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. I also find that such local innovation spillovers decline rapidly with distance. Second, I find that local innovation spillovers stem at least in part 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 lead venture capital funds from outside the area to invest more in the local area, and that conversely capital availability amplifies local innovation spillovers.

Keywords: innovation spillovers, knowledge diffusion, economic geography, patents, financing of innovation

JEL codes: K41, L24, O31, O34

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1 Introduction

Innovation activities tend to be geographically concentrated and in particular, much more so than manufacturing employment (Audretsch and Feldman, 1996). The success of innovation clusters such as Silicon Valley is often explained by local networks of innovative firms helping diffuse knowledge across firms (e.g. Saxenian, 1994). It has motivated large investments by governments to promote such clusters (e.g. Lerner, 2011). 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 (Katz and Muro, 2013).[1] Supporters of such policies often stress that knowledge produced by large firms will benefit neighboring smaller firms, as appears to be the case with Seattle's innovation cluster that began developing after Microsoft relocated its headquarters in 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 (Carlino and Kerr, 2014). Indeed, establishing a causal link is difficult because of the "reflection problem" (Manski, 1993) whereby innovation trends for all firms are driven by the same underlying factors. For instance, innovative firms may cluster in areas with attractive attributes, such as leading research universities, benign weather conditions, tax advantages, etc. In this case, common innovation trends would not result from positive spillovers but simply from local area characteristics.

To disentangle local innovation spillovers from the effects of local conditions, I instrument listed firms' innovation in a given geographical area with a regulatory shock in a different state. The shock is caused by the staggered adoption by individual states of business combinations (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" or to "play it safe" (Bertrand and Mullainathan, 2003; Gormley and Matsa, 2014). This resulted in a decrease in innovation by listed firms, even in areas outside their state of incorporation

[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 (2004c), Feldman and Kogler (2010) and Carlino and Kerr (2014).

(Atanassov, 2013).

BC laws provide an appealing instrument because they cause local areas to experience variations in innovation driven by out-of-state shocks and because they affect innovation by listed firms but not by private firms. My hypothesis is that local innovation spillovers happen mostly because changes in listed firms's innovation in a given area directly affect innovation by private firms in the same area. I limit the concerns that local private firms may be affected by other changes produced by BC laws by removing state-year unobserved heterogeneity and by controlling for important economic characteristics at the local area level. I also provide multiple cross-sectional tests consistent with the fact that local innovation spillovers happen because knowledge diffuses locally.

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 address and employer. Inventor addresses allow me to allocate innovations to different Commuting Zones (CZ), i.e. local geographic areas encompassing all metropolitan and non-metropolitan areas in the US (e.g. Tolbert and Size, 1996; Autor and Dorn, 2013). I consider that a firm is active in a CZ if it files patents in that CZ. 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 geography of patenting. On average, listed firms file patents in 12 different CZs vs. 1.5 for private firms. Moreover, listed firms file less than 20% in their state of incorporation.

Local areas experience variations in innovation driven by out-of-state shocks at different points in time, depending on when a given state adopts a BC law, and 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 by neighboring listed firms as implied by the adoption (or not) of BC laws in their state of incorporation.

In the first part of the paper, I study how important local innovation spillovers are and how local they are. I find that listed firms generate positive and economically significant innovation spillovers onto private firms in the same local area. On average, a change in one patent to the stock of patents held by listed firms in a CZ leads to a similar change in 0.14 patent filed by private firms in the same CZ. This result is robust to the inclusion

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

of controls for CZ-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, innovation by listed firms in a given CZ have spillovers mostly for private firms in the same CZ. For private firms in other CZs within 100 miles, innovation spillovers are still positive, but small: the elasticity is divided by a factor of more than three. Beyond 100 miles, innovation spillovers are undistinguishable from zero.

Next, I turn to the mechanisms underlying local innovation spillovers. Agglomeration can foster innovation by reducing the costs of accessing inputs, workers and knowledge, knowledge diffusion being likely to be particularly important (Carlino and Kerr, 2014). In the second part of the paper, I study two main channels of knowledge diffusion (Audretsch and Feldman, 2004): learning across 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 listed firms innovating locally, i.e. 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 assimilate and apply new knowledge may be more important (e.g. Moretti, 2004b). For each CZ, I calculate the supply of college graduate workers at the beginning of the period. I find that CZs in the 75th percentile of the distribution of educated workers experience local innovation spillovers that are twice as large as those of CZs in the 25th percentile. I find similar results using instruments that exploit historical differences in the supply of colleges to predict the fraction of educated workers.

Second, I find evidence of knowledge diffusion via employees moving across local firms. In a first test, I exploit variations across states in the enforcement of non-compete clauses that limit worker mobility, I find that CZs in states that restrict non-compete clauses experience local innovation spillovers that are twice as large as those in states that do not.

I also study how variations in the stock of patents by listed firms affect 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 CZ innovate more, VC funds located outside that CZ increase the volume of their investments in that CZ. On average, a one standard deviation increase in the stock of patents by listed firms in a CZ 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 (e.g. Chen et al. 2010).

Second, I examine whether conversely, exogenous fluctuations in local capital availability amplifies local innovation spillovers (e.g. by enabling local firms to finance innovations). To do so, I instrument the amount of VC capital available locally using variation in state pension funds. Because state pension funds invest disproportionably in local investment funds (e.g. private equity, venture capital funds), local investment funds raise capital more easily when local pension pools are larger (e.g. Bernstein et al. 2010; Hochberg and Rauh, 2012; Gonzalez-Uribe, 2014). I find that CZs in the 75th percentile in the distribution of VC financing experience local innovation spillovers that are twice as large as those in CZs in the 25th percentile.

Finally, I conduct robustness checks and, in particular, I assess the sensitivity of my results to two alternative channels: a product market competition channel, whereby changes in competition triggered by BC laws would affect innovation by private firms and, a demand channel whereby in response to BC laws, listed firms would generate a demand for technologies that increases innovation by private firms. The findings suggest that these alternative channels are unlikely to play a major role in explaining the comovements in the innovation activity of listed and of private firms.

Taken together, the paper's results show evidence that sizeable local innovation spillovers exist, that are at least partly driven by knowledge diffusion via learning across local firms as well as employee and inventor mobility across local firms. Furthermore, these spillovers attract capital to the area which in turn amplifies the spillovers. These findings point to possible policy implications. Indeed, 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 innovation clusters stem from innovation spillovers, subsidies can be justified.[4] My findings also suggest that local innovation spillovers can be amplified by policies promoting intrastate labor mobility (e.g. by restricting non compete clauses), improving the supply of skilled labor (e.g. via the construction of college institutions) and improving access to capital.

The paper proceeds as follows. Section 2 reviews the relevant literature and states my hypotheses. Section 3 presents the data. Section 4 describes the framework and discusses specification and measurement errors. Section 5 reports the empirical results. Section 6 concludes.

2 Literature Review and Hypothesis Development

2.1 Literature Review

My paper contributes to the literature studying how corporate investment is shaped by the economic environment and in particular by neighboring firms. This question has been studied for investment in general (Dougal, Parsons and Titman, 2013; Fresard and Foucault, 2014), as well as for firm creation (Doms, Lewis and Robb, 2010; Guiso, Pistaferri and Schivardi, 2014) and innovations in particular (e.g., 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.[5] 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, a recent stream of the corporate finance literature has recently begun to studied how performance and behavior are shaped by firms' economic and geographic proximities to other firms with respect to stock prices and sales (Cohen and Frazzini, 2008; Barrot and Sauvagnat 2014), leverage (Leary and Roberts, 2014), corruption (Parsons, Sulaeman and Titman, 2014) and/or bankruptcy (Bennmelech, Bergman, Milanez and

[4]The existence of spillovers constitutes a rationale for location-based policies but does not imply these to improve aggregate welfare. See e.g. Glaeser and Gottlieb (2008) or Kline and Moretti (2014).

[5]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. A similar approach is used in Lychagin et al. 2010

Mukharlyamov, 2014).

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 "mimick" 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. 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.

Therefore, I also relate 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., Bernstein and Nadiri, 1989; Griliches, 1992; Adams and Jaffe, 1996; Peri 2005 or Bloom et al., 2013 and references therein), the supply of college graduates (e.g., Rauch, 1993; Moretti, 2004a, 2004b), population density (e.g., Ciccone and Hall, 1996; Glaeser, 1999; Glaeser and Resseger, 2010) or firm density (Carlton, 1983; Rosenthal and Strange, 2003; Henderson, 2003; Greenstone, Hornbeck and Moretti, 2010; Guiso and Schivardi, 2011; Guiso et al. 2014).

Finally, my paper builds on the literature studying the importance of anti-takeover laws, by studying spillovers produced by changes in corporate governance. The literature typically estimates the evolution of firm outcomes when the firm is *directly* affected by a change in corporate governance and in particular, how this type of change can lead firms to take less risk.[6] One important feature of my paper is that I do not examine firms that are directly affected by antitakover laws at the firms *surrounding* them.

2.2 Hypothesis Development

A priori, the effect of innovation by listed firms on local private firms is unclear. Innovation by firms in the same area may be strategic substitutes for at least two reasons. If firms are rivals and an increase in innovation by a given firm improves its competitive position, it will reduce the marginal profitability of other firms regarding innovative investment,

[6] Antitakeover laws have been associated with reductions in firm leverage (Garvey and Hanka, 1999), managerial's ownership (Cheng, Nagar and Rajan, 2004) and patenting (Atanassov, 2013). Such laws have lead to increases in cash holdings (Yun, 2009), bond values (Francis, Hasan and Waisman, 2010) and acquisitions of "cash-cow" firms (Gormley and Matsa, 2014). The previous literature has studied wages (Bertrand and Mullainathan, 2003) or ROA (Giroud and Mueller, 2010).

leading them to innovate less (Jones and Williams, 1998, 2000, Bloom et al. 2013).[7] In addition to this "business stealing effect", negative spillovers can also occur because of "labor stealing". Studying spillovers at the local labor market level implies that innovative firms compete for skilled labor. To innovate more, listed firms may try to poach inventors from private firms by offering them higher wages. If private firms are not able to retain skilled labor, innovation by listed firms will generate negative spillovers, which might occur for instance because labor has a quasi-fixed cost component and small private firms are more credit constrained than listed firms (e.g., Benmelech, Bergman and Seru, 2011).

Innovations across neighboring firms can also be strategic complements because knowledge is non-exclusive and non-rival (Arrow, 1962). Once introduced, knowledge is subsequently available to other local firms, which increases their ability to innovate because they can use this outside pool of knowledge. Proximity will matter because knowledge can be vague, difficult to codify and - as such - transmitted mostly via social interaction. For example failed experiments may produce knowledge for people nearby but such knowledge is less likely to reverberate in far away areas.[8] Proximity can also increase the likelihood that other inventors hear about about new inventions before inventors located further away, giving them a time advantage. Using patent citations as a proxy for knowledge spillovers, Jaffe et al. (1993) and subsequent papers (e.g., Belenzon and Schankerman, 2013) find that patent citations are highly localized and decline quickly with distance, which implies that the surrounding stock of existing knowledge should generate spillovers on local firms by affecting their ability to innovate, but only at a limited geographical scale.

Finally, both the local stock of knowledge and innovation activity by local listed and private firms might be determined by an omitted variable. For instance proximity with universities is positively linked with firms' innovative activities (Audretsch and Feldman, 1996; Andersson et al., 2009; and Kantor and Whalley, 2014). Similarly, the quality of life provided by local amenities such as nice weather, the absence of violent crime, the presence of multiple goods (restaurants, arts, etc.) attract educated workers (Shapiro, 2006; Glaeser et al. 2010) which conversely is likely to affect innovation by local firms.[9] Therefore, it is also quite possible that local innovation spillovers do not exist, or are of rather limited scope, and are overestimated in naive regressions that neglect endogeneity concerns. In

[7] Of course, if innovation between rivals are strategic complements, an increase in innovation by a firm will lead other firms to innovate more.

[8] The literature makes the distinction between *hard information* and what is often called *"tacit knowledge"*. See for instance Jacobs (1969) or the discussion in Glaeser et al. (1992) and Feldman and Kogel (2010).

[9] In their survey about agglomeration, Glaeser and Gottlieb (2009) note that "no variable can better predict city growth over the past 50 years than January temperature".

my setting, it implies that the patenting growth of private firms should not react to an exogenous change in innovation by listed firms.

If on the contrary listed firms' innovation generate local innovation spillovers for private firms, we should observe the following:

H1: Innovation by listed firms affects the patenting growth of private firms located in the same area and this effect quickly declines with distance.

Merely offering evidence of the existence of local innovation spillovers does not inform us about why they happen. One important mechanism is likely to be that knowledge produced by listed firms, as proxy by their patents, spreads locally to private firms. Notwithstanding the challenge to identify knowledge diffusion,[10] the literature on agglomeration has suggested two main channels.

First, knowledge spreads locally because physical proximity increases the ability of workers to exchange ideas and learn about important incipient knowledge (e.g., Saxenian, 1994; Crescenzi, Nathan and Rodriguez-Pose, 2013). But spatial proximity is not sufficient in and of itself to ensure the transmission of knowledge. Individuals must overcome other dimensions of distance, both cognitive and social, to efficiently exchange knowledge. Therefore, the magnitude of spillovers should depend on both the degree of technological overlap between firms (Jaffe, 1986) and on workers' abilities to recognize, assimilate and apply new knowledge, which may be higher among educated workers (e.g., Cohen and Levinthal, 1990; Moretti, 2004b). Although we cannot exactly follow knowledge diffusion in this case, this channel implies the following hypothesis:

H2: Local innovation spillovers between listed and private firms should increase with the degree of technological proximity, intensity of information flow and density of skilled workers in the area.

The second channel of knowledge diffusion locally involve inventors moving from their employer to both existing firms and newly started spin-outs in the same area. Indeed, knowledge is embedded in inventors. By switching employers locally, inventors create regional networks of collaboration through which knowledge can be transferred (Almeida and Kogut, 1999; Breschi and Lissoni, 2009; Singh and Agrawal, 2011).

A close variation is if inventors move from their employer to create a spin-out. In this case, new entrepreneurs build on knowledge learned when working for their previous

[10] As noted by Krugman (1991) *"knowledge flows are invisible, they leave no paper trail by which they may be measured and tracked"*.

employers. The increase in the knowledge stock will foster entrepreneurship through spin-outs because such vehicles may be the best means for an employee with a given endowment of new knowledge to capture the returns from that knowledge (Audretsch, 1995). According to Aggrawal, Cockburn, Galasso and Oettl (2014), this argument explains why regions with large labs are more innovative, i.e., because they are more likely to spawn spin-outs unrelated to lab-owning firm's overall business.

Thus, I propose my third hypothesis:

H3: Local innovation by listed firms should foster inventors moving locally from their employer to existing private firms or new spin-outs.

Finally, if listed firms' innovation generate innovation by private firms in the same area, we may expect venture capital funds from outside the area to invest more in areas where local innovation spillovers happen. Conversely, we should expect capital availability to determine the magnitude of local innovation spillovers. Indeed, if an increase in the amount of local patents filed by listed firms improves private firms' abilities to innovate, they may not be able to effectively do so if they are credit constrained. Thus, I posit my final hypothesis:

H4: Venture capital funds from outside the area should concentrate their investments in areas where local innovation spillovers are more important. Conversely, capital availability should amplify the magnitude of innovation spillovers.

If the foregoing propositions are true, it would suggest that capital mobility, can contribute to the gaps between cities by allocating resources to those cities where potential spillovers are higher.

3 Data

3.1 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 2000) 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 localization) and about 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. I follow the procedure developed in Hall, Jaffe and Trajtenberg (2001) and Bessen (2009) to match patents through Compustat to identify patents filed by listed 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%. Therefore, a shock on the patenting activity of publicly listed firms can plausibly affect innovation by private firms.

I keep only those patents filed by US corporations in my sample and exclude patents filed by foreign firms, universities, and government agencies.[11] 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[12] 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 has been created.[13]

Patents have long been used as an indicator of innovative activity (Griliches 1990); this measure, however, contain two sources of "noise" that limit the perfect correspondence between patents and ideas. First the propensity to patent a new idea may vary across firms and cities, and some new ideas may not meet the criteria for patentability, or firms may rely on secrecy or other means to protect innovation. Despite these drawbacks, there is nevertheless a strong relationship between R&D and the number of patents in the cross-section of firms (R-squared is 0.9; see Griliches 1990). Second, patents can be heterogeneous in the number of ideas they contain (e.g., Jaffe and Trajtenberg, 2002). However, as noted by Peri (2005), this problem is largely attenuated in studies using patents aggregated at a geographical level (in contrast with firm-level studies) because differences in the quality of patents is likely to average out in the aggregate. The problem of potential differences in

[11]I exclude foreign firms because these firms frequently file patents with the USPTO to protect their innovations on US soil but actually seek financing and conduct their R&D in their home country (see Acharya and Subramanian 2009).

[12]The data are available at http://dvn.iq.harvard.edu/dvn/dv/patent

[13]I am extremely grateful to Juanita Gonzalez Uribe for sharing with me the mapping between latitude-longitude in the patent database and county geographical coordinates.

patenting is addressed using fixed effects.

3.2 Geographic Area: Commuting Zones

The geographical unit of observation I use to estimate the local effect of innovation by listed firms is the Commuting Zone (CZ). The CZ concept was developed by Tolbert and Sizer (1996), who used county level commuting data from the 1990 Census to create 741 clusters of counties that are characterized by strong commuting ties within CZs and weak commuting ties across CZs.[14]

I restrict my analysis to CZs in which I can observe patents during the 1975-2000 period, which results in a balanced panel of 685 distinct CZs, mapping 48 states in the US (the three missing states are Alaska, Hawaii and the District of Columbia).

CZs have three main advantages. First, they are based on economic geography rather than political boundaries and, as such, are a suitable candidate to estimate the scope of innovation spillovers. Second, they cover the entire United States (as opposed to metropolitan statistical areas (MSAs), for instance, that do not contain rural areas, which represents two third of all counties in the US). Finally, using the cross-walk developed by Dorn (2009), CZs can be consistently constructed using the Census Public Use Microdata Areas (PUMAs).

Therefore, CZs represent an appealing geographic level because to estimate how a shock on a group of firms affects the behavior of non-affected neighboring firms, the geographical unit must satisfy the following three criteria. 1) it must be sufficiently small so that spillovers can plausibly occur because, the literature finds that spillovers occur on relatively small scales. 2) its geographical boundaries must be constant over time, which makes otherwise natural candidates such as MSAs unappealing. 3) it must offer sufficient information in terms of the characteristics of the labor market or the population, which makes counties somewhat unappealing because they cannot be identified in the Census Public Use Micro Areas (PUMAs) and as such, strongly limit the amount of information that researchers can construct.

Because I'm interested in geographical spillovers, I aggregate patents at the CZ level. However, this decision implies that I will capture innovation spillovers both within and between industries. This aggregation is actually attractive because I am studying innovation spillovers on the production of other new ideas, which can occur across sectors. For instance, Jaffe et al. (1993) report that up to 25% of citations occur *across* five broad

[14] CZs have been used in the recent literature, such as by Autor and Dorn (2013), Autor, Dorn and Hanson (2013); Adelino, Ma and Robinson (2014) and Chetty et al. (2014).

technological fields. When looking at the 3-digit level (approximately 450 technological fields) approximately 40% of citations are across fields.[15] These high numbers suggest the existence of important inter-sector spillovers and justify aggregating all patents at the CZ level.[16]

3.3 Local Labor Markets Characteristics

I construct different characteristics at the CZ 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).[17] 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 (*empstatd* between 10 and 12). Residents of institutional group quarters such as prisons and psychiatric institutions are dropped (*gqtype* different from 0) as well as unpaid family workers (*classwkrd*=29). All calculations are weighted by the Census sampling weight (*perwt*) multiplied by the weight from Dorn (2009). Population estimates on a yearly basis are from the Census.[18]

Data on venture capital activity and venture capital funds availability come from the VentureXpert database. I identify the CZ in which the fund is located and where it makes an investment using the zipcode information provided by Venture Xpert and by mapping the zipcode with its county. I then map counties with CZs using Dorn's (2009) correspondence table.

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.

[INSERT TABLE 1 ABOUT HERE]

[15] These five broad technological fields include the following: 1) Drugs and Medical Technology; (2) Chemicals and Chemical Processes Excluding Drugs; (3) Electronics, Optics, and Nuclear Technologies; (4) Mechanical Arts; and (5) All Other.

[16] As noted by Henderson et al. (2005), one reason is that plain imitation cannot be patented (given that novelty is a prerequisite to be allowed to fill a patent). Therefore, there must be some technological distance for spillovers to occur.

[17] 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".

[18] Appendix A.1 details the construction of the variables.

4 Identification Strategy

4.1 Empirical Specification

Since Griliches (1979), the standard approach to study innovation spillovers has been to add a measure of external knowledge stock available to the firm innovation production function. The justification for using the stock of knowledge and not only the flow of new knowledge is that because knowledge is non rival (Arrow, 1962): even past knowledge can increase firm ability to innovation currently.[19]

In my case, the innovative output of private firms located in CZ c, state s and year t denoted Y_{cst}, will depend on various time-varying characteristics at the CZ level, denoted X_{cst}, and on the stock of external knowledge accumulated from past and current innovation activities by listed firms that I proxy using the stock of patents by listed firms. Using a log-transformation of the innovation production function, the log level of innovative output in CZ c, state s and year t is equal to:

$$Log(Y_{cst}) = \alpha_c + \delta_t + \beta \; Log(StockListedPatents_{c(t-1)}) + LogX_{ct} + \gamma_{st} + \epsilon_{cst} \tag{1}$$

The stock of patents by listed firms filed in CZ c is constructed using the standard perpetual inventory method with a 15% depreciation rate.[20] The stock of listed patents in year t is $Stock_t = (1-\eta)Stock_{t-1} + \textit{Listed Patents}_t$ where $\textit{Listed Patents}_t$ is the number of new patents filed by listed firms in year t and η=0.15.[21] α_c, and δ_t denote CZ and year fixed effects. CZ fixed effects capture time-invariant determinants of innovation in the different CZs, such as geographic characteristics or the presence of an important university. Year fixed effects control for aggregate shocks and common trends in innovation activity.[22] Finally, I add State $\times$ Year fixed effects denoted 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 or policy differences (e.g., marginal tax rate).

[19]See e.g. Peri (2005), Griffith et al. (2006) or Bloom et al. (2013) for recent applications.

[20]0.15 is the value suggested by Hall, Jaffe and Trajtenberg (2005). I also use a depreciation of 0.1 as in Keller (2002) or Peri (2005) and find similar results.

[21]I make the simplifying assumption that the initial stock of patents by listed firms is zero to reduce the number of assumptions I must make to initialize the stock.

[22]Such common shocks can be caused by changes in the legal and institutional environment at the federal level, such as the creation of the Court of Appeals for the Federal Circuit in 1982.

The parameter of interest is β, which measures the extent to which private firms react to the innovation activity of listed firms. Given the State $\times$ Year fixed effects, β captures only spillovers that occur within a state across CZs and does not include variations coming from CZs in different states. Because I aggregate innovation at the CZ level, I cluster standard errors at the CZ level. The main challenge when estimating this type of equation is that innovation activity of both private and listed firms in a given city is likely to be endogenous for two reasons. First, innovation by all firms in the area might be affected by unobserved shocks (e.g., a major technological breakthrough). Second, this specification is confronted with the "reflection problem" described in Manski (1993). Each firm adapts its investment and innovation strategy by reacting to the decisions of the other firms in its environment. As such the link between the two reflects the equilibrium reached by the endogenous answer of the various firms.

To correct for these problems, I predict variations in the supply of patents by listed firms that only come from characteristics unrelated to the area in which the firm is active and use this prediction as my instrument. Therefore, the fluctuations in the predicted measure of patents is uncorrelated with unobserved local conditions or private firm innovations. The shock on innovation by listed firms comes from the adoption of BC laws.

A challenge that arises when instrumenting innovation of a group of firms is that this instrument will likely affect other dimensions of firms' policies, violating the exclusion restriction. In the case of BC laws, we know for instance that they lead to higher wages (Bertrand and Mullanaithan, 2003) or lower profitability (Giroud and Mueller, 2010). Those changes may then generate variations in innovation by private firms. My identifying assumption is that variations in patents by private firms are mostly generated by variations in patents by listed firms and not by other listed firms' policies. As a way to validate this identification assumption, I provide multiple cross-sectional tests in the second part of the paper consistent with local innovation spillovers happening essentially because knowledge diffuses across firms in the same CZ. These results are harder to reconcile with other interpretations.

4.2 Exogenous Variations in Innovation by Listed Firms

4.2.1 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).[23]

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. 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 Mullanaithan, 2003). Second, risk-averse or career-concerned managers might undertake less risk than desired by a diversified shareholder and decide to "play it safe" (Gormley and Masta, 2014). Both types of behavior have been found to increase after BC laws were adopted.

One remaining problem is that 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.

4.2.2 Building an instrument from BC law adoptions

To instrument variations in patents by listed firms at the CZ level, I adopt a two-step procedure. First, I estimate the expected number of patents generated by the BC laws and then I aggregate this estimate at the CZ-year level and use it as my instrument.[24]

Because the effect of BC law adoption on innovation is likely to be non-linear and to obtain a more precise estimate of its effect, I start my analysis at the listed firm-CZ-year level. It allows me to remove heterogeneity both across firms but also across firm-CZs.

After I drop all patents in CZs located in the state of incorporation of the firm, I predict fluctuations in patents by listed firms in the CZs in which the firm is active using

[23] For a detailed history of first and second generation of antitakeover laws, see Kahan and Kamar, 2002; Bebchuck, Cohen and Ferrel, 2002 or Bertrand and Mullanaithan, 2003).

[24] See Wooldridge (2002) for a discussion of this two step-procedure and Paravisini (2008) for example in banks' allocation of government funds or Boustan (2010) for example in the case of black migration across US cities.)

the adoption of BC laws after I filter Firm $\times$ CZ and year fixed effects. I follow Atanassov (2013) and run a standard difference-in-differences strategy, in which I explain the number of patents that the listed firm i, files in CZ c, and year t as follows:

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

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 $\times$ CZ fixed effects and δ_t denote year fixed effects.

I then predict the value of patents using only βBC_{it} and aggregate it at the CZ-year level. The predicted number of patents in CZ c in year t is thus equal to: $\widehat{ListedPatents}_{ct}$ = exp $[\sum_{i \in CZ} \beta BC_{ict}]$-1

Therefore, I obtain fluctuations in the number of patents by listed firms that only come from the adoption of BC laws and not from local economic activity or productivity shocks in the CZ. I then use the predicted value of patent flow $\widehat{ListedPatents}_{ct}$ to create a predicted value of the stock of patents by listed firms using the same perpetual inventory method that is described in section 4.1. From there, I can run a standard 2SLS regression using the predicted value $\widehat{StockListedPatents}_{ct}$ to instrument the actual stock of patents by listed firms $StockListedPatents_{ct}$ in a given CZ.

It should be noted that even if the adoption of a BC law constitutes a plausible source of *variation* in the number of patents filed by listed firms exogenous to local CZ attributes, 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 productivity shock. In that event, listed firms are more likely to conduct their research activity there, producing 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 of new listed firms in my sample.

To address this problem, I use patents by listed firms that are present for the entire period of my analysis (25 years) and consider that they begin their innovative activities from the beginning in all the CZs in which they will patent at some time. As such, the only variation in patents by listed firms comes from adopting the BC law. One problem with this strategy is that it reduces the number of listed firms, as it leaves me with 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. Nevertheless, I restrict the analysis to the balanced sample.

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 0.04% to 0.06% depending on the specification, always highly significant at the 1% level and equivalent in magnitude to the estimation finds in Atanassov (2013). I also check in column (2) whether the results hold when I include Industry × Year fixed effects that absorbs time varying fluctuations at the industry level (such as technology or sale shocks). In column (3) I also add also CZ × Year fixed effects, which absorb any CZ-specific time-varying shocks that are shared by all firms in the same CZ, such as business activity or productivity shocks.[25] Finally, Column (4) excludes listed firms incorporated in Delaware and column (5) excludes patents filed in California. In all cases the results continues to be negative and strongly significant.

[INSERT TABLE 2 ABOUT HERE]

I also check that the results are not capturing a trend. To do so, I plot the evolution of patenting activity around the regulation date. In Figure 2, 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, which is consistent with my identifying assumption that BC laws are not endogenous to innovation. Figure 2 also shows that the effect of regulation materializes only progressively after the event date which is expected because firms are likely to adjust progressively to new environments.

[INSERT FIGURE 2 ABOUT HERE]

Identifying the effects of innovation by listed firms on private firms exploits the fact that CZs will be more or less affected by the shock generated by the adoption of BC laws. Therefore, Figure 1 maps the distribution of patents filed by listed firms before 1984 (the last year before the adoption of the first BC law) that will be affected at some point in time by BC laws.

[25] For example assume that I have only two firms in a given CZ, 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 shows that listed firms affected by BC laws represent an important part of all patents filed by listed firms throughout the US and is not limited to a specific area. This widespread distribution reduces the risks that my identification will only capture evolution that is specific to a limited number of geographic areas.[26]

[INSERT FIGURE 1 ABOUT HERE]

4.3 First-Stage Results

Using BC laws to predict innovation by listed firms in states outside their state of incorporation ensures that this prediction is not correlated with CZ characteristics where listed firms innovate. Figure 3 graphs the first stage relationship between the predicted stock of patents by listed firms and the actual stock, after I filter CZ and State $\times$ Year fixed effects and cluster at the state level. I find a strong positive relationship between the two measures, which confirms that the prediction provides a valid instrument. The coefficient for the first stage is 0.45 with a t-statistic of 16, which is well above the conventional threshold for a strong instrument.[27] I obtain similar results when I use changes in the stock of patents rather than the level.

[INSERT FIGURE 3 ABOUT HERE]

5 Local Innovation Spillovers

5.1 Baseline Results

I begin by investigating the effect of the stock of patents filed by listed firms on the number of patents filed by private firms in a given CZ in the following year. The results are reported in Table 3. Column (1) shows the naive OLS. The elasticity of patents filed by private firms

[26] It should be noted that the identification actually does not come uniquely from the comparison between CZs with more or fewer listed firms affected by a BC law, but also from the *composition* of the different states of incorporation. Indeed, because of the difference-in-differences strategy employed in the first stage, firms affected by BC laws are in both the control and treated groups. Therefore, a CZ with a majority of firms incorporated in New York will be affected by the reform beginning in 1985 (the year in which the BC law was adopted in NY), whereas a CZ with a majority of firms incorporated in Massachusetts will only be affected after 1989.

[27] Because I use a predictive value for the stock of patents by listed firms, I correct the standard errors using 1,000 bootstrap replications over firms by randomly drawing with replacements firms in the sample of states in which they operate.

to the stock of patents filed by listed firms is 24%. Columns (2) to (5) report the estimated elasticity when I instrument the stock of patents filed by listed firms using the adoption of BC laws. In every case, the effect is strongly significant at the 1% level and with an elasticity between 21% and 18%. The fact that the IV estimate does not differ substantially from the OLS estimate suggests that the size of the bias is limited in this context.

Column (3) explores how the effect evolves with distance. I define *Stock Listed Patents Close* CZ_{ct} as the stock of patents by listed firms filed in the four closest neighbor surrounding the CZ c. I also calculate the stock of patents by listed firms filed in the *next* four closest neighbors labeled "$DistantCZ_{ct}$". I identify close neighbors and distant neighbors by calculating the geographical distance between each CZ using the average latitude and longitude of all zipcodes located in the CZ.[28] I find that the stock of patents by listed firms filed in close neighboring CZs has a small positive effect on innovation by private firms, but the effect become undistinguishable from zero for distant neighbors. This sharp decrease with distance is consistent with other papers documenting that "knowledge does not travel well".[29] It 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.

In columns (4) and (5), I follow Moretti (2004b) and add various controls at the CZ level that might influence my estimation. Column (4) adds "demographic" controls such as the share of African-Americans and women in the population, in addition to population density and the share of population living in an urban area, given the importance of cities in fostering innovation (e.g., Glaeser and Gottlieb, 2009 or Carlino and Kerr, 2014 for surveys). In column (5) I add economic and education controls. Education controls include the number of doctorates granted each year, the number of existing college institutions reported by the Integrated Postsecondary Education Data System (IPEDS) and the R&D conducted at local universities. Economic controls capture various economic and technologic dimensions: *Personal Income per Capita*, *Number of Firms* that I proxy using

[28] E.g., similar strategies have been used for instance in Wilson (2009) for states and Dessaint and Matray (2014) for counties.

[29] Given that the average distance for CZs in the neighborhood zone is approximately 100 miles and the distance for CZs 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 (2002) find that geographic spillovers concentrate at a scale of approximately 30 miles, whereas Botazzi and Peri (2003) find that knowledge spillovers exists between 0 and 450 miles in their study of European regions. In the US, Lychagin et al. (2010) 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. Similarly, studying the clustering of R&D labs, Carlino et al. 2012 find the scale of the clustering they observe is comparable to local labor markets, which are equivalent to CZs.

the number of establishments from the CBP, *Share of self employed* among the working population, *Industry specialization* defined as the local Hirschmann-Herfindahl Index for the 10 economic sectors available in the BEA.[30] *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 CZ is); *Technology age* which is defined as the average age of technologies exploited in a CZ captures the fact that CZs working in newer, more fertile technologies may generate more patents. I also add the amount of venture capital investment made. Reassuringly, the coefficient for the stock of knowledge filed by listed firms is stable across the different specifications. Because several of those variables are likely to be directly influenced by the stock of patents filed by listed firms, I use only demographic controls in the rest of the paper because they are less likely to react immediately to innovation by listed firms and also control for the number of establishments.[31]

In term of economic magnitude, an elasticity of 0.2 implies that changing the stock of patents by listed firms by 1% changes similarly the number of patents filed by private by 0.2%. In term of within CZ standard deviation, I find that on average, a within CZ one standard deviation variation in the stock of patents by listed firms explains nearly 20% of the within CZ standard deviation of patents filed by private firms during the sample period. 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 has a local stock of around 100 patents in a given CZ. If I relocate this activity to a new Commuting Zone, it will generate around 14 additional patents by private firms, which represents a 18% increase compared to the within CZ standard deviation of patents filed by private firms. This suggests a substantial effect that could explain why cities and states compete to attract R&D activities (Wilson, 2009).

[INSERT TABLE 3 ABOUT HERE]

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

[30] Those sectors include the following: Agriculture, Mining, Construction, Manufacturing, Transportation, Wholesale trade, Retail trade, Finance, Services, Public Administration.

[31] See for instance Gormley and Matsa (2013) for a discussion of the problem to include endogenous controls in a regression.

5.2 Knowledge Diffusion Channels

How and why does knowledge spread locally? What are the channels through which knowledge is transferred? 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.

5.2.1 Effect Depending on Learning Opportunities

Technological proximity

If knowledge transmission plays an important role in the existence of local innovation spillovers, we should expect the magnitude of innovation spillovers to vary as a function of the technological proximity among listed firms and private firms in the same area.

I use two different proxies to capture the degree of technological proximity: the propensity of private firms to build on innovation produced by listed firms and the degree of technological overlap between listed firms and private firms.

I proxy the propensity of private firms to use innovation produced by listed firms and produced locally from patent citations. I define the propensity to use innovation produced by listed firms as follows. I examine all the citations *made by* patents filed by private firms in a given CZ. I then calculate the share of citations of listed firms' patents over the total number of citations made. Finally, I aggregate the foregoing data at the CZ-year level.

To proxy technological overlap, I use the measure of technological proximity introduced by Jaffe (1986). For each CZ, I calculate the number of patents granted to each firm by technological categories.[32] The share of patents granted to firm i located in CZ 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 CZ 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 0 to 1, depending on the degree of technological overlap between firms. The closer this index is to 1 the more that firms located in CZ c overlap in technological classes.

One drawback of the Jaffe distance is that it considers proximity only within the same technology class. It is all the more so problematic that an important fraction of knowledge flows are inter-industries (around 40% of citations are across 3-digit technologies, Jaffe et

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

al., 1993). I use the Mahalanobis Distance developed by Bloom et al. (2013) that allows to calculate a degree of technological proximity between different technology classes (see the Appendix C.2 of Bloom et al. (2013) for a detailed description of the metric).

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%), which suggests that I'm capturing different dimensions of technological proximity.[33] To obtain the marginal additional effect that each proxy create with respect to the mean effect of *Stock Listed Patents*, I demean all the proxies and interact them with the main variable *Stock Listed Patents*.

Column (1) of Table 4 reports the result when I interact the stock of patents held by listed firms 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 technologies 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 11%. Columns (2) and (3) show a similar amplification when I interact the stock of patents filed by listed firms 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.

[INSERT TABLE 4 ABOUT HERE]

Density of skilled workers

Marshall is among the first to notice that social interactions among workers create learning opportunities that enhance their productivity (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".[34]

The challenge with this channel is that economists cannot directly observe communications, discussions or gossips among workers. Instead, I exploit the prediction that spillovers

[33] However the two measures of technological proximity based on the distance defined by Jaffe (1986) or Bloom et al. (2013) is very high.

[34] 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."

should be more important in areas in which workers can interact and learn more easily from one another. In particular, I expect two CZs facing the same shock on listed firms' innovation to react differently depending on the density of skilled workers. Indeed, to engage in fruitful knowledge exchanges, being geographically close is not sufficient. Workers must first have the capacity to understand and assimilate new knowledge and second to share social ties to a certain degree. 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, (...)".

The different proxies for local workers' ability to learn from one another and the intensity of social interactions are built on the analysis of Moretti (2004b) Glaeser and Resseger (2010) and Belenzon and Schankerman (2013), among others. I use the supply of scientists and engineers (S&E) and college graduates in a given CZ at the beginning of my sample period.

To construct the two proxies, I use 1970 census data (1% Form 2 Metro Sample) and the methodology of Autor and Dorn (2013) to aggregate Census Public Micro Samples at the CZ level. Scientists and engineers are identified using the consistent *occupation* variable in 1990.[35]

Table 5 shows how the density of skilled workers in a CZ 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 the stock of patents by listed firms has a greater effect when the supply of S&E is higher.[36] Column (2) shows a similar result when I proxy learning opportunities using the supply of college graduates.[37] 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 CZs in the first quartile of the distribution.

[INSERT TABLE 5 ABOUT HERE]

The inherent limit of cross-sectional tests is that potentially, unobserved characteristics may be correlated with the variables used in the cross-section. For instance, CZs 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

[35] For the Census in 1970, I use the crosswalk provided by Dorn (2009) that is kindly made available on his webpage.

[36] Because all my proxies are time invariant, the simple term is absorbed by the CZ fixed effect.

[37] Similarly, Kantor and Whalley (2014) find that academic research spillovers are more important when the university is located in a county with a higher level of college-educated workers.

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 comes from Beaudry, Doms and Lewis (2010)[38] 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 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. Beaudry et al. (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.[39]

High school enrollment in 1880 is a good predictor of the share of educated workers a century later. The coefficient is equal to .12 with an F-test of 13. Column (3) of Table 5 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 comes from Moretti (2004a), who shows that the presence of college and universities created in the nineteenth century following the "land-grant movement" 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,[40] land-grant institution is unlikely to be correlated with unobservable factors that affect innovation today.[41]

Using the list of all land-grant institutions provided in the appendix of Nervis (1962),

[38] I am deeply thankful to Ethan Lewis for answering my questions about his instrument.

[39] See Beaudry et al. (2010) for a detail discussion of the instrument.

[40] See Moretti, 2004a and 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."

[41] Doms and Lewis (2006) and Shapiro (2006) also use this instrument. Shapiro (2006) shows that there is no difference in the human capital distribution between land-grant and non land-grant cities from 1850 to 1880, i.e. before the land-grant movement. In addition, the correlation between land-grant establishments and college-educated workers arose strongly after 1940 when college attendance began to increase, a time when these institutions might have played a significant causal role.

I create a dummy variable *Land-Grant* which is equal to one if the CZ contains at least one land-grant institution. I end up with 63 distinct CZs with at least one land-grant institution (in only six cases the CZ 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 strong effect both economically and statistically. The presence of a land-grant college in a CZ increases the share of college workers by 20%, with a t-stat over 9.4. It implies a F-test of 89, which is well above the 10 recommended by Stock and Yogo (2005) to have a strong instrument.

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 CZ has one land-grant institution) increases the innovation spillovers generated by listed firms.

5.2.2 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. Beginning with the case study of Saxenian (1994) who compares Silicon Valley with Route 128 (Boston), the ability for inventors to change jobs has been identified as a mechanism that fosters collaboration and learning. 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. Adopting the Jaffe, Trajtenberg, and Henderson (1993) "paper trail" methodology to identify knowledge spillovers, Almeida and Kogut (1999) and Breschi and Lissoni (2009) provide evidence that knowledge is transferred locally by individuals who move from one organization to the other, but who do not relocate geographically.

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 mobility rate of employees, non-compete laws should affect the speed at which knowledge diffuses locally (Stuart and Sorenson, 2003; Garmaise, 2009; Marx et. al. 2007, 2010; Sorenson and Samila, 2011; Belenzon and Schankerman, 2013).

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.[42] The second follows Garmaise (2009) and is an index ranging from 0 to 7 and count the number of employer-friendly provisions: higher values indicate stronger enforceability 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 stock of patents filed by listed firms. I expect that if knowledge is diffused by labor mobility, more stringent non-compete laws should limit local innovation spillovers.

Table 6 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 Fallick et al. (2006) show that cities in California are characterized by a higher rate of mobility of high-skilled workers (what they called "job-hopping") 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. These results confirm quantitatively the conjecture of Saxenian (1994) that the ability for employed inventors to change jobs may be an important determinant of a city's innovative capacities.

[INSERT TABLE 6 ABOUT HERE]

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 the stock of patents filed by listed firms affects the number of mobile inventors within a CZ. 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.[43]

[42] See Stuart and Sorenson (2003), Table 1 p.190)

[43] 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,

To measure inventor moving across local firms, I follow papers such as Marx et al. (2009) or Hombert and Matray (2014) and identify an inventor as changing employers when she files two successive patent applications that are assigned to different firms. Because I'm interested in innovation spillovers in a given CZ 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 CZ.[44]

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 CZ c, but who previously worked in a listed firm located in the same CZ. *Share of Mobile Inventors from Listed Firms*$_{ct}$ is the fraction of mobile inventors who worked in a listed firms located in the same CZ over the total of all mobile inventors who arrive in private firms in year t in CZ c, and *Share Inventors Previously in Listed Firms*$_{ct}$ is the share of all inventors working for private firms in year t in CZ c that formerly worked for a listed firm located in the same CZ.

I also explore a variation on the theme of inventor mobility: entrepreneurial spin-out.[45] 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; Agrawal et al. 2014). 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 CZ 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 (a total of 112,929 new firms).

Table 7 shows how innovation by listed firms in a given CZ can affect inventor mobility flow from listed firms to private firms in the same area. Column (1) finds that an increase

D'Amour, and Fleming (2009) develop a disambiguation algorithm to create unique inventor identifiers. The data are available at http://dvn.iq.harvard.edu/dvn/dv/patent and the disambiguation algorithm is discussed in Lai, D'Amour, and Fleming (2009).

[44]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 follow Marx, Strumsky, and Fleming (2009) and 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.

[45]According to Audretsch and Feldman (2004), spin-out is one of the most important mechanisms through which knowledge is transmitted locally.

in the stock of patents by listed firms 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 the stock of 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 CZ increases with the local stock of patents by listed firms, 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.

[INSERT TABLE 7 ABOUT HERE]

5.3 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 CZ fosters innovation by local private firms, we should expect VC funds from outside the CZ 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. Indeed, if an increase in the amount of local stock of patents by listed firms improves private firms' ability to innovate, they may not be able to do so if they are credit constrained. Therefore, better capital availability should allow firms to seize new innovative investment opportunities and therefore increase the magnitude of local innovation spillovers.

5.3.1 Capital Inflows

To study whether VC funds from outside the CZ follow potential innovation spillovers, I investigate the behavior of VC funds using the VentureXpert database. The main advantage of using VentureXpert is that the database records both the geographic localization (zipcode) of the VC fund and the localization of the company in which the fund makes an investment, which 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 CZs to attract out-of-town VC money: the number of investments made and the total value of all investments made in a given CZ-year. Each variable is in log and calculated only for non-local VC funds.

Chen et al. (2010) have shown that the VC industry is highly clustered in three metropolitan areas (combined statistical areas or CSAs) in the US, that they call "venture capital centers": San Francisco/San Jose, Boston, and New York. Because of this feature, I estimate the different models on the entire sample and then I exclude the 16 CZs that belong to these three centers.

Column (1) of Table 8 shows the result for the number of different investments and reports that the stock of patents filed by listed firms in a given CZ in the previous years increase the likelihood that this CZ attracts investment from VC funds located in other CZs. Column (3) show similar results when I use the total money invested in a CZ-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 et al. 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).

[INSERT TABLE 8 ABOUT HERE]

We now have clear evidence that VC activity has a *causal* effect in fostering entrepreneurial companies (Kortun and Lerner, 2000; Samila and Sorenson, 2011) and does not simply "chase deals" (Gompers and Lerner, 1998). However, my results show that VC investments are indeed partially driven by demand and that more funds are driven into areas that become more innovative. If capital endogenously follow local innovation spillovers, a related question is whether *exogenous* fluctuations in capital availability amplify spillovers.

5.4 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 so, I interact the variable *Stock Listed Patents* with the total amount of investments made by VC funds. The hypothesis behind these tests is the following: if innovations by listed firms generate new innovation opportunities for private firms, the effect should be more important when these private firms can more easily finance new innovative investments.

Because the previous section showed that capital flows endogenously react to the stock of patents by listed firms, I must be able to generate exogenous variations 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 (Hochberg and Rauh, 2012). 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 variations in the amount of money they can invest (e.g., Bernstein et al. 2010; Gonzalez Uribe, 2014).

I obtain data for local and state public pensions from the State and Local Government Public-Employee Retirement Systems annual survey conducted by the Census Bureau and available since 1970.[46] 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.[47]

Table 9 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 the stock of patents by listed firms, I instrument VC investments by the amount of local and state public pension funds in column (2). The first stage produces an F-test of 30, which rules out the risk of having a weak instrument. The IV estimate yields similar results and shows that exogenous variations in the amount of VC capital available amplify local innovation spillovers. The magnitude of the amplification is important because, as moving from the 25th percentile to the 75th 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 CZs belonging to a "VC center" and shows a similar effect.

[INSERT TABLE 9 ABOUT HERE]

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

[47] Ideally, I would like to be able to use *within* state variations in VC capital availability, but I use VC investment at the state level because the instrument is at the state 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 narrow such differences.

6 Robustness

6.1 Alternative Stories

There are three possible alternative explanations for my results. First, changes in the production of innovation by listed firms may affect competitive pressure on local private firms. Second, listed firms can be consumers of local private firms. Third, the adoption of BC laws affect innovation by private firms via the M&A market.

In this section, I discuss the consistencies of these three explanations with my results and provide new results to rule out those alternative theories.

The first possible concern is that listed firms compete locally with private firms. In this case, as shown by Aghion et al. (2005) model, an increase in local innovation activity by listed firms might force private firms to innovate in response, which seems unlikely to be the case in my setting for several reasons. First, CZs are small geographical areas and we can expect innovative firms to compete industry-wide, at the state level at the very least and most likely at the national and international levels. Nevertheless, I find a limited effect for innovative activities of local listed firms even in neighboring CZs (column (3) of Table 3). Second, as noted in section 3.2, to capture between-industry spillovers, I aggregate innovation activity at the CZ level, reducing the likelihood that all firms compete in the same product markets. Third, it is unclear why the inverted-U shape theory of Aghion et al. (2005) would imply that innovation by listed firms would have a greater effect when the density of college graduated or engineers is higher or when non-compete covenants are not enforceable. Similarly, the framework of Aghion et al. (2005) has no predictions regarding spin-out formation or inventor mobility. It seems also unlikely that out-of-town VC funds would invest more in the CZ if competition was higher for local private firms, because their expected profits would be lower.

Finally, I perform two additional tests. In column (1) of Table 10, I follow Agrawal et al. (2014) and add to my baseline regression the Herfindahl Index of patents across firms in each CZ, as well as the square term of HHI as a proxy for local competition. In column (2), I use the classification of Mian and Sufi (2014) and restrict my estimation to firms in tradable industries. I expect those firms to compete on a broader scale than the CZ and therefore to be less sensitive to local competition. In column (3), I exclude from my sample the biggest listed firms from each CZ (specifically I calculate for each CZ-year the fraction of patents filled by each listed firm and exclude the top 10%) because I expect those firms to generate the largest competitive pressure on their local environment. In all cases, I find similar results.

[INSERT TABLE 10 ABOUT HERE]

The second competing explanation is that rather than being competitors, listed firms and private firms are "allies" instead. For instance, it is possible that listed firms generate a demand for technologies that increases innovation by private firms. However, as with the previous alternative explanation, it is unclear why we should find an effect on inventor mobility, why the effect should nearly disappear when we look at neighboring CZs or why the effect should be bigger when the share of college-educated workers is higher or when non-compete covenants are not enforceable.

If this explanation was the main reason for my result, it is also difficult to understand why the effect is the same when I look at innovation in tradable industries (because those industries are more likely not to be dependent on local suppliers). In column (4) of Table 10, I also restrict my estimate to listed firms that are active in at least five different CZs.[48] I expect firms active in multiple CZs not to generate similar demands in each CZ. Therefore, if the demand channel was the main explanation, I should find a smaller effect. However, my result is not affected when I focus on those firms.

The third possible explanation is that the adoption of BC laws affect innovation by private firms is 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, 2013). We know from Gormley and Matsa (2014) that the adoption of BC laws increases listed firms takeover activities. However, the acquires are concentrated among listed firms with greater risk of distress and which target "cash cows" and in diversified segments. As such, the effect on the M&A market for innovative firms is unlikely to be affected. In addition, it is unclear why in this case the effect of innovation

[48] I find similar results when I look at firms in at least two or ten CZs.

spillover would be so local or why it would be affected the presence of by non compete laws. In addition in columns (5) and (6), I estimate whether innovation by listed firms in a given CZ affect the likelihood to observe the acquisition of a private firm (column (5)) or a private high-tech firm (column (6)) in the same CZ. I 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.

6.2 Additional Robustness Checks

In Table 11, I explore the robustness of my main result. In column (1), I follow Kerr and Lincoln (2010) and add a specific technological trend at the CZ level to my main specification. Differences in sectoral growth rates or changing propensities to seek patents might affect my findings if for instance, the CZs in which patents by listed firms increase more are simultaneously initially more specialized in a growing sector. I thus include a measure of expected CZ-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 CZs / firms. In columns (2) and (3) I exclude various CZs to ensure that my estimate does not reflect the specificities of certain cities (and in particular the most innovative ones). In column (2), I exclude all the CZs 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 CZs 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 CZs located in the state in which the listed firm has its headquarter. Again, my results remain unaffected.

[INSERT TABLE 11 ABOUT HERE]

7 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 by local information transmission locally 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. I also find that variations in the amount of capital available amplifies the magnitude of innovation spillovers. This last result suggests that finance could be an important factor to explain the important disparities between cities in terms of economic specialization, entrepreneurship, 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 researches.

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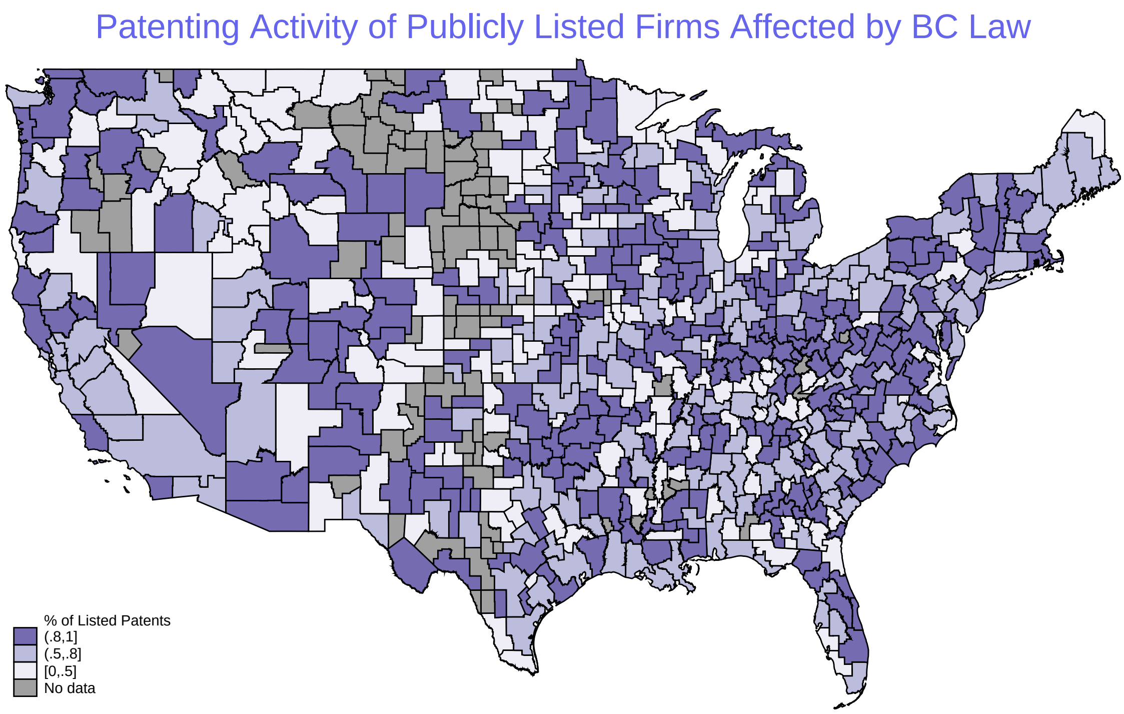
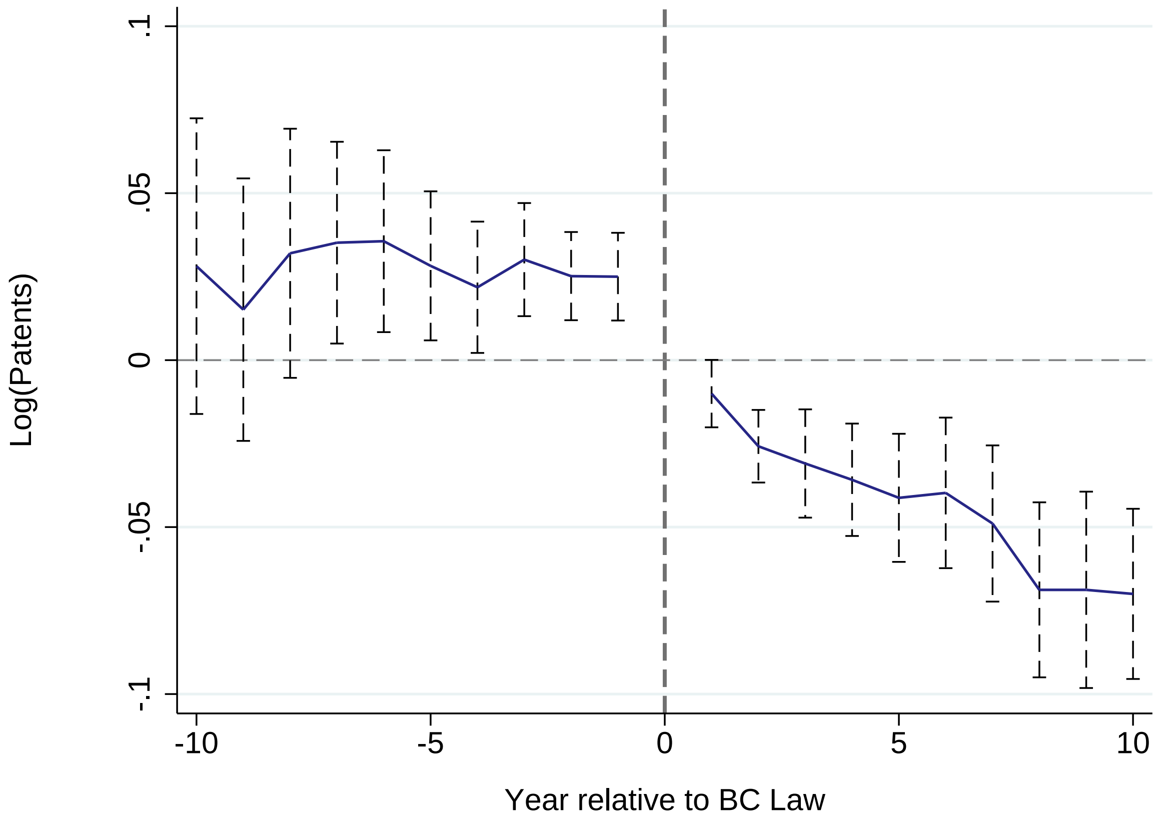
Figure 1. Fraction of Patents by listed firms Affected by BC Laws



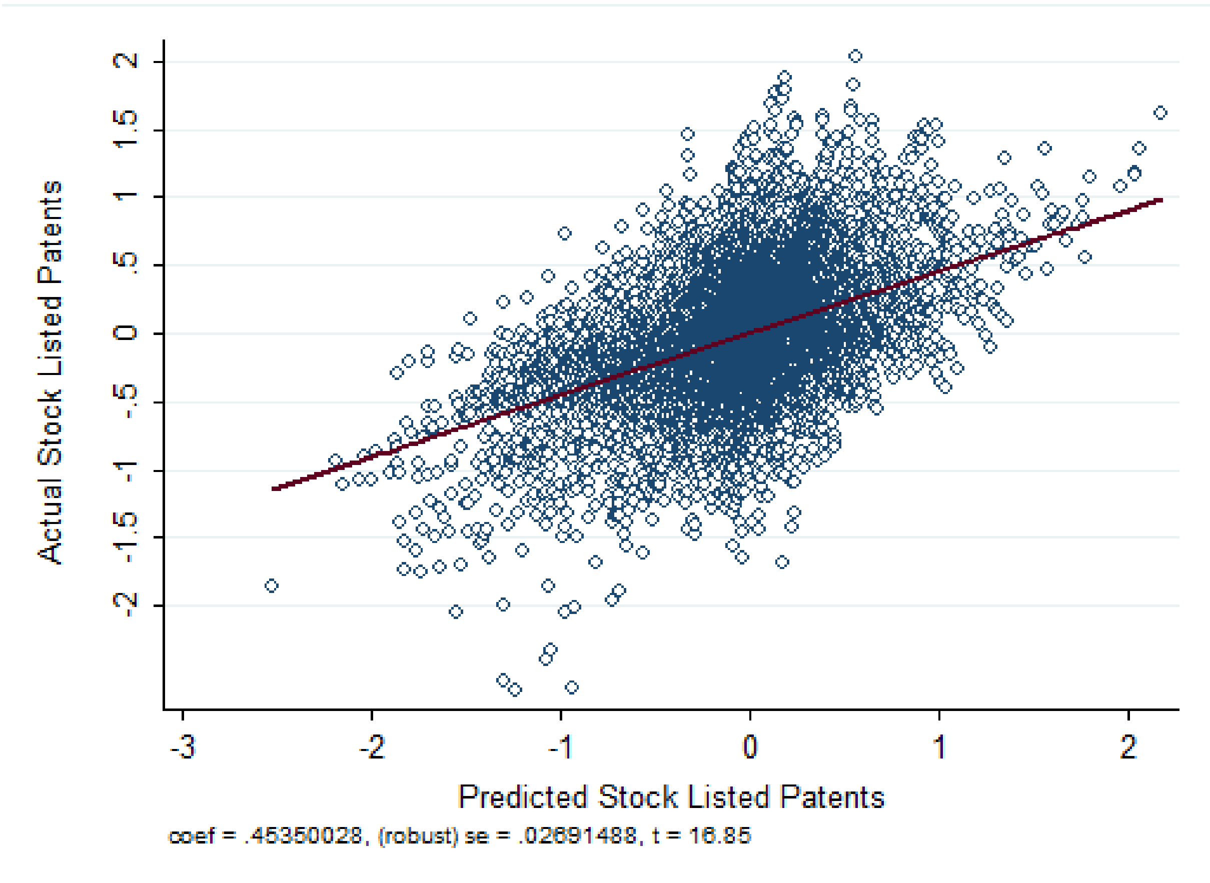
This map shows the geographic dispersion of publicly listed firms that will be affected by the adoption of BC laws. I calculate the fraction of patents filed by listed firms affected over the total of patents filed by listed firms for each Commuting Zone.

Figure 2. 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.

Figure 3. First-Stage Regression: Relationship Between Actual and Predicted Stock of Patents by Listed Firms: 1975-2000



The figure represents the partial correlation between the actual and the predicted stock of listed patents, after CZ and States × Year fixed effects have been removed. Each point in the scatter diagram represents a CZ-Year's residuals of actual and predicted stock of listed patents after fixed effects have been removed.

Table 1. Summary Statistics

This table provides summary statistics for the main variables used in the paper. Statistics have been computed at the CZ-Year level. Variables are described in section 3

	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

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

Dependent variable is the log of patents filed by Compustat firms in a given year and Commuting Zone (CZ) for the sample of firms present from 1975 to 2000. All regressions include Firm $\times$ CZ and Year and fixed effects (FE). Column (2) adds Industry $\times$ Year FE. Column(3) adds CZ $\times$ Year FE. Column (4) excludes all firms incorporated in Delaware. Column (5) excludes all innovation activity in California. Standard errors are clustered by CZ.

Sample	All	All	All	Exc. Delaware	Exc. California
	(1)	(2)	(3)	(4)	(5)
Post BC	-0.04***	-0.06***	-0.05***	-0.06***	-0.05***
	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)
Observations	183168	183168	183168	87630	169525
Lab (Firm x CZ) FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	-	-	-	-
CZ x Year FE	-	-	Yes	Yes	Yes
Industry x Year FE	-	Yes	Yes	Yes	Yes

Table 3. Effect of Innovation by Listed Firms on Innovation by Private Firms

685 CZs, 1975-2000. The dependent variable is the log of patents filed by private firms. All regressions include CZ, Year and State x Year fixed effects. Column(1) is the stock of the actual number of patents filed by listed firms in a given CZ. Column(2) instruments the stock of patents by listed firms using the adoption of BC laws. Column (3) adds the stock of knowledge in *Close CZs* CZs defined as the 4 closest CZs and *Distant CZs* defined as the next 4 closest. Columns (4) and (5) add various controls at the CZ-Year level. Standard errors are in parentheses and clustered at the CZ level.

Estimation	OLS (1)	IV (2)	IV (3)	IV (4)	IV (5)
Stock Listed Patents	0.24*** (0.02)	0.21*** (0.04)	0.20*** (0.04)	0.18*** (0.04)	0.17*** (0.04)
Stock Listed Patents_Close CZs			0.06** (0.03)		
Stock Listed Patents_Distant CZs			-0.01 (0.06)		
Observations	17125	17125	17125	17125	17125
CZ Demographic	-	-	-	Yes	Yes
CZ Economic	-	-	-	-	Yes
CZ FE	Yes	Yes	Yes	Yes	Yes
State-Year FE	Yes	Yes	Yes	Yes	Yes

Table 4. Innovation Spillovers Depending on Technology Proximity

685 CZs, 1975-2000. The dependent variable is the log of patents filed by private firms. In all regressions, *Stock Listed Patents* is instrumented. Each column interacts *Stock Listed Patents* with a proxy of 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). All regressions include CZ, Year and State x Year fixed effects. Standard errors are clustered at the CZ level.

	(1)	(2)	(3)	(4)	(5)
Stock Listed Patents	0.17***	0.17***	0.19***	0.16***	0.18***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Stock Patent Public ×	1.92***			1.61***	1.63***
Tech. Prox. (Citation Listed Firms)	(0.37)			(0.37)	(0.34)
Stock Patent Public ×		0.61***		0.50***	
Tech. Prox. (Jaffe Distance)		(0.10)		(0.11)	
Stock Patent Public ×			0.04***		0.03***
Tech. Prox. (Mahalanobis Distance)			(0.01)		(0.01)
Observations	17125	17125	17125	17125	17125
CZ Controls	Yes	Yes	Yes	Yes	Yes
CZ FE	Yes	Yes	Yes	Yes	Yes
State-Year FE	Yes	Yes	Yes	Yes	Yes

Table 5. Innovation Spillovers Depending on Skilled Worker Supply

685 CZs, 1975-2000. The dependent variable is the log of patents filed by private firms. In all regressions, *Stock Listed Patents* is instrumented. All regressions include CZ, Year and State x Year fixed effects. Columns (1) reports the effect when the stock of patents by listed firms is interacted with the supply of scientists and engineers (S&E) in a given CZ-year. Column (2) uses the supply of college graduates in a given CZ-year. Columns (3) and (4) instrument the supply of college graduate. In column (3), the instrument is the share of 15-19-year-olds enrolled in school in the past year in 1880, constructed from 1880 US Census-10% (Ruggles and al. 2010). The F-test is 13. In column (4), the instrument is a dummy equal to one if the CZ contained a college created via the "Land Grant Movement" in 1862 and 1890 (Nervis, 1962). The first stage F-test is 48. Standard errors are in parentheses and clustered at the CZ level.

	(1)	(2)	(3)	(4)
Stock Listed Patents	0.18***	0.18***	0.20***	0.17***
	(0.04)	(0.04)	(0.04)	(0.04)
Stock Listed Patents × S&E Supply	0.05***			
	(0.01)			
Stock Listed Patents × College Graduate		0.91***		
		(0.16)		
Stock Listed Patents × College Graduate (IV 1)			0.89**	
			(0.38)	
Stock Listed Patents × College Graduate (IV 2)				1.12***
				(0.36)
Observations	17125	17125	17125	17125
CZ Controls	Yes	Yes	Yes	Yes
CZ FE	Yes	Yes	Yes	Yes
State-Year FE	Yes	Yes	Yes	Yes
F-test(Enrollement 1880)	-	-	13	-
F-test(Land Grant)	-	-	-	48

Table 6. Innovation Spillovers Depending on Non-Compete Laws

685 CZs, 1975-2000. The dependent variable is the log of patents filed by private firms. *Stock Listed Patents* is instrumented in all regressions. All regressions include CZ, Year and State x Year fixed effects. Column (1) reports the effect when the stock of patents filed by listed firms is interacted with a dummy indicating whether the CZ is in a state that enforce non-compete covenants (Stuart and Sorenson, 2003). Column (2) excludes 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 CZ level.

Sample	All (1)	Exc. California (2)	All (3)	Exc. California (4)
Stock Listed Patents	0.21*** (0.03)	0.21*** (0.03)	0.32*** (0.07)	0.34*** (0.07)
Stock Listed Patents × Presence of Non-Compete Law	-0.08* (0.04)	-0.09** (0.04)		
Stock Listed Patents × Intensity of Non-Compete Law			-0.04** (0.01)	-0.04*** (0.01)
Observations	17125	16675	17125	16675
CZ Controls	Yes	Yes	Yes	Yes
CZ FE	Yes	Yes	Yes	Yes
State-Year FE	Yes	Yes	Yes	Yes

Table 7. Effect on Inventor Mobility from Listed Firms to Private Firms

685 CZs, 1975-2000. This table shows the mobility of inventors to private firms within the same CZ. *Stock Listed Patents* is instrumented in all regressions. Column (1) examines the number of inventors who move from listed firms to private firms. 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 CZ. 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 CZ). All regressions include CZ, Year and State x Year fixed effects. Standard errors are in parentheses and clustered at the CZ level.

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)
Stock Listed Patents	0.06***	0.05***	0.02***	0.09***
	(0.02)	(0.01)	(0.00)	(0.02)
Observations	17125	17125	17125	17125
CZ Controls	Yes	Yes	Yes	Yes
CZ FE	Yes	Yes	Yes	Yes
State-Year FE	Yes	Yes	Yes	Yes

Table 8. Capital Inflow: Investments by Non-Local VC Funds

685 CZs, 1975-2000. *Stock Listed Patents* is instrumented in all regressions. In columns (1) and (2), the dependent variable is the number of VC investments made by non local VCs. Columns (3) examine the total amount invested by non-local VC funds. Column (2), (4) exclude from the sample CZs considered as VC centers (Chen et al. 2010). All dependent variables are in log. All regressions include CZ, Year and State x Year fixed effects. Standard errors are in parentheses and clustered at the CZ level.

Dependent variable	**# Investments**		**Total Value**	
	(1)	(2)	(3)	(4)
Stock Listed Patents	0.045** (0.022)	0.045** (0.021)	0.227** (0.097)	0.218** (0.097)
Observations	17125	16775	17125	16775
CZ Controls	Yes	Yes	Yes	Yes
CZ FE	Yes	Yes	Yes	Yes
State-Year FE	Yes	Yes	Yes	Yes
Sample	All	Exc. VC centers	All	Exc. VC centers

Table 9. Innovation Spillovers Depending on Fund Availability

685 CZs, 1975-2000. The dependent variable is the log of patents filed by private firms. *Stock Listed Patents* is instrumented in all regressions. Column (1) reports the effect when the stock of patents filed 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 CZs considered as VC centers (Chen et al. 2010). Standard errors are in parentheses and clustered at the CZ level.

	(1)	(2)	(3)
Stock Listed Patent	0.16***	0.17***	0.17***
	(0.02)	(0.02)	(0.09)
Stock Listed Patent × VC	0.02***		
	(0.00)		
Stock Listed Patent × VC (IV)		0.05***	0.05***
		(0.01)	(0.01)
Observations	17125	17125	16775
CZ Controls	Yes	Yes	Yes
CZ FE	Yes	Yes	Yes
State-Year FE	Yes	Yes	Yes
F-test(State Pension)	-	30	30
Sample	All	All	Exc. VC centers

Table 10. Alternative Stories

685 CZs, 1975-2000. The dependent variable is the log of patents filed by private firms. *Stock Listed Patents* is instrumented in all regressions. All regressions include CZ, Year and State x Year fixed effects. In column (1) I add the Herfindahl Index and its square term of firms in a given CZ. Column (2) restricts the sample to tradable firms (using Mian and Sufi (2014) classification). Column (3) excludes listed firms that are in the last decile of patents filed in a given CZ-year. Column (4) is restricted to listed firms active in at least 5 CZs. Columns (5) and (6) 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 CZ-year cell. Data on M&A come from SDC Platinium. Standard errors are in parentheses and clustered at the CZ level.

Dependent variable	# Patents Private Firms				Any M&A Private Firms	Any M&A Innovative Private Firms
Sample	**All**	**Tradable**	**Exc. Biggest Firms**	**At least 5 CZs**	**All**	**All**
	(1)	(2)	(3)	(4)	(5)	(6)
Stock Listed Patents	0.18***	0.21***	0.17***	0.17***	0.02	-0.01
	(0.04)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Observations	17125	17125	17125	17125	17125	17125
CZ Controls	Yes	Yes	Yes	Yes	Yes	Yes
CZ HHI	Yes	-	-	-	-	-
CZ FE	Yes	Yes	Yes	Yes	Yes	Yes
State-Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 11. Effect of Innovation by Listed Firms on Innovation by Private Firms: Robustness

685 CZs, 1975-2000. Dependent variable is the log of patents filed by private firms. In all regressions, *Stock Listed Patents* is instrumented. All regressions include CZ, Year and State x Year fixed effects. Column (1) includes a measure of expected CZ-level patenting based on its initial specialisation times a time trend. Column (2) excludes CZs 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 CZs different from the state of headquarter. Standard errors are in parentheses and clustered at the CZ level.

Sample	All (1)	Exc. TechPole (2)	Exc. TechStates (3)	Exc. Delaware (4)	Exc. State HQ (5)
Stock Listed Patent	0.16*** (0.02)	0.16*** (0.02)	0.18*** (0.02)	0.17*** (0.02)	0.17*** (0.02)
Observations	17125	16875	16550	17125	17125
Techno Trend	Yes	-	-	-	-
Czone Controls	Yes	Yes	Yes	Yes	Yes
Czone FE	Yes	Yes	Yes	Yes	Yes
State-Year FE	Yes	Yes	Yes	Yes	Yes

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 popupation 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 CZ.

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 CZ 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 CZ-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. Effect of Innovation by Listed Firms on Innovation by Private Firms

685 CZs, 1975-2000. The dependent variable is the log of patents filed by private firms. All regressions include CZ, Year and State x Year fixed effects. Column(1) is the stock of the actual number of patents filed by listed firms in a given CZ. Column(2) instruments the stock of patents by listed firms using the adoption of BC laws. Column (3) adds the stock of knowledge in *Close CZs* CZs defined as the 4 closest CZs and *Distant CZs* defined as the next 4 closest. Columns (4) and (5) add various controls at the CZ-Year level. Standard errors are in parentheses and clustered at the CZ level.

Estimation	OLS (1)	IV (2)	IV (3)	IV (4)	IV (5)
Stock Listed Patents	0.24***	0.21***	0.20***	0.18***	0.17***
	(0.02)	(0.04)	(0.04)	(0.04)	(0.04)
Stock Listed Patents_Close CZs			0.06**		
			(0.03)		
Stock Listed Patents_Distant CZs			-0.01		
			(0.06)		
Population				5.57***	1.95**
				(0.58)	(0.83)
Urban				0.57***	0.50**
				(0.22)	(0.22)
Share Black				-1.32	-1.74
				(1.40)	(1.26)
Share Female				4.23*	3.09
				(2.38)	(2.34)
College Institutions					0.08
					(0.08)
Doctors					0.07***
					(0.02)
R&D Universities					0.02***
					(0.01)
Nb Establishments					1.54***
					(0.37)
Personal Income					0.67***
					(0.16)
Share of Self Employed					-0.01
					(0.08)
Industry Specialisation					0.07
					(0.14)
Technology Specialisation					0.05
					(0.04)
Technology Age					-0.04**
					(0.01)
VC Investment					-0.00
					(0.00)
Observations	17125	17125	17125	17125	17125
CZ Demographic	-	-	-	Yes	Yes
CZ Economic	-	-	-	-	Yes
CZ FE	Yes	Yes	Yes	Yes	Yes
State-Year FE	Yes	Yes	Yes	Yes	Yes