggregate welfare. See e.g. Kline and Moretti (2014).

innovation spillovers can be amplified by policies promoting intrastate labor mobility, by restricting non-compete clauses, by improving the supply of skilled labor (for instance via the construction of college institutions), and by improving access to capital.

Literature Review This paper contributes to several strand of literature. First and foremost, it relates to the literature studying how the stock of external knowledge available in the surroundings of economic agents affects their productivity and their ability to innovate. The dominant approach in this literature is to regress productivity, wages (used as a proxy for productivity) or innovation on a proxy for the stock of knowledge available such as the stock of R&D (e.g. Peri, 2005), the supply of college graduates (e.g. Rauch, 1993; Moretti, 2004), population density (e.g. Ciccone and Hall, 1996) or firm density (e.g. Greenstone, Hornbeck, and Moretti, 2010; Guiso and Schivardi, 2011).

Second, it relates to the literature studying how corporate investment is shaped by the firm's neighbors. This question has been studied for investment in general (Dougal, Parsons, and Titman, 2015; Dessaint, Foucault, Frésard, and Matray, 2018), as well as for firm creation (Doms, Lewis, and Robb, 2010; Guiso, Pistaferri, and Schivardi, 2014) and innovations in particular (Peri, 2005; Bloom, Schankerman, and Van Reenen, 2013). I add to this literature by providing a new method of studying innovation spillovers and by providing evidence for specific channels through which these local innovation spillovers can occur. I also use a finer measure of geographic proximity by using inventor addresses rather than firms' headquarters as the location of innovation.[6] Finally, I study the specific interactions between publicly listed and private firms, which is a subject that has received little attention thus far.

More broadly, I relate to the literature on urban literature and agglomeration. Most papers have focused on fixed characteristics, while a few recent papers are exploring how finance can produce changes in these agglomeration forces both within countries (e.g. Hombert and Matray, 2017 for the U.S., Bau and Matray, 2020 for India), sectors (Hombert and Matray, 2019) and across countries (Xu, 2019).

In this burgeoning literature, two very different mechanisms are at play that explain the comovement of behaviors. The first mechanism is that managers either infer information from their peers or simply "mimic" these peers, and the second is that neighboring firms have a direct effect on their peers' inputs or cash-flows. My paper is about the second mechanism. I show that innovation by private firms is affected because a key input in their own innovation production functions varies: the local stock of external knowledge produced by listed firms.

6. Indeed, it is not clear that information regarding failed or successful innovative projects will be communicated by CEOs. Inventors appear more likely to spread knowledge locally, in particular by moving across firms.

2 Data

2.1 Innovation

I use patents filed with the US Patent and Trademark Office (USPTO), as compiled in the National Bureau of Economic Research (NBER) Patents File (Hall, Jaffe, and Trajtenberg, 2002) to measure innovation. These data contain all patents granted in the US, including information about the patentee (including a unique identifier, institutional characteristics, nationality, and geographic location) and the patent (year of application, technology class, and number of citations received). An appealing feature of the NBER Patents File is that it covers the entire universe of patents filed in the US, including patents filed by young and private firms.

Both listed firms and private firms play an important role in innovation activity in the US. Throughout my sample period, the fraction of patents filed by listed firms is relatively stable at approximately 50%-60%.

I keep only those patents filed by US corporations in my sample and exclude patents filed by foreign firms, universities, and government agencies. I date patents by the year in which the application was filed to avoid anomalies resulting from a lag between the application and the grant dates. I consider all patents filed between 1975 and 2000 (the first year and last year where the truncation bias is limited).

To obtain the location of the inventors at the county level, I use the Harvard Patent Database[7] which provides the latitude and longitude for each inventor associated with a patent. These coordinates can then be used to obtain the exact county in which a patent was created (Hombert and Matray, 2018.

2.2 Geographic Area: Commuting Zones

Commuting zones are 741 clusters of counties that are characterized by strong commuting ties within commuting zones and weak commuting ties across commuting zones. I restrict my analysis to commuting zones in which I can observe at least one patent during the period 1975–2000, which results in a balanced panel of 685 distinct commuting zones, mapping to 48 states in the US (the three missing states are Alaska, Hawaii and the District of Columbia).

Commuting zones have two main advantages. First, they are based on economic ties rather than political boundaries and, as such, are a more suitable candidate for estimating the scope of innovation spillovers. Indeed, they are sufficiently small so that spillovers can plausibly occur (as knowledge spillovers tend to occur on relatively small scales) and their geographical boundaries can be defined in a constant way over time, allowing the analysis over long time period. Second, they cover the entire United States (as opposed

7. The data are available at http://dvn.iq.harvard.edu/dvn/dv/patent

for instance to metropolitan statistical areas, which captures only a third of all counties in the U.S.).

To measure the existence of geographical spillovers, I aggregate patents at the commuting zone level. This is motivating by the fact that innovation can trigger the production of other new ideas across sectors. For instance, Jaffe, Trajtenberg, and Henderson (1993) report that up to 25% of citations occur *across* five broad technological fields. When looking at the 3-digit level (approximately 450 technological fields) approximately 40% of citations are across fields. Aggregating at the commuting zone level allows to capture these potential cross-sectors spillovers.

2.3 Local Labor Markets Characteristics

I construct different characteristics at the commuting zone level using various datasources. The main source is the Census Integrated Public Use Micro Samples for the years 1970, 1980, 1990, and 2000 (Ruggles et al., 2010).[8] I apply the usual restrictions to compute labor market characteristics: individuals must be between 16 and 64 and be working in the year preceding the survey and I drop residents of institutional group quarters such as prisons and psychiatric institutions as well as unpaid family workers. Population estimates on a yearly basis are from the Census.[9]

Data on venture capital activity and venture capital funds availability come from the VentureXpert database. I identify the commuting zone in which the fund is located and where it makes an investment using the zipcode information provided by Venture Xpert. Finally, data regarding educational attainment, number of colleges and federal R&D expenses are from the National Science Foundation's CASPAR database. Table 1 provides summary statistics for the main variables used in the paper.

3 Identification Strategy

3.1 Empirical Specification

To test the existence of innovation spillovers from listed firms onto private firms, one would ideally like to regress innovation by private firms on innovation by listed firms in the same area. The main challenge when doing so is that innovation activity of both private and listed firms in a given city is likely to be determined by common specific location factors, such as the proximity with universities or the quality of local amenities. Therefore, it is also quite possible that local innovation spillovers do not exist, or are of

8. The Census samples for 1980, 1990, and 2000 include 5% of the US population, the 1970 Census and ACS sample include 1% of the population. The Census 1970 corresponds to the "Census Metro2".

9. Appendix A.1 details the construction of the variables.

Table 1: . Summary Statistics

This table provides summary statistics for the main variables used in the paper. Statistics have been computed at the commuting zone-Year level. Variables are described in section 2

	Mean	Std. Dev.	p(25)	p(50)	p(75)
Patents Private Firms	45	175	1	5	19
Patents Listed Firms	64	269	0	3	17
Stock Listed Patents	293	1,212	2.5	12	78
Population Density	.41	.62	.1	.21	.42
Firm Density	.93	1.5	.24	.45	.92
Share Urban	.52	.21	.37	.52	.68
Share Black	.09	.12	.01	.04	.12
Share Women	.51	.011	.51	.51	.52
Share College Educated	.39	.094	.32	.39	.46
Share S&E	.017	.0091	.01	.01	.02
Fraction Citation Listed Firms	.3	.086	.26	.3	.35
Fraction Citation Local Firms	.033	.035	.01	.02	.05
Mobile Inventors from Listed Firms	5	16	0	0	2
Share Inventors Previously in Listed Firms	.066	.11	0	0	.11
Spin outs	3.9	15	0	0	2
# Non Local VC Investments	6.3	49	0	0	0

rather limited scope, and are overestimated in naive regressions that neglect such omitted variable problems.

A way to address this problem is to use a shifter of listed firms' lab activities that is orthogonal with the unobserved local conditions that might affect private firms' innovation. I do so by using the adoption of BC laws and focusing on listed firms' labs outside their state of incorporation and estimate the following equation:

$$Log(Y_{cst}) = \alpha_c + \delta_t + \beta \ \textit{Shock Listed Firms}_{ct} + LogX_{ct} + \gamma_{st} + \epsilon_{cst} \tag{1}$$

Where Y_{cst} is the innovative output of private firms located in commuting zone c, state s and year t. *Shock Listed Firms*$_{ct}$ is defined as: $\sum_i w_{i,0} \times BC_{it}$, namely the weighted average of the adoption of BC law for all firms with a lab in commuting zone c, where the weights $w_{i,0}$ are given by the fraction of patents by firm i in the total amount of listed patents at the beginning of the period.[10] α_c and δ_t denote commuting zone and year fixed effects respectively. Commuting zone fixed effects capture time-invariant determinants of innovation in each area, such as geographic characteristics or the presence of an important university. Year fixed effects control for aggregate shocks and common trends in innovation activity produced by legal and institutional changes at the federal level, such as the creation of the Court of Appeals for the Federal Circuit in 1982. Finally,

10. As it is common in the literature, I define patents by listed firms as the stock of patents that listed firms have produced in commuting zone c at time t using the standard perpetual inventory method. The stock of listed patents in year t is $Stock_t = (1-\eta)Stock_{t-1} + \textit{Listed Patents}_t$ where *Listed Patents*$_t$ is the number of new patents filed by listed firms in year t and η=0.15.

I add state×year fixed effects denoted by γ_{st} to remove any time varying shocks or state characteristics that might affect innovation by all firms, such as state business cycles, or time-varying state institutional and policy differences (e.g. marginal tax rate).

The parameter of interest is β, which measures the extent to which private firms react to the overall shocks affecting listed firm labs. Given the state×year fixed effects, β only captures spillovers that occur within a state across commuting zones and does not include variation coming from commuting zones in different states. I cluster standard errors at the commuting zone level.

Such a strategy makes it possible to causally estimate the existence of spillovers from listed firm *activities* on private firms' innovation. It might not pin down the exact elasticity between listed patents and private patents if the adoption of BC law affects other characteristics of listed firms' labs.[11]

I discuss in Section 5 the extents and limits under which it is possible to consider *Shock Listed Firms*$_{ct}$ as an instrument for listed firms' innovation and to interpret β as the elasticity between private and listed patents.

3.2 Exogenous variation in Innovation by Listed Firms

3.2.1 Antitakeover Laws

In the 1980s and early 1990s, states adopted what are generally referred to as the "second generation" of antitakeover laws. The most stringent of these are called "business combination laws" (BC laws).[12]

BC laws strongly limit the likelihood that a firm will be the target of a highly leveraged hostile takeover, by restricting a raider's ability to sell the assets of the acquired firm. Because these takeovers are frequently financed by means of the sale of certain of the target's assets, BC laws have effectively insulated managers from hostile takeovers by giving management the right to "veto" a takeover by making it more difficult to finance. Therefore, their adoption can be considered as a valid source of variation in corporate governance. In particular, BC laws allow managers to follow preferences that are not necessary aligned with shareholders' best interests. Two types of these preferences would lead to a decline in innovation. First managers might exert less effort based on their intention to "enjoy the quiet life" (Bertrand and Mullainathan, 2003). Second, risk-averse

11. In other word, it might not be possible to treat *Shock Listed Firms* as an instrument as the exclusion restriction not only requires that the shock is uncorrelated with local productivity shocks (which it is), but also that it affects private firms innovation only through the change in innovation by listed firms and not other listed firm policies. In the case of BC laws, we know for instance that they lead to slightly higher wages and a small decline in firm efficiency (Bertrand and Mullainathan, 2003). Those changes may in itself create spillovers onto private firms and affect their innovation policies. While this does not affect the validity of the shock to study how an exogenous shock on listed firms spills over onto local private firms, it does change the interpretation of *why* private firms' innovation change.

12. For a detailed history of first and second generation of antitakeover laws, see Kahan and Kamar (2002), Bebchuk, Cohen, and Ferrell (2002) or Bertrand and Mullainathan (2003).

or career-concerned managers might undertake less risk than desired by a diversified shareholder and decide to "play it safe" (Gormley and Matsa, 2016). Both types of behavior have been found to increase after BC laws were adopted.

One might be concerned that the adoption of BC laws would have a direct impact on *both* listed and private firms. This is unlikely for two reasons. First, private firms are closely held and therefore have much lower agency problems between the management team and the owner of the firm, in particular because in the vast majority of cases there is no separation between the equity owners and the firms' top management team. As such, managers cannot become more or less insulated from equity holders and agency costs do not vary with the adoption of BC laws. Second, because private firms are closely held, a raider will always have to deal directly with the owner of the firm who can refuse or accept the transaction. The opinions of the non-owner managers are irrelevant and the adoption of BC laws does not change that.

3.2.2 Exogenous shock on innovation by listed firms using BC law adoptions

I start by showing that the adoption of BC laws is an exogenous shifter of innovation by listed firms in the different commuting zones they have labs. After I drop all patents in commuting zones located in the state of incorporation of the firm, I estimate the following equation:

$$Log(1 + ListedPatents_{ict}) = \alpha_i \times \gamma_c + \delta_t + \beta BC_{it} + \epsilon_{it} \tag{2}$$

where BC_{it} is a dummy variable equals to one if firm i is incorporated in a state that has passed a BC law after year t. $\alpha_i \times \gamma_c$ denote firm×commuting zone fixed effects and δ_t denote year fixed effects.

Identifying assumptions. Using the adoption of business combination law as a shock to innovation conducted by listed firms face two problems. First, the adoption of the law may change or reflect the state's economic context. To deal with this, I exploit the geographic dispersion of innovation by listed firms. For instance, listed firms file only 20% of their patents in their state of incorporation. So I exclude from my analysis innovation by firms in their state of incorporation. For example, I consider a firm incorporated in Virginia but that files patents in Austin. When Virginia passes a BC law in 1988, the firm reduces its innovation in all areas, including Austin. I use this to study the impact on innovations by local private firms in Austin.

Second, even if the adoption of a BC law constitutes a plausible source of exogenous variation in the number of patents produced by listed firms already located in a given area, one source of endogeneity remains. Indeed, the allocation of *where* a listed firm decides to conduct its research activity initially is not a random decision. For instance, assume that Austin-San Marcos (Texas) experiences a positive productivity shock that increases innovation of both listed and private firms. In that event, listed firms are more likely to conduct their research activity there. The number of listed firms affected by the shock will therefore increase, leading to an increase in the estimated amount of innovation produced by listed firms. The higher volume of innovation by listed firms will be matched by more innovation by private firms, as both type of firms benefit from a positive productivity shock. leading to a spurious correlation between patents filed by listed firms and private firms. However, after the first year, the evolution of patents by listed firms will again only depend on the BC laws. Therefore, the threat to identification comes from the entry (and exit) of listed firms in and out of my sample.

This problem would also arise in context where the econometrician predicts within firm variation with an instrument, but then aggregate the prediction at the industry level (such as for instance in Bloom, Schankerman, and Van Reenen (2013)). To see this, note that we can decompose growth of total patents over h years g_t^h into five margins:

$$
\begin{aligned}
g_t^h = & \underbrace{log\left(\frac{P\bar{a}t_t(I_{t\cap t-h})}{Pa\bar{t}_{t-h}(I_{t\cap t-h})}\right)}_{i_t^h = \text{ intensive margin}} \\
& \underbrace{+\underbrace{log\left(\frac{N_t(I_t)}{N_t(I_{t\cap t-h})}\right)}_{\text{entry extensive}} + \underbrace{log\left(\frac{P\bar{a}t_t(I_t)}{P\bar{a}t_t(I_{t\cap t-h})}\right)}_{\text{entry intensive}}}_{\text{entry margin}} \underbrace{-\underbrace{log\left(\frac{N_{t-h}(I_{t-h})}{N_{t-h}(I_{t\cap t-h})}\right)}_{\text{exit extensive}} - \underbrace{log\left(\frac{Pa\bar{t}_{t-h}(I_{t-h})}{Pa\bar{t}_{t-h}(I_{t\cap t-h})}\right)}_{\text{exit intensive}}}_{\text{exit margin}}
\end{aligned}
$$

where I_t is the set of firms that innovates in year t, $N_t(I_t)$ is the number of firms that innovate in year t, and $P\bar{a}t_t(I_t)$ is the average number of patents per firm during year t. $\cap$ denotes the set of firms that innovate both in year t *and* in year $t-h$. The total entry and exit margin can be decomposed into the number of firms that enters and exits and the average number of patents filed by entering and exiting firms.

This decomposition highlights that while the firm level instrument will address endogeneities raising from the intensive margin, it does *not* remove the biases coming from the decisions of firms to enter and exit the sample, which are likely correlated with unobserved local productivity shocks.

To address this problem, I focus on listed firms present for the entire period of my analysis and consider that they are present from the beginning in all the commuting zones in which they will patent at some point in time. This ensures that the only variation in patents by listed firms comes from the adoption of the BC law.[13]

13. One potential problem with this strategy is that it reduces the number of listed firm to 1,491 firms. I also run a similar regression with the complete sample (16,914 firms) to generate a prediction based on this sample and find similar results, which suggests that the magnitude of the bias that entry could produce is very small.

Estimation. Table 2 shows the effect of adopting a BC law on listed firms' innovation for the balanced sample from 1975 to 2000. Adopting a BC law generates a decline in patenting between 4% to 6%, depending on the specification, always highly significant at the 1% level. Columns (2) to (5) report various robustness. Column (2) add industry×year fixed effects to absorb time-varying fluctuations at the industry level (such as technology or sale shocks). Column (3) add commuting zone×year fixed effects to absorb any commuting zone-specific time-varying shocks shared by all firms in the same commuting zone, such as localized business cycles or productivity shocks.[14] Column (4) excludes listed firms incorporated in Delaware and column (5) excludes patents filed in California.

Table 2: Effect of BC Laws on Patenting by Publicly Listed Firms

Dependent Variable	Patents					R&D
Sample	All			Exc. Delaware	Exc. California	All
	(1)	(2)	(3)	(4)	(5)	(6)
BC Adoption	-0.04***	-0.06***	-0.05***	-0.06***	-0.06***	-0.02**
	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)
Fixed Effects						
Commuting Zone	✓	✓	—	—	—	—
Firm	✓	✓	✓	✓	✓	✓
Year	✓	—	—	—	—	—
Industry×Year	—	✓	✓	✓	✓	✓
Commuting Zone×Year	—	—	✓	✓	✓	✓
Observations	183,168	183,168	183,168	87,630	169,525	34,550

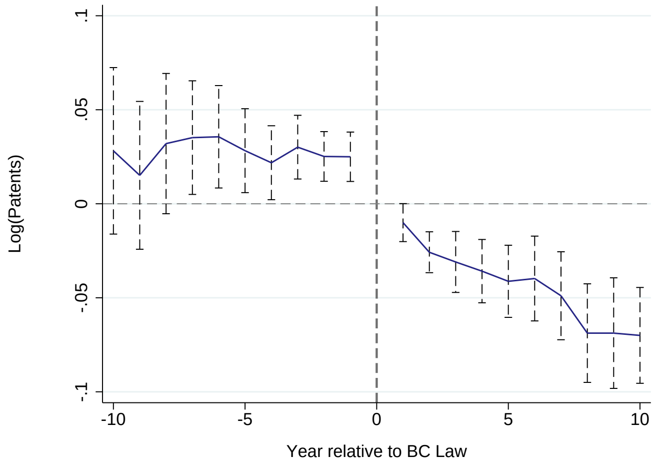
Dependent variable is the log of patents filed by Compustat firms in a given year and commuting zone for the sample of firms present from 1975 to 2000. Column (2) adds industry×year FE. Column(3) adds commuting zone×year FE. Column (4) excludes all firms incorporated in Delaware. Column (5) excludes all innovation activity in California. In column (6), the sample is at the firm-year level and R&D is scaled by firm capital. Standard errors are clustered by commuting zone.

I also check that the results are not capturing a trend by plotting the evolution of patenting activity around the regulation date. In Figure 1, I estimate equation (2) but replace the adoption of the BC law with dummy variables for each year from 10 years before to 10 years after the regulation. Reassuringly, there is no trend before the event date. Figure 1 also shows that the effect of regulation materializes only progressively after the event date, which is expected because firms likely need time to adjust to new environments.

Identifying the effects of innovation by listed firms on private firms exploits the fact that commuting zones will be more or less affected by the shock generated by the adoption of BC laws. Figure 2 maps the distribution of patents filed by listed firms before 1984

14. For example assume that I have only two firms in a given commuting zone, the identification comes from the fact that one firm will be incorporated in New York where a B.C. law was adopted in 1985, whereas the other is incorporated in California (where such a law never adopted).

Figure 1: Effect of BC Laws on Patenting by Publicly Listed Firms



The figure shows the evolution of innovation around regulation dates. The specification is the same as equation (2) except that the dummy for the adoption of business combination law is replaced by a collection of variables $I(k)$, where $I(k)$ is a dummy equal to one exactly k years after (or before if k is negative) the state implements the regulation. The solid line plots the point estimates for $k = -10, \ldots, 10$, using the regulation year $k = 0$ as the reference year. The dashed lines plot the 95% confidence interval.

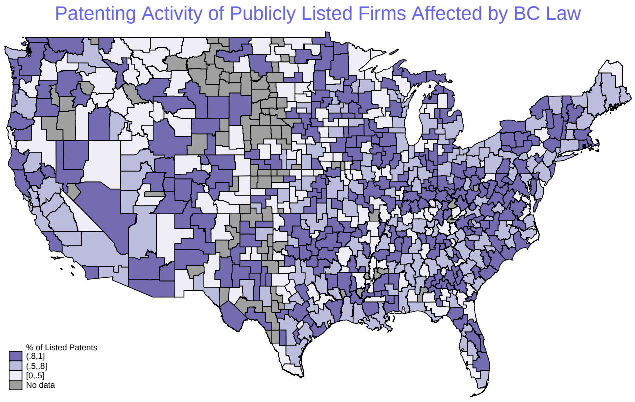
(the last year before the adoption of the first BC law). This map shows the distribution of patenting activity by listed firms that will be affected at some point in time by BC laws. Figure 2 shows that listed firms affected by BC laws represent an important part of all patents filed by listed firms throughout the US, which reduces the risks that my estimation will only capture evolution that is specific to a limited number of geographic areas.

Discussion. What margin of adjustment can explain why listed firms experience a reduction in their production of patents?[15] A challenge when estimating the effect of the adoption of BC laws on R&D spending is that most R&D spending are actually wages of employees involved in the research activities of the firm.[16] Since Bertrand and Mullainathan (2003) show that managers insulated from takeover risks increase wages for the firm's white-collars, this might translate into higher R&D "spending", even though effort to innovate have actually gone down. Patents are therefore a much better proxy for the knowledge produced by listed firms in this context, as they provide a measure of the amount of knowledge produced by listed firms that can be observed and reuse by local private firms. With this caveat in mind, replacing patent by the amount of R&D scaled

15. Note that this is not crucial in my settings as all I need is a shock unrelated with the area where the firm is active. What is crucial is that the shock explains actual variation in patents by listed firms as it is case.

16. Wages can account for 80% to over 90% of firm total R&D spending.

Figure 2: Fraction of Patents by listed firms Affected by BC Laws



This map shows the geographic dispersion of publicly listed firms that will be affected by the adoption of BC laws. I calculate the fraction of patents filed by listed firms affected over the total of patents filed by listed firms for each Commuting Zone.

by firm asset in equation 2 yields a negative coefficient of 2 percentage point, significant at the 5% level, which represents a 18% decline relative to the sample mean (column (6) of Table 2). Taken at face value, this implies an elasticity of R&D spending to patent around 0.3% (0.06/0.18), meaning that when listed firms reduce their R&D spending by 1% (the input) due to the shock, they reduce the amount of patent produced by 0.3% (the output).

4 Local Innovation Spillovers

Baseline estimation. I begin by investigating the effect of a change in innovation by listed firms on the number of patents filed by private firms in a given commuting zone in the following year. The results are reported in Table 3. Column (1) shows the naive OLS from equation 1. The elasticity of patents filed by private firms to patents produced by listed firms is 0.24. Columns (2) to (5) report the effect when I instead use the average shock on listed firms coming from the adoption of BC laws in different states. In every case, the effect is negative and strongly significant at the 1% level, implying that an increase in the number of listed firm research labs that are shocked, reduces innovation by private firms in the same commuting zone.

In columns (3) and (4), I add various controls at the commuting zone level that might affect the propensity of private firms to innovate. Column (3) adds economic and demographic controls: share of African-Americans, share of women, population density, share of population living in an urban area, share of self employed, and industrial specialization.[17] In column (4) I add innovation-specific controls: number of doctorates granted

17. *Industry specialization* is defined as the local Hirschmann-Herfindahl Index for the 10 economic

each year, number of existing college institutions reported by the Integrated Postsecondary Education Data System (IPEDS), *Technology specialisation* defined as the local Herfindahl of technology classes (thus in both cases, the greater this measure, the more highly specialized that a given commuting zone is); *Technology age*, defined as the average age of technologies exploited in a commuting zone captures the fact that commuting zones working in newer, more fertile technologies may generate more patents (Hombert and Matray, 2017) and the amount of venture capital investment made. Because several of those variables are likely to be directly influenced by innovation produced by listed firms, I only use demographic controls and the number of establishments in the rest of the paper.[18]

While the point estimate of the coefficient of interest remains relatively stable, it does slightly fluctuate, which might reflect that multiple channels connect the BC laws to private firms' innovative activities, besides the effect of innovation by listed firms. However, coefficient movements alone are not fully informative of the degree of robustness. To quantify the effect to which further unobserved characteristics might drive the results, I compute the bounds in Oster (2019) and obtain a value for the δ parameter of 5.7, well above the recommended value of 1. This implies that it is unlikely that further unobserved characteristics could be driving down the results.[19]

Effect of distance. Column (5) explores how the effect evolves with distance. I define *Shock Listed Firms-Close* CZ_{ct} as the sum of patents produced by listed firms in the four closest neighbor surrounding the commuting zone c. I also calculate the sum of listed patents produced in the *next* four closest neighbors labeled "*Distant* CZ_{ct}". I identify close neighbors and distant neighbors by calculating the geographical distance between each commuting zone using the latitude and longitude of each commuting zone centroid.[20] I find that innovation made by listed firms in close neighboring commuting zones has a small positive effect on innovation by private firms, but the effect becomes indistinguishable from zero for distant neighbors. This sharp decrease with distance is consistent with other papers documenting that "knowledge does not travel well".[21] It

sectors available in the BEA. Those sectors include the following: Agriculture, Mining, Construction, Manufacturing, Transportation, Wholesale trade, Retail trade, Finance, Services, Public Administration.

18. See Angrist and Pischke, 2008 for a discussion about the problems created by "bad controls".

19. In practise, bounds can be approximated using the following equation: $\beta^* \approx \tilde{\beta} - \delta \times [\mathring{\beta} - \tilde{\beta}] \times \Big[(R^{max} - \tilde{R})\Big] / \tilde{R} - \mathring{R}$ where "$\tilde{}$" denotes the variable estimated with all the controls and "$\circ$" denotes variables estimated only when *Shock Listed Firms* is included as a control. I set R^{max} to one, which is the most conservative. δ is estimated assuming that β^* is equal to zero.

20. Similar strategies have been used for instance in Wilson (2009) for states and Dessaint and Matray (2017) for counties.

21. Given that the average distance for commuting zones in the neighborhood zone is approximately 100 miles and the distance for commuting zones in the remote neighboring zone is approximately 190 miles, my estimation is in the ballpark of that found by other papers. For instance Duranton and Overman (2005) find that geographic spillovers concentrate at a scale of approximately 30 miles, whereas Bottazzi and Peri (2003) find that knowledge spillovers exists between 0 and 450 miles in their study of European

also implies that analyses attempting to estimate spillovers in innovation at the state level are likely to underestimate their existence because they occur on a much smaller scale.

Table 3: Listed Firm Spillovers on Innovation by Private Firms

	(1)	(2)	(3)	(4)	(5)	(6)
Listed Patents	0.201***					
	(0.021)					
Predicted Listed Patents						0.203***
						(0.042)
Shock Listed Firms		-0.097***	-0.092***	-0.095***	-0.093***	
		(0.020)	(0.020)	(0.020)	(0.020)	
Shock Listed Firms-Close CZs					-0.058*	
					(0.032)	
Shock Listed Firms-Distant CZs					0.033	
					(0.062)	
Fixed Effects						
Commuting Zone	✓	✓	✓	✓	✓	✓
State×Year	✓	✓	✓	✓	✓	✓
Economic Controls	—	—	✓	✓	—	—
Innovation Controls	—	—	—	✓	—	—
Observations	17,125	17,125	17,125	17,125	17,125	17,125

The dependent variable is the log of patents filed by private firms. In column (2) to (5), *Shock* is defined in equation 1 as the weighted sum of the adoption of BC laws for listed firms. *Shock Listed Firms-Close CZs* is the average shock affecting listed firms in the four closest commuting zones around private firms and *Shock Listed Firms-Distant CZs* is the average shock affecting listed firms listed firms in the the next four closest commuting zones. Columns (3) and (4) add various controls at the commuting zone-year level. In column (6), *Predicted Listed Patents* is the log of listed patents predicted by the adoption of BC laws. The regression is estimated with a 2SLS procedure to correct the standard errors. Standard errors are in parentheses and clustered at the commuting zone level.

Discussion of magnitudes. One issue with this reduced form shock is that it makes the economic interpretation of the magnitude complicated. I address this problem by predicting the amount of listed patents using the overall shock faced by listed firms in the commuting zone and use a 2SLS estimation to adjust standard errors. This offers an automatic rescaling of the coefficient β in equation 1 and allows an interpretation in term of elasticity — since I am regressing a log on a log.[22] The point estimate is equal

regions. In the US, Lychagin, Pinkse, Slade, and Van Reenen (2016) find that the effect disappears after around 300 miles and Belenzon and Schankerman (2013) find that knowledge spillovers decline at a distance of up to 150 miles.

22. It is important to note that while this 2SLS offers a convenient rescaling of the coefficient of interest, the estimation is not an IV per se as the exclusion restriction might be violated. Indeed, the adoption of BC laws might have other effects on listed firms behaviors that directly affect the innovation of private firms. I discuss these possibilities in the next section.

to 0.2, implying that changing the amount of innovation made by listed firms by 1% changes the number of patents filed by private by 0.2%. To have an estimation in term of patents, I have to multiply the elasticity by the ratio of the stock of patents filed by private firms over the stock of patents filed by listed firms. It implies that a variation in 1 patent filed by listed firms generates a similar variation in 0.14 patent filed by private firms. Another possibility is to perform the following thought experiment. The average listed firm's research lab in a commuting zone has a local stock of around 100 patents. If I relocate this activity to a new commuting zone, it will generate around 14 additional patents by private firms, which would move the commuting zone at the 25^{th} percentile of the distribution to the 75^{th} percentile in term of innovation by private firms. This substantial effect could explain why cities and states compete to attract R&D activities (Wilson, 2009).

Having established that innovation spillovers occur and are closely bounded spatially, I now explore how the local production of knowledge by listed firms proxy by their patents filed in a given commuting zone spreads across firms in the same area.

5 Spillovers of Innovation

While the effect of the adoption of BC laws on listed firms innovation is particularly striking, the adoption of BC laws can change the "overall efficiency" of listed firms, which, in return, can spill over onto local private firms located in the same area as affected listed firms' research labs. I explore this possibility in Section 5.1. Finding limited support for this possibility, I then unpack these "innovation spillovers" and test two channels: competition in the market for ideas (Section 5.2) and knowledge diffusion (Section 5.3).

5.1 Overall Decline in Dynamism?

The adoption of BC laws might spill over onto private firms via a change in overall decline in listed firm dynamism through three specific channels. First, listed firms become less productive overall (Bertrand and Mullainathan, 2003), reducing the pressure that private firms face in general. Second, listed firms can be consumers of local private firms. Third, the adoption of BC laws may affect innovation by private firms via the M&A market.

To test if the change in innovation by private firms is just a "side-product" of an overall change in the dynamism of private firms, I look at the number of small firms, employment and average wages of firms in non-innovative industries. To do so, I use the County Business Pattern data that report employment and total wages at the county-industry level and focus on firms with less than ten employees. I classify an industry as not innovative if it is below the median of R&D spending distribution in Compustat at the sic-3 digit. Columns (1) to (3) of Table A.2 in the Appendix show that there is no discernible effect for this group.

The innovation of private firms could still be indirectly affected by a decline in listed firms' overall efficiency if local private firms supply innovation for listed firms nearby. This possibility seems inconsistent with the very fast decline of spillovers with distance shown in column (3) of Table 3, unless we are willing to assume that customers-suppliers are always in the same commuting zone, but never farther apart from around 200 miles. This seems highly at odds with U.S. data. Using the Census Bureau's Commodity Flow Survey, Holmes and Stevens (2012) reports that the average distance between suppliers and customers are 529.6 miles and that less than a third of suppliers and customers are closer than 100 miles.[23] This "supplier channel" also makes no prediction regarding the role played by channels fostering knowledge diffusion and in particular the mobility of high skill workers, something I find strong evidence for. In particular, Section 5.3.2 shows that the spillovers are entirely muted in states where labor regulation highly impend inventors from moving to different firms in the same state, which should not matter if the spillovers were driven by suppliers-customers link.

In column (4) of Table A.2, I restrict my estimate to private firms in downstream industries, who are therefore selling products close to final consumers and remove from the sample all private firms in upstream industries that are more dependent on other firms' demand. I measure the degree of upstreamness using the U.S. I-O table and the methodology in Antràs, Chor, Fally, and Hillberry (2012) and consider an industry is upstream if it is above the sample median. In column (5), I remove from the sample all listed firms that report private firms among their main suppliers in Compustat Segment.[24] In both cases the point estimate of the variable *Shock Listed Firms* remains virtually unchanged.

The third possible explanation is that the adoption of BC laws affects innovation by private firms via the M&A market. One possibility is that entrepreneurs innovate in order to sell their startup to a large corporation. If the adoption of BC laws reduces listed firms' takeover demand, it might reduce potential targets' incentives to innovate (e.g. Phillips and Zhdanov (2003)). However, it is unclear why in this case the effect of innovation spillover would be so local or why it would be affected by the degree of inventor mobility. In addition, in columns (6) and (7), I estimate whether innovation by listed firms in a given commuting zone affects the likelihood to observe the acquisition of a private firm (column (6)) or a private high-tech firm (column (7)) in the same commuting zone. I

23. The SCF is a survey of the shipments originating in manufacturing, wholesale, and mining establishments. It allows for each firm in the survey to know the exact origin at the zipcode level of shipments made to the surveyed firm and therefore to construct average distance between customers and suppliers.

24. Regulation SFAS No. 131 requires firms to report selected information about operating segments in interim financial reports issued to share-holders. In particular, firms are required to disclose certain financial information for any industry segment that makes up more than 10% of consolidated yearly sales, assets, or profits as well as the identity of any customer representing more than 10% of the total reported sales.

identify the localisation of an acquired private firm using SDC Platinium. Similarly, I consider a private firm as "high-tech" if SDC indicates that the firm operates in an high-tech industry. In both cases, I find no effect.

Overall, these results provide evidence that the change in innovation by private firms is driven by a change in *innovation* by listed firms, rather than a change in other behaviors from listed firms affected by the adoption of BC laws. Since it appears unlikely that the adoption of BC laws affect private firms' innovation via another channel than the innovation of listed firms, in the remaining of the paper, I rescale *Shock Listed Firms* by the log of listed firms patents, by creating the variable *Predicted Listed Patents* such that the effect of the BC law adoption have a direct interpretation as the elasticity between listed firms' innovation and private firms' innovation.[25]

I now turn to understand the channels explaining the existence of these spillovers of innovation. There are two reasons for why a decline in innovation produced by listed firms would reduce innovation by private firms nearby. First, a change in innovation by listed firms can change the degree of competition faced by private firms in the market for ideas, thereby affecting their incentives to innovate. Second, innovation produced by listed firms can expand the amount of knowledge that private firms can use to innovate themselves, in particular since innovation activity generates "knowledge spillovers".

5.2 Competition in the Market for Ideas

The effect of competition by innovative listed firms on private firms is a priori ambiguous and will depend on the effect of competition on pre-innovation rents and post-innovation rents.[26] If we assume that lower competition reduces incentives to innovate, the competition channel would be consistent with the existence of spillovers of innovation. However, to explain these spillovers, it will have to be the case that not only listed and private firms compete in the same markets, but also that the direct competitors of private firms are in the same commuting zone, since I found that innovation spillovers decline quickly with distance. There are reasons to doubt that listed and private firms are often competing neck to neck. For instance, Holmes and Stevens (2014) using U.S. census data show that large and small firms in the same narrowly defined industry are unlikely to compete with each other and that instead are performing different functions.

To test directly if the colocation of competitors can explain innovation spillovers, I

25. Using directly the predicted variable would underestimate the standard errors. I correct for this problem by estimating 2SLS regressions.

26. If competition reduces pre-innovation rents, an increase in competition increases firms incentives to innovate to escape the competition (sometimes refers to as the "Arrow effect" (Arrow, 1972). By contrast, when competition reduces post-innovation rents, higher competition will reduce innovation (sometimes refers to as the "Schumpeter effect" (Arrow, 1972). Hombert and Matray (2018) show that when innovation improves firm product differentiation rather than firm productivity, the Arrow effect should dominate. They then estimate empirically that the return to innovate increases with product market competition.

Table 4: Innovation Spillovers: Competition with Listed Firms

Sample	Tradable (1)	High international openess (2)	Low geographic concentration (3)	Non-overlapping technologies (4)
Predicted Listed Patents	0.21*** (0.04)	0.19*** (0.04)	0.23*** (0.04)	0.20*** (0.04)
Fixed Effects				
Commuting Zone	✓	✓	✓	✓
State×Year	✓	✓	✓	✓
Commuting Zone Controls	✓	✓	✓	✓
Observations	17,125	17,125	17,125	17,125

The dependent variable is the log of patents filed by private firms. In all regressions, *Predicted Listed Patents* is the log of listed patents predicted by the adoption of BC laws. The regression is estimated with a 2SLS procedure to correct the standard errors. In column (1) I restrict to firms in tradable industries. Column (2) restricts to manufacturing industries with a value of openess ([import+export]/domestic production) above the median sample. In column (3) I drop industries with a geographical HHI of their patents above the sample median. In column (4) I drop private firms that patent in the same technologies than listed firms in the commuting zone. Standard errors are clustered at the commuting zone level.

run four tests reported in Table 4. First, I restrict the sample to firms in the tradable sector, as these firms are more likely to compete with firms across the country. Second, I restrict to industries that are more open to international trade, as a proxy for the degree to which firms compete not only across the country but also across the world. To do so I estimate the ratio of import plus export over value of domestic shipment and restrict to industries with a value above the median.[27] Third, I compute the geographical concentration of patents for all technological classes (industries) and restrict the analysis to industries that are not concentrated geographically. Concretely, I compute a geographical Herfindahl index for each technology class based on the share of a technology's patent that falls in each commuting zone. I then remove from the sample technologies with a concentration above the sample median. This implies that each innovator in the sample now has competitors in multiple commuting zones. Third, I remove private firms that are innovating in the same technological classes as the listed firms present in their commuting zone.

In all cases the point estimate remain stable and very close to the one estimated using the whole sample. In particular, column (4) forces the estimation to be made by looking at private firms that are *not* competing with listed firms. While the result may at first appears puzzling, it is important to remember that a large fraction of citations occur across very broad technological classes.[28] The fact that private firms innovating

27. imports and exports at the sic-year level come from Pete Schott website and value of domestic shipment from the NBER manufacturing dataset. Because custom data only record flows of good, this test is restricted to manufacturing firms.

28. Jaffe, Trajtenberg, and Henderson (1993) report that up to 25% of citations occur *across* five

in "Computers" benefits from the innovation of listed firms that innovate in "Drugs" or "Chemicals", suggests that the diffusion of knowledge plays an important role in explaining innovation spillovers, which is what I explore next.

5.3 Knowledge Diffusion Channels

How and why does knowledge spread locally? In this section, I explore two channels through which knowledge diffuses from innovative listed firms to other private firms in the same area: learning across local firms and inventors moving across existing firms or founding or joining local spin-outs.

5.3.1 Effect Depending on Learning Opportunities

Technological proximity. To test if the magnitude of innovation spillovers varies with the degree technological proximity between listed and private firms in the same area, I build two proxies for the potential of learning and re-estimate equation 1 by interacting the patents produced by listed firms with these proxies.[29]

First, I use the propensity of private firms to build on the knowledge produced by local listed firms with patent citations. I measure the fraction of listed patents cited by private firms in a given area over the total of all the citations made by all firms.

Second, I measure technology overlap following Jaffe (1986). For each commuting zone, I calculate the number of patents granted to each firm by technological categories.[30] The share of patents granted to firm i located in commuting zone c in each technological class s (s=1, ...425) is then arranged in a vector $T_{ic} = (T_{ic1}, \ldots\ T_{ic425})$. The technological proximity in commuting zone c is defined as the uncentered correlation coefficient between the vectors of all firm i,j pairings, calculated as: $TECH\ CORR_c = (T_{ic}T'_{jc})/[(T_{ic}T'_{ic})^{1/2}(T_{jc}T'_{jc})^{1/2}]$. The index ranges from zero to one, depending on the degree of technological overlap between firms. The closer this index is to one, the more that firms located in commuting zone c overlap in technological classes. One drawback of the Jaffe distance is that it considers proximity only within the same technology class. I correct for this problem by using the Mahalanobis Distance developed by Bloom, Schankerman, and Van Reenen (2013) that allows me to calculate a degree of technological proximity between different technology classes.

broad technological fields. When looking at the 3-digit level (approximately 450 technological fields) approximately 40% of citations are across fields.

29. To obtain the marginal additional effect that each proxy create with respect to the mean effect of *Listed Patents*, I demean all the proxies and interact them with the main variable *Listed Patents*.

30. I use the disaggregated 3-digit (425 distinct) technological categories. Results are similar when I use the smaller division in 36 categories.

Table 5: Innovation Spillovers Depending on Technology Proximity

	(1)	(2)	(3)	(4)	(5)
Predicted Listed Patents	0.17***	0.17***	0.19***	0.16***	0.18***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Predicted Listed Patents	1.92***			1.61***	1.63***
×*Tech. Prox. (Citation Listed Firms)*	(0.38)			(0.38)	(0.35)
Predicted Listed Patents		0.61***		0.50***	
× *Tech. Prox. (Jaffe Distance)*		(0.11)		(0.11)	
Listed Patents			0.04***		0.03***
× *Tech. Prox. (Mahalanobis Distance)*			(0.01)		(0.01)
Fixed Effects					
Commuting Zone	✓	✓	✓	✓	✓
State×Year	✓	✓	✓	✓	✓
Commuting Zone Controls	✓	✓	✓	✓	✓
Observations	17,125	17,125	17,125	17,125	17,125

The dependent variable is the log of patents filed by private firms. In all regressions, *Predicted Listed Patents* is the log of listed patents predicted by the adoption of BC laws. The regression is estimated with a 2SLS procedure to correct the standard errors. Each column interacts *Predicted Listed Patents* with a proxy of technology proximity. Column (1) uses the fraction of citations of patents by listed firms made by private firms. Column (2) uses the degree of overlap in technological classes based on the procedure developed by Jaffe (1986). Column (3) uses the degree of proximity across technological classes based on the Mahalanobis distance defined by Bloom et al. (2013). Column (4) uses proxies in columns (1) and (2). Column (5) uses proxies in columns (1) and (3). Standard errors are clustered at the commuting zone level.

The correlation between the technological proximity measured by the propensity to cite patents by listed firms and the two other proxies based on technological overlap across patent classes is quite low (between 20% and 30%), implying that these separate proxies allow me to capture different dimensions of technological proximity.

Table 5 reports the results. Column (1) shows the interaction with the propensity of private firms to cite listed firms' patents. Consistent with the intuition that spillovers should be more important when private firms rely more on knowledge produced by listed firms, I find that the interaction term is positive and strongly significant. In terms of economic magnitude, increasing the fraction of citations of listed firms' patents by one standard deviation increases innovation spillovers by a factor of two. Columns (2) and (3) show a similar amplification when I interact listed patents with the degree of technological proximity using the Jaffe distance and the Mahalanobis distance. Finally, columns (4) and (5) include in the regression two different measures of proximity (citations of listed firms and Jaffe distance or citation and Mahalanobis distance) and finds that each has a positive impact on spillovers. This result confirms that each measure captures a different dimension of learning opportunities that matters for local innovation spillovers.

Density of skilled workers. Marshall is among the first to notice that social interactions among workers create learning opportunities that enhance their productivity (Marshall, 1890). As he writes in his *Principles of Economics*: "(...) so great are the advantages which people following the same skilled trade get from near neighborhood to one another. The mysteries of the trade become no mysteries; but are as it were in the air, and children learn many of them unconsciously".[31]

The challenge with this channel is that economists cannot directly observe communication, discussions or gossip among workers. Instead, I exploit the prediction that spillovers should be more important in areas in which workers can interact and learn more easily from one another. In particular, I expect two commuting zones facing the same shock on listed firms' innovation to react differently depending on the density of skilled workers.[32]

I construct two measures of skilled workers: the fraction of scientists and engineers and the fraction college graduates in a given commuting zone at the beginning of my sample period. I use 1970 census data and aggregate Census Public Micro Samples at the commuting zone level.

Table 6 shows how the density of skilled workers in a commuting zone affect the magnitude of local innovation spillovers generated by listed firms. Consistent with the intuition that having a greater "brain density" fosters local innovation spillovers, I find that innovation by listed firms has a greater effect when the supply of scientists and engineers is higher.[33] Column (2) shows a similar result when I proxy learning opportunities using the supply of college graduates. The effect is economically sizable and implies that the last quartile of the college graduate distribution experiences spillovers that are twice as large as those experienced by commuting zones in the first quartile of the distribution.

The inherent limit of cross-sectional tests is that, unobserved characteristics may be correlated with the variables used in the cross-section. For instance, commuting zones with a higher supply of college graduates might also differ in other dimensions such as investment opportunities which could also foster local innovation spillovers. Ideally, we would like to instrument every variable. Although I cannot (unfortunately) find different instruments for each variable, the literature on agglomeration economics has suggested two possible instruments for the share of college graduates.

The first instrument builds on Beaudrey, Doms, and Lewis (2010) and uses the share of 15–19 year-olds enrolled in school in 1880, which proxies for the local availability of high schools at that time. To provide a valid instrument, this deep lagged variable must

31. Or as Glaeser, Kallal, Scheinkman, and Shleifer (1992) write more directly: "After all, intellectual breakthroughs must cross hallways and streets more easily than oceans and continents."

32. In her study of knowledge sharing in the Silicon Valley, Saxenian (1999) notes: "The initial social connections often have a basis in shared educational experiences, technical backgrounds, (...)".

33. Because all my proxies are time invariant, the simple term is absorbed by the commuting zone fixed effect.

Table 6: Innovation Spillovers Depending on Skilled Worker Supply

	(1)	(2)	(3)	(4)
Predicted Listed Patents	0.18***	0.18***	0.20***	0.17***
	(0.04)	(0.04)	(0.04)	(0.04)
Predicted Listed Patents × *S&E Supply*	0.05***			
	(0.01)			
Predicted Listed Patents × *College Graduate*		0.91***		
		(0.16)		
Predicted Listed Patents × *College Graduate (IV 1)*			0.89**	
			(0.38)	
Predicted Listed Patents × *College Graduate (IV 2)*				1.12***
				(0.36)
Fixed Effects				
Commuting Zone	✓	✓	✓	✓
State×Year	✓	✓	✓	✓
Commuting Zone Controls	✓	✓	✓	✓
Observations	17,125	17,125	17,125	17,125
F-test(Enrollement 1880)	—	—	13	—
F-test(Land Grant)	—	—	—	48

The dependent variable is the log of patents filed by private firms. In all regressions, *Predicted Listed Patents* is the log of listed patents predicted by the adoption of BC laws. The regression is estimated with a 2SLS procedure to correct the standard errors. Column (1) reports the effect when the patents by listed firms is interacted with the supply of scientists and engineers (S&E) in a given commuting zone-year. Column (2) uses the supply of college graduates in a given commuting zone-year. Columns (3) and (4) instrument the supply of college graduate. In column (3), the instrument is the share of 15-19 year-old enrolled in school in 1880, constructed from 1880 US Census-10%. In column (4), the instrument is a dummy equal to one if the commuting zone contained a college created via the "Land Grant Movement" in 1862 and 1890 (Nervis, 1962). Standard errors are in parentheses and clustered at the commuting zone level.

be uncorrelated with current local economy specialization and technology development, which would not be the case if school enrollment in 1880, for instance, was correlated with physical capital at that time and if capital has built up over time. In this case, capital accumulation would make the area more productive, violating the exclusion condition of the instrument. Beaudrey, Doms, and Lewis (2010) argues that capital and skill were more substitutes than complements prior to the twentieth century (Goldin and Katz, 2008). Therefore, the reasons why some areas had better high schools in 1880 were unlikely to be related to economic and technological development in 1880 and in the following periods.

High school enrollment in 1880 is a good predictor of the share of educated workers a century later with an F-stat of 13. Column (3) of Table 6 reports the effect of increasing the share of the college-educated population on the magnitude of local innovation spillovers when I instrument *College Graduate* by *School Enrollment 1880*. Again, I find a positive effect, with a similar order of magnitude.

The second instrument uses the presence of college and universities created in the nineteenth century following the "land-grant movement", which still strongly predicts cross-sectional variation in college share today. Following two acts in 1862 and 1890, the federal government gave every state a grant to establish colleges, which resulted in the creation of 69 colleges and universities, with each state having at least one. Because this program was undertaken more than a century ago and was not dependent on natural resources,[34] land-grant institution is unlikely to be correlated with unobservable factors that affect innovation today.

Using the list of all land-grant institutions provided in the appendix of Nervis (1962), I create a dummy variable *Land-Grant* which is equal to one if the commuting zone contains at least one land-grant institution. I end up with 63 distinct commuting zones with at least one land-grant institution (in only six cases the commuting zone contains two land-grant institutions). When I regress the average share of college graduates over the sample period on the *Land-Grant* dummy, I obtain a very significant effect, with a F-stat of 89.

Column (4) shows the result when I instrument *College Graduate* by *Land-Grant* and confirms again that increasing the share of college graduates (in this case because the commuting zone has one land-grant institution) increases the innovation spillovers generated by listed firms.

5.3.2 Local Inventor Mobility and Spin-outs

The second channel through which knowledge can be transferred locally from one firm to another is by inventors moving across firms in the same area. New workers can share ideas regarding how to organize research production, information about new technologies or about failed experiments that they experienced with previous employers.

I use two strategies to test this channel. First, I build on the literature studying the effects of "Non Compete Covenants Law". These laws restrict intrastate job mobility, because they specify a period during which employees cannot take a job with a competing company (typically within the same industry) located in the same state. By affecting the mobility rate of employees, non-compete laws should affect the speed at which knowledge diffuses locally (e.g. Stuart and Sorenson, 2003; Jeffers, 2019).

I create two measures of state-level differences in enforcing non-compete covenants. The first follows Stuart and Sorenson (2003) and is a dummy variable *Presence of Non-Compete Laws*: this variable equals one if the state enforces non-compete covenants. The second follows Garmaise (2009) and is an index ranging from 0 to 7 that counts the number of employer-friendly provisions: higher values indicate stronger enforceability

34. See Moretti (2004a), Nervis (1962) for a detail history of the land grant movement. From today's perspective, Moretti argues that "the geographical location of land-grant colleges seems close to random."

Table 7: Innovation Spillovers Depending on Non-Compete Laws

Sample	All	Exc. California	All	Exc. California
	(1)	(2)	(3)	(4)
Predicted Listed Patents	0.21***	0.21***	0.32***	0.34***
	(0.03)	(0.03)	(0.07)	(0.07)
Predicted Listed Patents×Presence of Non-Compete Law	-0.08*	-0.09**		
	(0.04)	(0.04)		
Predicted Listed Patents ×Intensity of Non-Compete Law			-0.04**	-0.04***
			(0.01)	(0.01)
Fixed Effects				
Commuting Zone	✓	✓	✓	✓
State×Year	✓	✓	✓	✓
Commuting Zone Controls	✓	✓	✓	✓
Observations	17,125	16,675	17,125	16,675

The dependent variable is the log of patents filed by private firms. In all regressions, *Predicted Listed Patents* is the log of listed patents predicted by the adoption of BC laws. The regression is estimated with a 2SLS procedure to correct the standard errors. All regressions include commuting zone, year and state×year fixed effects. Column (1) reports the effect when patents by listed firms are interacted with a dummy indicating whether the commuting zone is in a state that enforce non-compete covenants (Stuart and Sorenson, 2003). Columns (2) and (4) exclude California. Column (3) uses the degree of enforceability of non-compete laws as an interaction term reported in Garmaise (2009). Standard errors are in parentheses and clustered at the commuting zone level.

of non-compete laws. Therefore, an increase in *Intensity of Non-Compete Law* implies greater difficulty for employees to move from one firm to another.

I then interact each variable with the patents produced by listed firms. I expect that if knowledge is diffused by labor mobility, more stringent non-compete laws should limit local innovation spillovers.

Table 7 shows that the magnitude of spillovers is affected by non-compete laws. Column (1) reports the result when I use the dummy variable *Presence of Non-Compete Laws*. Being in a state that enforces non-compete covenants reduces innovation spillovers by 0.8, which is nearly half of the average effect. In columns (2) and (4), I exclude California from the sample because cities in California are characterized by a higher rate of mobility of high-skilled workers than cities in other states and are also more innovative. I find a slightly stronger effect. Column (3) shows the result when I use the degree of enforceability of non-compete laws and confirms that enforcement of non-compete covenants (an increase in the index) limits knowledge diffusion locally by reducing labor mobility, which ultimately reduces local innovation spillovers. The point estimate of the interaction term is equal to -0.04, which implies that an increase in the enforcement of non-compete covenants strongly reduces local innovation spillovers. Taken together, these results suggest that states can have an important impact on the ability for local agglomerations to generate innovation spillovers by affecting the rate of labor mobility across local firms.

The second strategy to identify whether local innovation spillovers are the result of inventors moving across firms in the same area is to estimate directly whether variation in innovation by listed firms affects the number of mobile inventors within a commuting zone. To perform this estimation, I use the unique inventor identifier provided by Lai, D'Amour, and Fleming (2009) that permits me to track inventors across firms and zipcodes.[35]

To measure inventor moving across local firms, I follow papers such as Marx, Strumsky, and Fleming (2009) or Hombert and Matray (2017) and identify an inventor as changing employers when she files two successive patent applications that are assigned to different firms. Because I am interested in innovation spillovers in a given commuting zone from listed firms to private firms, I define an inventor as moving if: (i) the inventor's employer is different from the previous employer, (ii) the current employer is a private firm and the former employer is a listed firm, and (iii) the inventor was working in the same commuting zone.[36]

I construct the following three measures: *# Mobile Inventors from Listed Firms*$_{ct}$ is the number of inventors who work in a private firm at year t in commuting zone c, but who previously worked in a listed firm located in the same commuting zone. *Share of Mobile Inventors from Listed Firms*$_{ct}$ is the fraction of mobile inventors who worked in a listed firms located in the same commuting zone over the total of all mobile inventors who arrive in private firms in year t in commuting zone c, and *Share Inventors Previously in Listed Firms*$_{ct}$ is the share of all inventors working for private firms in year t in commuting zone c that formerly worked for a listed firm located in the same commuting zone.

I also explore a specific type of inventor mobility: entrepreneurial spin-out. In this case, inventors formerly employed by a listed firm may decide to leave their employer, to join a newly founded local spin-out in which they can exploit the knowledge and experience they previously accrued (Audretsch, 1995; Gompers, Lerner, and Scharfstein, 2005). I define a spin-out as follows. Using the unique firm identifier in the NBER patent data, I identify first all the new private firms that appear in the database. Then, I look at all the inventors who work for a new firm in the first year after it appears. If at least one of the inventors formerly worked for a listed firm in the same commuting zone previously, I consider the new firm to be a spin-out. I end up with 22,627 spin-outs, which represents 20% of the total of new firms I observe in the patent data.

35. Although patent data include the names of the inventors of every patent, they do not, however, provide consistent listings of inventor names or unique inventor identifiers. To overcome this problem, Lai, D'Amour, and Fleming (2009) develop a disambiguation algorithm to create unique inventor identifiers

36. When I observe a firm change, I do not know precisely when it occurred within the time interval between the two observations, which is however, unlikely to be a major problem because the average time between two consecutive observations is only 2.4 years. In the main analysis, I consider that the move occurs at the midpoint of the time window between the two observations. In unreported regressions, I obtain similar results when assuming that the move occurs at the earliest date or at the latest date.

Table 8: Effect on Inventor Mobility from Listed Firms to Private Firms

Dependent variable	# Mobile Inventors from Listed Firms	Share Mobile Inventors from Listed Firms	Share Inventors Previously in Listed Firms	# Spin-outs
	(1)	(2)	(3)	(4)
Predicted Listed Patents	0.06***	0.05***	0.02***	0.09***
	(0.02)	(0.01)	(0.00)	(0.02)
Fixed Effects				
Commuting Zone	✓	✓	✓	✓
State×Year	✓	✓	✓	✓
Commuting Zone Controls	✓	✓	✓	✓
Observations	17,125	17,125	17,125	17,125

This table shows the mobility of inventors to private firms within the same commuting zone. In all regressions, *Predicted Listed Patents* is the log of listed patents predicted by the adoption of BC laws. The regression is estimated with a 2SLS procedure to correct the standard errors. Column (2) reports the fraction of mobile inventors who come from listed firms over the total of mobile inventors to private firms. Column (3) uses the fraction of inventors currently employed by private firms who formerly worked for a listed firm in the same commuting zone. Column (4) reports the number of spin-outs (defined as new private firms employing, in the first year they file patents, inventors formerly employed by a listed firm in the same commuting zone). Standard errors are in parentheses and clustered at the commuting zone level.

Table 8 shows how innovation by listed firms in a given commuting zone can affect inventor mobility flow from listed firms to private firms in the same area. Column (1) finds that an increase in listed patents generates a higher number of inventors who move from listed firms to private firms. Column (2) shows that this effect is not simply due to an increase in overall mobility, but that inventors formerly working for listed firms represent a higher fraction of mobile inventors who come to work at a new private firm. Finally, column (3) adopts a static view and checks whether this increased local flows of mobile inventors affect the composition of employment in private innovative firms. I find that inventors who formerly worked for a listed firm represent an increasing fraction of inventors employed by private firms. In terms of magnitude, doubling patents by listed firms increases the share of inventors employed by private firms who formerly worked for listed firms by 50%. Finally, column (4) shows that spin-out creation in the commuting zone increases with patents produced by listed firms locally, which provides direct evidence that local innovation spillovers are produced in part because former employees join spin-outs created in the same area and benefit in this manner from the knowledge produced in their previous firm.

6 Local Innovation Spillovers and Venture Capital

In this section, I investigate how local innovation spillovers interact with investment by VC funds. If innovation by listed firms active in a commuting zone fosters innovation by local private firms, we should expect VC funds from outside the commuting zone to invest more in the local area where those innovation spillovers occur. Conversely, we should expect capital availability to affect the magnitude of local innovation spillovers as private firms are likely to be credit constraints.

6.1 Capital Inflows

To study VC funds geographical investments, I use VentureXpert, which records both the geographic localization (zipcode) of the VC fund and the localization of the company in which the fund makes an investment. This allows me to identify precisely when and where investments are made and whether the investments come from a fund located in a different area.

I use two different proxies for the ability of commuting zones to attract out-of-town VC money: the number of investments made and the total value of all investments made in a given commuting zone-year. Each variable is in logs and calculated only for non-local VC funds.

Because the VC industry is highly clustered in three metropolitan areas (combined statistical areas or CSAs) in the US (San Francisco/San Jose, Boston, and New York) I estimate the different models on the entire sample and then I exclude the 16 commuting zones that belong to these three areas.

Column (1) of Table 9 shows the result for the number of different investments and reports that patents filed by listed firms in a given commuting zone in the previous years increase the likelihood that this commuting zone attracts investment from VC funds located in other commuting zones. Column (3) show similar results when I use the total money invested in a commuting zone-year. Columns (2) and (4) report that the effects are similar when I exclude "VC centers" from the sample.

This result is notable because non-local investments are rare in the VC industry (Chen, Gompers, Kovner, and Lerner, 2010). Indeed, VC firms must to interact frequently with companies in which they invest, to either monitor or coach the management team (e.g. Lerner, 1995).

6.2 Effect Depending on Capital Availability

In this section, I investigate whether venture capital availability influences the magnitude of spillovers, something that has received little attention in the literature thus far. To do

Table 9: Capital Inflow: Investments by Non-Local VC Funds

Dependent variable	# Investments		Total Value	
	(1)	(2)	(3)	(4)
Predicted Listed Patents	0.045**	0.045**	0.227**	0.218**
	(0.022)	(0.021)	(0.097)	(0.097)
Fixed Effects				
Commuting Zone	✓	✓	✓	✓
State×Year	✓	✓	✓	✓
Commuting Zone Controls	✓	✓	✓	✓
Observations	17,125	17,125	17,125	17,125
Sample	All	Exc. VC centers	All	Exc. VC centers

In all regressions, *Predicted Listed Patents* is the log of listed patents predicted by the adoption of BC laws. The regression is estimated with a 2SLS procedure to correct the standard errors. In columns (1) and (2), the dependent variable is the number of VC investments made by non local VCs. Columns (3) and (4) examine the total amount invested by non-local VC funds. Columns (2) and (4) exclude from the sample commuting zones considered as VC centers (Chen et al. 2010). All dependent variables are in log. Standard errors are in parentheses and clustered at the commuting zone level.

so, I interact the variable *Listed Patents* with the total amount of investments made by VC funds.

To generate exogenous variation in the local availability of capital, I build on the literature showing that public pension funds display a "home-bias" and are more likely to invest the asset under their management in local private equity funds and venture capital funds. As a result, fluctuations in public pension assets in the home-state of VC funds will affect the ability of domestic VC funds to raise capital, which will generate variation in the amount of money they can invest.

I obtain data for state public pensions from the State and Local Government Public-Employee Retirement Systems annual survey conducted by the Census Bureau and available since 1970.[37] I compute the amount of asset holdings of the state pension fund for every year and use it as the instrument for the total amount of VC investments made at the state level.

Table 10 reports the results for the different proxies. In column (1), I use the volume of investment made by VC funds in log in a given state-year and find that greater levels of VC investment increase the magnitude of local innovation spillovers. The interaction term is positive and statistically significant at the 1% level. However, because VC investments are likely to be endogenous with innovation activity realized by listed firms, I instrument VC investments by the amount of local and state public pension funds in column (2).

37. Data from 1993 forward may be directly downloaded from https://www.census.gov/govs/retire/. Historical data are available upon request.

The first stage produces an F-stat of 30. The IV estimate yields similar results and shows that exogenous variation in the amount of VC capital available amplify local innovation spillovers. The magnitude of the amplification is important because, as moving from the 25^{th} percentile to the 75^{th} percentile increases the elasticity by more than 0.4, which is twice the size of the average effect. Column (3) reproduces the analysis when I again exclude those commuting zones belonging to a "VC center" and shows a similar effect.

Table 10: Innovation Spillovers Depending on Fund Availability

	(1)	(2)	(3)
Predicted Listed Patents	0.16***	0.17***	0.17***
	(0.02)	(0.02)	(0.09
Predicted Listed Patent× VC	0.02***		
	(0.00)		
Predicted Listed Patent× VC (IV)		0.05***	0.05***
		(0.01)	(0.01)
Fixed Effects			
Commuting Zone	✓	✓	✓
State×Year	✓	✓	✓
Commuting Zone Controls	✓	✓	✓
Observations	17,125	17,125	17,125

The dependent variable is the log of patents filed by private firms. In all regressions, *Predicted Listed Patents* is the log of listed patents predicted by the adoption of BC laws. The regression is estimated with a 2SLS procedure to correct the standard errors. Column (1) reports the effect when the patents produced by listed firms is interacted with the amount of VC investments made in the state (in log and demean to restore main effects). Column (2) instruments the amount of VC investments using the value of assets held by local and state pension funds. In the first stage, the coefficient on this variable is 0.30 with an F-statistic of 30. Column (3) excludes from the sample commuting zones considered as VC centers (Chen et al. 2010). Standard errors are in parentheses and clustered at the commuting zone level.

Overall, these results demonstrate that capital relocates to areas in which local innovation spillovers occur and that in return, capital availability amplifies the magnitude of these local innovation spillovers, which thus suggests that capital mobility can contribute to increase differences between geographic entities rather than to narrow such differences.

7 Robustness

In Table A.3, I explore the robustness of my main result. In column (1), I add a specific technological trend at the commuting zone level to my main specification. Differences in sectoral growth rates or changing propensities to seek patents might affect my findings if for instance, the commuting zones in which patents by listed firms increase more are simultaneously initially more specialized in a growing sector. I thus include a measure of expected commuting zone-level patenting based on pre-period technological specialisation and national patenting trends. To predict patenting growth based on initial specialization, I calculate the initial innovation specialization using the 37 different "technological subcategory" (variable *subcat* in the NBER Patent database) and interact this specialization with the aggregate patenting growth of each in each of the 37 categories. I interact the variable with a time trend and add it as a control. In columns (2) to (4) I exclude various commuting zones / firms. In columns (2) and (3) I exclude various commuting zones to ensure that my estimate does not reflect the specificity of certain cities (and in particular the most innovative ones). In column (2), I exclude all the commuting zones that belong to one of the five main high-tech clusters identified by Belenzon and Schankerman (2013): Austin, Boston, Raleigh-Durham, San Diego, and Silicon Valley (namely San Francisco-Oakland-San Jose). In column (3), I directly exclude all the commuting zones within California and Massachusetts which are the two most innovative states. In both cases, the estimates are similar to the initial result. Finally, column (4) excludes patents by listed firms that are incorporated in Delaware and column (5) exclude patents that are filed in commuting zones located in the state in which the listed firm has its headquarter. Again, my results remain unaffected.

8 Conclusion

Using a novel strategy to generate local shocks on the innovation activities of listed firms, I provide evidence for the existence of complementarities between the innovation of listed firms and private firms. Those complementarities explain why a shock on the innovation production of some firms can transmit to the rest of the local economy, although other firms are not directly hit by the shock.

I then explain these complementarities with local information transmission and identify different channels through which this transmission may occur. In particular, the ease with which workers can exchange ideas and learn from one another, the possibility for workers to move from one firm to another and to create their own firms are all channels through which knowledge is transmitted within the local area. Those results also suggest that state policies can play an important role in affecting the magnitude of local innovation spillovers by shaping the ability for local markets to absorb new knowledge and affecting labor mobility.

Finally, I find that local innovation spillovers generated by listed firms induce venture capital funds from outside the area to invest more into areas where local innovation spillovers happen because these places become more productive. I also find that variation in the amount of capital available amplifies the magnitude of innovation spillovers. This last result suggests that finance could be an important factor for explaining the important disparities between cities in terms of economic specialization, entrepreneurship and growth, etc. If capital follows innovation and in return magnifies economic spillovers, small differences between areas can become rapidly amplified

Assessing exactly and to what extent capital flow is responsible for how agglomerations are formed, sustained and strengthened offers interesting avenues for future research.

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A Appendix

A.1 Construction of variables

Education Variables:

All Data for the education variables are available from WebCASPAR (https://ncsesdata.nsf.gov/webcaspar/)

Number of College Institutions: Data comes from IPEDS Enrollment Survey (Years available: 1967-2012). I obtain the list of enrolled students by institutions using the "Fall Enrollment (NSF popuplation of institutions)" survey. Institutions are located by zipcodes. I then map the zipcodes with county identifiers and then counties with Commuting Zone using the crosswalk from David Autor Website.

Number of Earned Doctorates: Data comes from NSF Data sources "NSF Survey of Earned Doctorates/Doctorate Records File" (Years available: 1966-2012). I use the "Number of Doctorate Recipients by Doctorate Institution". Institutions are identified by their zipcodes. I map zipcode with counties and counties with commuting zone.

R&D conducted by Universities: Data comes from NSF Data sources "NSF Survey of Research and Development Expenditures at Universities and Colleges/Higher Education Research and Development Survey" (Years available: 1972-2012).

Commuting Zone Characteristics:

Population and population characteristics come from Census "Population Estimates" (http://www.census.gov/popest/data/historical/)

Urbanisation: Share of population living in an urban area. Data comes from Census. Available from NHGIS https://www.nhgis.org/

Density: Total population scaled by area in square miles (variable $v27$) from Census of Population and Housing, 1990 (ICSPR 21983).
(http://www.icpsr.umich.edu/icpsrweb/ICPSR/studies/21983)

Share Black: Share of population who is black. Data comes from Census "Population Estimates". Data are collected at the county level and aggregated at the commuting zone level.

Share Women: Fraction of women over total population. Data comes from Census "Population Estimates".

Industry Specialisation: Data comes from BEA Local Area Personal Income. Industries are measured using total employment per sector. The list of sectors is the following: Agriculture (linecode 70), Forestry (linecode 100), Mining (linecode 200), Construction (linecode 300), Manufacturing (linecode 400), Transport (linecode 500), Wholetrade (linecode 610), Retail (linecode 620), FIRE (linecode 700), Services (linecode 800), Government (linecode 900).

Share Self-Employed: defined as total self-employed (linecode 260) divided by total population (linecode 100). Data comes from BEA Local Area Personal Income. Table "Personal income, per capita personal income, population".

Technology Age: for each technology class (*nclass*) year, I calculate the median age of innovative firm (defined as the number of years since first appearance in the database). I then take the average for each commuting zone-year cell.

A.2 List of Scientists and Engineers: Census 1990 occupation

Engineers correspond to the following occupations: Aerospace engineers (44) Metallurgical and material engineers (45), Petroleum, mining and geological engineers (47) Chemical engineers (48), Civil engineers (53), Electrical engineers (55), Industrial engineers (56), Mechanical engineers (57), Engineers and other professionals, n.e.c (59).

Scientists correspond to the following occupations: Computer systems analysts and computer scientists (64), Operations and systems researchers and analysts (65), Actuaries (66), Mathematicians and statisticians (68), Physicists and astronomists (69), Chemists (73), Atmospheric and space scientists (74), Geologists (75), Physical scientists, n.e.c. (76), Agricultural and food scientists (77), Biological scientists (78), Foresters and conservation scientists (79), Medical scientists (83).

Table A.1: . Business Combination Laws Adopted by State and Year

This table reports the states that adopted a business combination law along with the year in which the law was adopted. To identify when BC laws were adopted in each state, I use the dates for 30 states that adopted laws between 1985 and 1991, as reported in Bertrand and Mullainathan (2003) and augment their list using Pinnell (2000)-Oregon in 1991, and Iowa and Texas in 1997.

Arizona (1987)	Nevada (1991)
Connecticut (1989)	New Jersey (1986)
Delaware (1988)	New York (1985)
Georgia (1988)	Oklahoma (1991)
Idaho (1988)	Ohio (1990)
Illinois (1989)	Oregon (1991)
Indiana (1986)	Pennsylvania (1989)
Iowa (1997)	Rhode Island (1990)
Kansas (1989)	South Carolina (1988)
Kentucky (1987)	South Dakota (1990)
Maine (1988)	Tennessee (1988)
Maryland (1989)	Texas (1997)
Massachusetts (1989)	Virginia (1988)
Michigan (1989)	Washington (1987)
Minnesota (1987)	Wisconsin (1987)
Missouri (1986)	Wyoming (1989)
Nebraska (1988)	

Table A.2: . Alternative Stories

Dependent variable	Employment	Average Wage	Number of Firms	Patents Private		Any M&A Private Firms	Any M&A Private Innovative Firms
Sample	Non-Innovative Industries			Exc. Upstream Private	Exc. Private Supplier	All	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Shock Listed Firms	0.001	0.002	0.005	0.088***	0.091***	0.011	-0.001
	(0.005)	(0.008)	(0.007)	(0.019)	(0.018)	(0.021)	(0.01)
Fixed Effects							
Commuting Zone	✓	✓	✓	✓	✓	✓	✓
State×Year	✓	✓	✓	✓	✓	✓	✓
Commuting Zone Controls	✓	✓	✓	✓	✓	✓	✓
Observations	17,125	17,125	17,125	17,125	17,125	17,125	17,125

In columns (1) to (3), dependent variables are computed using the County Business Pattern and restricting to industries with below median investment in R&D. In column (4) remove from the dataset all industries with a "Upstreamness" values above the sample median, as defined by Antràs, Chor, Fally, and Hillberry (2012). Column (5) remove all listed firms that reports at least one private firm as a supplier in Compustat Segment. Columns (6) and (7) use as a dependent variable a dummy equal to one if at least one private firm (column (5)) or one private and innovative firm (column (6)) has been observed in a commuting zone-year cell. Data on M&A come from SDC Platinium. Standard errors are in parentheses and clustered at the commuting zone level.

Table A.3: Effect of Innovation by Listed Firms on Innovation by Private Firms: Robustness

Sample	All (1)	Exc. TechPole (2)	Exc. TechStates (3)	Exc. Delaware (4)	Exc. State HQ (5)
Predicted Listed Patents	0.16***	0.16***	0.18***	0.17***	0.17***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Fixed Effects					
Commuting Zone	✓	✓	✓	✓	✓
State×Year	✓	✓	✓	✓	✓
Commuting Zone Controls	✓	✓	✓	✓	✓
Technological Trend	✓	—	—	—	—
Observations	17,125	17,125	17,125	17,125	17,125

The dependent variable is the log of patents filed by private firms. In all regressions, *Predicted Listed Patents* is the log of listed patents predicted by the adoption of BC laws. The regression is estimated with a 2SLS procedure to correct the standard errors. All regressions include commuting zone, Year and State x Year fixed effects. Column (1) includes a measure of expected commuting zone-level patenting based on its initial specialisation times a time trend. Column (2) excludes commuting zones belonging to one of the following "Tech Pole": Austin-San Marcos (TX) Boston-Worcester-Lawrence-Lowell-Brockt (MA), Raleigh-Durham-Chapel Hill (NC) or San Francisco-Oakland-San Jose (CA). In column (3) I exclude California and Massachusetts. Column(4) excludes listed firms whose state of incorporation is in Delaware. Column (5) uses only public patents in commuting zones different from the state of headquarter. Standard errors are in parentheses and clustered at the commuting zone level.