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LOCAL HUMAN CAPITAL AND INNOVATION SPILLOVERS [1]

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Local Human Capital and Innovation Spillovers*

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Short Bios

Liudmila Alekseeva is a PhD candidate in Finance at IESE Business School. Liudmila's research concerns the role of human capital in the performance of firms and the impact of automation technologies on labor markets. Liudmila received a Bachelor degree from the Saint Petersburg State University (Russia) and a Master of Science degree from the Bocconi University (Italy). She also participated in academic exchange programs in the Rensselaer Polytechnic Institute (USA) and the Vienna University of Economics and Business (Austria). Prior to joining the MRM program, Liudmila worked in the audit of financial institutions with PwC Russia and had a strategy consulting experience with Bank Uralsib and technology startups in Russia.

Miguel Antón is Associate Professor in the Department of Financial Management at IESE Business School. His research interests lie on corporate finance, corporate governance, and Fintech. Together with his co-authors, he is currently studying the impact of common ownership (i.e., investors holding sizeable ownership stakes in several companies in the same or in related industries) on executive compensation and innovation. Prof. Antón received his undergraduate and master's degrees in economics from the University of Navarra. He holds an MSc in finance and economics from CEMFI, and he received his PhD degree in finance from The London School of Economics. He has been a visiting fellow at Harvard University, and has presented at top international conferences (AFA, WFA, EFA). He has also given seminars in more than a dozen institutions, including Harvard Business School, the Federal Reserve Bank of New York, the Rotman School of Management in Toronto, HEC Paris, Instituto de Empresa in Madrid, Universidade Nova de Lisboa, and others. He is also a research consultant to private institutions. Prior to his academic career, Prof. Antón worked for The Bank of New York, and for BBVA in the research department.

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Non-technical Summary

When most developed economies face declining productivity growth and stable or shrinking working-age populations, only innovation can offer potential for an increase in productivity and continuing economic growth. Therefore, it is not a surprise that every firm tries to bring the new groundbreaking technology to the market. And the examples of firms such as Alphabet, Amazon, Microsoft, Apple, and others show that in this rush for productivity growth, the one who can offer the most innovative solution wins.

For a long time, location in a large innovative cluster such as Silicon Valley, New York, or Seattle was considered an almost necessary condition to become an innovation leader. In clusters, firms can reap the benefits of knowledge spillovers from nearby firms or just from the knowledge "in the air" (Marshall, 1920). However, it appears that the recipe to locate in a cluster to grow innovation is not universal. R&D efforts of your peers can not only foster your innovation via exchanging useful ideas, but also discourage your innovative efforts if peers in a related product area are likely to win over your customers (Bloom, Schankerman and Van Reenen, 2013). But what mechanism is defining which force will win - benefits from peers' knowledge spillovers or threats from product market competitors? This question was not yet considered in the literature.

The example of Amazon choosing the second headquarters' location can shed light on the possible answer. Looking for the perfect location of its second head office, Amazon turned down many lucrative offers from local governors offering great financial incentives in their cities. However, most of the cities that made bids for Amazon did not have a chance to be elected because they did not fulfill the basic requirements, such as availability of skilled human capital and sufficient population density. For Amazon, availability of resources that would boost its innovation potential is of the biggest importance, and these resources are not just tax incentives. Human capital is the resource that can recognise the value of knowledge spillovers, assimilate them, and implement in own innovation process. We therefore suggest that firms can benefit from knowledge spillovers and experience threats from product market rivals differently depending on the human capital available in the area of their location.

We provide empirical evidence on how the sensitivity of firms' R&D to spillovers generated by peers and rivals varies depending on the characteristics of local human capital. We perform a regression analysis and interact technological peers' and product market rivals' spillovers with the characteristics of the local human capital in the metropolitan statistical area (MSA) of firm location. We focus on the effect of value (measured as average educational attainment and median household income), density, and a potential future growth in density of human capital as main human capital characteristics. We measure R&D spillovers from firms' technological peers (SPILLTECH) and product market rivals (SPILLSIC) as peers' and rivals' accumulated R&D, weighted by their proximity to the analysed firm, respectively following methods in Bloom, Schankerman and Van Reenen (2013) and Lucking, Bloom and Van Reenen (2018). And we look at the effects in both locations (headquarters and inventors).

We find support to our predictions. First, when educational attainment or density of human capital is higher, more product market rivals' R&D is associated with a stronger increase in the firm's R&D expenditure. Despite that, on average, firms do not show a corresponding higher R&D output, proxied by the number of patents. Thus, competition for ideas seems to be higher in such areas and motivates firms to invest more in R&D but also seems to make patenting harder.

Second, when human capital is both more valuable and dense, both knowledge exchange and competition for ideas seem to be stronger. Results show that in dense MSAs (and MSAs with a higher potential future density increase) which have a more valuable human capital, higher technological peer's knowledge spillovers (SPILLTECH) are associated with a more positive effect on the firm's number of patents. Meanwhile, higher product market rivals' R&D (SPILLSIC) is associated with an increasingly negative effect on the number of firm's patents. Thus, the total effect on the innovation output depends on the relative strength of these two positive and negative effects moderated by the density and value of human capital at the firm's location.

To better identify the mechanism driving our results, we carry out multiple tests that strengthen the importance of learning for the firms' R&D investment decisions. These tests are consistent with the fact that co-located firms can exchange knowledge via learning, sharing, and matching.

The results offer implications for a range of regional growth policies and firm location decisions. Governments often try to incentivize innovative firms to locate in a specific region by offering tax incentives and trying to repeat the success of Silicon Valley, Boston, or Seattle. However, our analysis shows that firms' location can impact its R&D inputs and outputs via varying effect on the firm's ability to capture positive and mitigate negative effects of other firms' R&D. Therefore, without considering these effects from relocation or co-location, the policy directed at attracting all kinds of firms to the area might prove ineffective if the cost of invested government funds exceeds the benefits of regional growth or innovation productivity brought by the firm. More generally, our study shows the importance of human capital for the economic activity in a new light. If a growing effort to replace skilled human labor with more precise and productive automated algorithms (e.g., AI) succeeds, the economy risks to lose an important driver of ideas exchange and competition embedded in human capital. Therefore, attracting or maintaining the co-location of valuable human capital might be an important consideration for innovation and even competition policies.

Altogether, the study provides an empirical evidence on the indirect effects of human capital on innovation omitted by the literature so far. Local human capital affects benefits from knowledge spillovers and threats from competitors' R&D. The total effect of these two often opposite effects can determine the output of the firm's innovation activity. And this is a novel contribution to the investigation agenda on the factors that impact firms' innovativeness.

1 Introduction

A common assumption in agglomeration literature is that there exist knowledge spillovers that facilitate exchange of skills and ideas, adoption of technologies, and economies of scale. Agglomeration studies find that firms co-locating in urbanised areas are more productive (e.g., Marshall, 1920; Rauch, 1991; Ellison, Glaeser and Kerr, 2010) and innovate more (e.g., Audretsch and Feldman, 1996; Carlino, Chatterjee and Hunt, 2007). It was also shown that firms effectively build innovation on the local pool of knowledge (e.g., Jaffe, Trajtenberg and Henderson, 1993; Agrawal, Cockburn and Rosell, 2010; Arora, Belenzon and Lee, 2018) due to the existing knowledge "in the air" or due to a more efficient localized ideas exchange. However, besides positive effects of the knowledge spillovers considered in agglomeration literature, firms' innovation can be affected by the product market spillovers resulting from R&D performed by rivals operating in related product markets (Bloom, Schankerman and Van Reenen, 2013; Colino, 2017; Lucking, Bloom and Van Reenen, 2018). While knowledge (or technology) spillovers increase productivity and value of firms operating in similar technology areas, the market rivalry effect of R&D has a negative effect on firms' value due to the potential business stealing by firms operating in similar product markets. Thus, geographical location as well as location in technological and product market space can affect firms' R&D input and output.

This paper sheds new light on the role of innovation spillovers by considering positive agglomeration effect and potentially opposite effects of peers' and rivals' R&D efforts on firms' innovation. These various effects have not been yet considered together in the literature. More specifically, we suggest that the firm's geographical location's characteristics will influence its ability to internalise R&D spillovers from their technological peers and product market rivals, measured as in Bloom, Schankerman and Van Reenen (2013) and Lucking, Bloom and Van Reenen (2018).

Understanding of how local characteristics affect firm innovation is important for the policies aimed at fostering innovation and boosting regional growth. Governments are concerned with the possible ways to promote innovation in their area and to create productive clusters that could repeat the success of Silicon Valley, Boston, or Seattle. They often try to incentivise innovative firms to locate in a specific region by offering tax incentives which will pay off in the result of regional growth (Wilson, 2009; Lychagin et al., 2016). However, the policy directed at attracting all kinds of firms to the area might prove to be ineffective if the cost of invested government funds exceeds the benefits of regional growth or innovation productivity brought by the firm. We suggest that depending on location, firms might show various elasticity of innovative efforts and results to the existing innovation spillovers. In particular, local characteristics, such as the quality of human capital in the area, can allow firms to increase the positive effect on innovative results due to available knowledge spillovers. At the same time, local characteristics might not allow the firm to mitigate product market rivalry effects. In this case, benefits of R&D will accrue largely to competitors and the incentives of the firm to innovate in this region will fall. Thus, the decision about which firms should receive incentives from the government funds and locate in a chosen region should consider both, positive and negative, spillover effects and their dependency on the local characteristics (i.e., which type of spillovers will prevail). The same issues are relevant for the firm making decisions about headquarters' or research laboratories' locations, as its ability to benefit from R&D spillovers will depend on the local characteristics.

In this paper, we analyse value, density, and a potential future growth in density of human capital as important local characteristics. Human capital is considered a driver of productivity in the models of economic growth (Lucas, 1988; Romer, 1990) and in the empirical studies of regional differences in productivity (Rauch, 1991). We perform a regression analysis and include the interactions of technology and product market spillovers with the characteristics of the local human capital in the metropolitan statistical area (MSA) of firm location (both headquarters and inventor locations) to analyse the effects of interest. We measure human capital value in the MSA as average educational attainment (e.g., Gennaioli et al., 2013) and median household income (e.g., Glaeser and Mare, 2001). Density of human capital is measured by the population density and by the density of business establishments in the MSA. For the measure of the potential future growth of the MSA we use the PDI measure proposed by Memarian and Vergara-Alert (2018).

The analysis of the relationships involving human capital is subject to several endogeneity issues. The first issue concerns the simultaneity of two effects: changes in regional human capital affect innovation and innovation influences the flows of human capital to/from the region. The second issue stems from the possibility that the measures of human capital qualities proxy for some other regional characteristics related to innovation, for example investment opportunities. To address these issues, we use instrumental variables approach. First, we instrument contemporaneous human capital characteristics with lagged characteristics. Second, following the literature we use the presence of universities created during the "land-grant movement" in nineteenth century (Moretti, 2004) to instrument the value of human capital in the region. Additionally, we employ housing demand sensitivity calculated by Saiz (2010) to instrument the value and density of human capital in the area. Finally, we control for other MSA-level characteristics to test alternative explanations. Final endogeneity issue relates to the possible common shocks to investment opportunities.Bloom, Schankerman and Van Reenen (2013) use changes in the firm-specific tax charges of R&D to instrument R&D spillovers. We borrow the measure of this instrumental variable from Lucking, Bloom and Van Reenen (2018).

If the location characteristics are irrelevant for the firm's ability to capture spillovers, we should see the same sensitivity of R&D inputs and outputs to the R&D spillover measures of otherwise similar firms located in different areas. The results using the firm headquarters' location show, however, that local human capital does matter for the firm's innovation. In particular, higher local educational attainment is associated with a steeper positive effect of product market spillovers on the firm's R&D intensity. In other words, effect of the rivals' R&D stock on the firm's R&D effort is stronger in areas with more valuable human capital. In a subsample of firms located in high-density MSA, we find that a higher human capital value is associated with a more negative effect of product market spillovers on the firm's patenting.

Therefore, firms located in high-density-high-education areas will patent less compared to similar firms that have access to the same stock of product market spillovers but located in other areas. These results are consistent with the patent races effect – higher competition for ideas can motivate firms to invest more in R&D but can also make patenting harder. Additionally, in the subsample of firms located in high-density MSAs, a higher educational attainment is associated with a more positive effect of technology spillovers on patenting. Thus, such firms will patent more because they can exploit technology spillovers more effectively. These effects are robust to using instruments for endogenous MSA-level characteristics and controlling for variables measuring overall entrepreneurial attractiveness of the area, the presence of a patenting university, and the existence of non-compete agreements in the MSA.

Results of the analysis using firms' inventor location show that local human capital characteristics are important for the number of patents in the MSA of the research facilities, but they do not affect the magnitude of the spillovers impact on firms' R&D output. This result suggests the existence of different mechanisms of spillover impact on innovation through the headquarters, where strategic decisions about R&D are made, and through research laboratories, where scientists implement these decisions and accumulated knowledge.

The identified relationships do not reveal the underlying mechanism in action. However, based on the robust effect of educational attainment in the MSA on R&D intensity and patenting, learning abilities of the skilled human capital seem to play an important role in determining firms' ability to capture innovation spillovers. This is also supported by the findings that local legislation favouring employees' freedom to change jobs, as measured by the presence of non-compete provisions, plays an important role and is associated with a higher R&D investment and more patenting. Also, the presence of a patenting university in the MSA of the firm's research facility is associated with a higher number of patents in the MSA.

We build on two streams of academic literature: literature on the effects of innovation spillovers and agglomeration literature. We contribute to the literature by documenting that, due to their geographical location, firms do not have an equal access to the stock of technology (knowledge) spillovers and can experience varying competitive pressures due to varying effects of existing product market spillovers. Our results show that human capital in the area of firm location affects the sensitivity of firms' R&D to innovation spillovers.

The paper is structured as follows: Section 2 gives a short overview of the existing literature and suggests hypotheses, Section 3 provides description of the data used and explains variables construction, Section 4 presents an empirical methodology used in the study, analyses and discusses results, Section 5 concludes.

2 Literature Review and Hypotheses Development

2.1 Related literature

Innovation is an important driver of economic growth, and it is not surprising that academic literature in Finance, Industrial Organizations, and Strategy analyses affecting it factors. Extensive literature studies the impact of agglomeration and firms' co-location on productivity and innovation. Existing studies, however, have mostly concentrated their attention on positive effects of co-locating on firms' productivity and innovation via more effective exchange of ideas and skills, accelerated adoption of new technologies, and creation of economies of scale. A separate literature stream analysed the effect of knowledge spillovers and product market rivalry effect on firm innovation (Bloom, Schankerman and Van Reenen, 2013; Colino, 2017; Lucking, Bloom and Van Reenen, 2018). These two different types of R&D spillovers were shown to generate opposite effects on the firm's innovation. In our research, we combine these two streams of the literature: studies analysing the effect of firms' co-location on their productivity and studies analysing the impact of different types of spillovers resulting from peers' R&D efforts.

Since the beginning of the 20th century, urban economists have studied the connection between firm location and economic activity. The review of historical development of this literature is available in Ciccone and Hall (1996) who note that earlier studies focused on physical attributes of location while more recent studies analyse the impact of human capital on firms' productivity. Overall, agglomeration theory suggests that there are increasing returns to firm activities resulting from the reduction in transportation and coordination costs of co-located firms (Ciccone and Hall, 1996).

Lucas (1988) noted that cities are more than a collection of production factors. It would be cheaper for firms to produce outside cities, but the value of accumulated human capital holds the city together. Ellison, Glaeser and Kerr (2010) test the three Marshallian theories of industries' coagglomeration, predicting that agglomeration occurs because it reduces the costs of moving goods, people, and ideas, versus the theory of agglomeration due to the existence of shared natural advantages. The authors find that shared natural advantages are important for agglomeration of different industries (e.g., coastal area is important for oil refining and ship construction despite few other relationships between the industries), but that the cumulative effect of the Marshallian factors is still more important for industries agglomeration on state, MSA, and county level.

Built on the idea of colocation to save, among other, on ideas exchange costs, an extensive stream of research analyses the importance of innovators' geographic proximity for innovation. Jaffe, Trajtenberg and Henderson (1993) found evidence of localized knowledge spillovers, meaning that patents are more likely to be cited by new patents from the same state or Standard Metropolitan Statistical Area (SMSA). Audretsch and Feldman (1996) show that innovative activity tends to cluster more in industries where knowledge spillovers are crucial. Agrawal, Cockburn and Rosell (2010) find that inventors from large firms located in areas with no other major innovating peers tend to disproportionately cite their own prior patents relative to what would be expected from the distribution of innovative activity across all inventing firms in the technology field. However, a recent study by Arora, Belenzon and Lee (2018) contests the notion that knowledge transmission is localized (invention A is built on earlier local invention B) by finding evidence that inventors may instead draw from the pool of local knowledge rather than a specific local prior invention (invention A is built on a background knowledge that is also relevant for invention B). To establish this relationship, the authors use citation reversals (when citing patent is filed before the patent of the cited invention) and show that, for both, patents with citation non-reversals and citation reversals, the effect of distance on citation probability is negative and similar in size.

Not only patenting activity shows localization effect. The effect of local peers on investment decisions was analysed by Dougal, Parsons and Titman (2015). The authors identify that for the prediction of changes in the firm's investment rate, the level of investment expenditures incurred by the firm's local peers from different industries is as important as the investment expenditures of the firm's non-local industry counterparts.The authors also show that the role of local peers' investment for the prediction of a given firm's investment is especially pronounced in more growing areas (i.e., in areas with above-median wage per capita and population growth).

Research also finds that firms and inventors located in areas allowing for more effective exchange of ideas are expected to produce better outcomes. For example, Glaeser and Mare (2001) suggest that employment in dense urban areas, where ideas and skills are likely to spread, increases workers' productivity. Carlino, Chatterjee and Hunt (2007) reach a similar conclusion finding a statistically significant positive relationship between patenting intensity and employment density in highly urbanized MSAs. Knudsen et al. (2008) analyse the relationship between innovation output (number of utility patents) and the density of creative communities in the area. The study identifies that the areas with a higher density of creative communities have a higher patenting activity, showing the importance of interaction of scientific and creative workers.

Literature proposes various mechanisms responsible for the identified spillover effects. Glaeser and Mare (2001) and Carlino, Chatterjee and Hunt (2007) suggest that geographic proximity created by density facilitates information exchange among workers and firms. Knudsen et al. (2008) suggest that exchange of ideas is likely to occur because creative communities build spaces where they generate new and different ideas, and these spaces in turn attract technological innovators and help them to find new ideas. Dougal, Parsons and Titman (2015) emphasise the importance of top management communication in shaping the firm's investment strategy (peer effects on innovation are identified at firm headquarters' locations). Similarly, Fracassi and Tate (2012) find similar investment patterns of firms that share board members. The idea of interpersonal exchange of skills and ideas is also fundamental in Glaeser, Ponzetto and Zou (2016) modelling costs and benefits of dense cities and urban networks. Almeida and Kogut (1999) suggested that the flow of knowledge is driven by the local labour markets for patent-holders. The authors tracked careers of individual engineers and identified that a stronger presence of externalities in the Silicon Valley is explained by the movement of individual patent holders between firms within the region. One of the studies getting closer to the discovery of the mechanism of knowledge exchange is a recent paper by Chai and Freeman (2019) analysing the effect of temporary co-location of scientists at the conferences. The authors find that conferences increase subsequent collaborations for the attendees who did not have prior within-conference collaborations, compared to the control group of researchers not participating in the conference. The mechanism responsible for this result is matching, meaning that geographic proximity can reduce the effort and cost to search for potential collaborators.

In this paper, we combine ideas from previously described research with a separate stream of literature that challenged the common assumption that there is just one kind of spillovers, usually technological spillovers. In particular, Bloom, Schankerman and Van Reenen (2013) distinguish between technology spillovers and the product market rivalry effect of R&D. The authors showed that while technology spillovers can increase productivity of firms in similar technology space, product market spillovers would decrease firm value due to market stealing effect. Lychagin et al. (2016) use a similar empirical methodology and measure geographical spillovers, thus pointing out that not only the proximity in technological and product space among firms, but also the proximity in physical space determines whether a firm will benefit from innovative efforts of other firms. Anton et al. (2018) extend the analysis of technology and product market spillovers analysing their interaction with firms' common ownership. The authors find a positive relationship between common ownership and innovation when technological spillovers are high relative to product market spillovers. Colino (2017) adds the measure of dynamic spillovers reflecting cumulative knowledge proximity and based on the patent citations network. This measure accounts for the fact that past R&D may create future spillovers, not only contemporaneous ones. The author finds that dynamic spillovers are complementary to more static spillovers identified by Bloom, Schankerman and Van Reenen (2013) and are particularly important in industries with complex products built from multiple separately patentable elements.

Overall, theoretical literature and empirical evidence on agglomeration suggests that co-location helps firms to save on costs of transporting goods, people, and ideas, and increases workers' and firms' productivity as a result. It also supports the idea of existing local knowledge pool "in the air" (Marshall, 1920) that firms can benefit from. However, as also pointed out in the literature review chapter by Carlino and Kerr (2015), the exact mechanism of knowledge exchange in the result of co-location is not clearly identified in the literature. But the idea that geographic proximity facilitates the exchange of tacit knowledge via purposeful and accidental interactions among individuals proposed by Marshall (1920) is still underlying in much of the agglomeration literature. The literature advanced by Bloom, Schankerman and Van Reenen (2013), however, cautions that the information exchange in the result of R&D can lead to the benefits for the firm in the form of a higher productivity, as well as can be to the detriment of its innovation due to potential product market stealing.

2.2 Hypotheses

The two types of spillovers, in Bloom, Schankerman and Van Reenen (2013)'s formulation, are equally accessible to everyone operating in similar technology and product market spaces, and their effect can only decrease with distance from other firms (i.e., in Bloom, Schankerman and Van Reenen (2013) distance is significant for technology spillovers but not product market spillovers). On the contrary, a long history of agglomeration literature provides a substantial theoretical and empirical evidence on the significant effect of local human capital qualities on productivity and innovation of firms. Therefore, depending on these qualities, firms are likely to capture benefits and mitigate rivalry threats resulting from spillovers differently. If the characteristics of human capital in the area did not affect the ability of firms to internalise spillovers, we would see the same sensitivity of R&D inputs and outputs to the R&D spillovers of otherwise similar firms located in different areas.

Supporting this view, Moretti (2004a) finds that the productivity of plants located in cities experiencing a larger increase in human capital outside the firm is rising compared to the productivity of plants located in cities where human capital does not change. This finding presents an empirical support to the predictions of the general equilibrium model is which the share of educated workers in the city generates positive human capital spillovers and increases productivity of all plants in the city. Empirical research also shows that with the increase in urban density, the number of patents per capita (Carlino, Chatterjee and Hunt, 2007; Knudsen et al., 2008) and overall workers' productivity (e.g., Glaeser and Mare, 2001) increase. Moreover, in dense areas skills are accumulated faster (Glaeser and Mare, 2001) due to a higher chance of face-to-face interaction and switching jobs.

Substantial theoretical literature on human capital-based growth models advanced the idea that human capital is the basis for the understanding of existing knowledge and transferring it to others. Lucas (1988)'s model of endogenous growth emphasized the role of human capital in economic growth due to the fact that skilled workers are better able to receive knowledge from others. The ability of firms to recognise the value of knowledge, assimilate it, and implement it in business was named absorptive capacity by Cohen and Levinthal (1990). The authors showed that absorptive capacity is necessary for the innovation process. Therefore, we suggest that areas with a higher quality and density of human capital not just increase the productivity of firms' innovation activities, they change the sensitivity of the firms' innovation towards the available spillovers due to a higher ability to internalise available knowledge.

The relationships between technology and product market spillovers and innovation are modeled by Bloom, Schankerman and Van Reenen (2013). The idea behind the spillovers is that R&D efforts of firms cannot be perfectly appropriated and thus benefit other firms. For each of two types of innovation spillovers, the model generates two important predictions that are relevant for our analysis. First, technology (or knowledge) spillovers are expected to increase innovation productivity of other firms operating in the same technology space. Bloom, Schankerman and Van Reenen (2013) show that R&D by technologically similar firms increases the total factor productivity of a given firm and its stock of knowledge and thus patenting, given the R&D expense. Second, based on the theory, the effect of technology spillover on R&D expense is ambiguous because it depends on how much spillovers affect the marginal product of R&D, which is not known ex ante. Firms will increase (decrease) R&D spending if their technological peers' knowledge is complementary (a substitute). Lucking, Bloom and Van Reenen (2018) find a positive relationship between technology spillovers available to the firm and its R&D expenses before 1990 but negative relationship most of the time after that. They interpret this finding as a decreased over time strategic complementarity between the research efforts of technologically similar firms.

In sum, technology spillovers create a pool of knowledge created by technological peers that firms can benefit from and two similar firms having access to equal technology spillovers can, potentially, equally benefit from them. However, because as shown above, the ability of workers to absorb existing knowledge and understand new is higher when the human capital level and density are higher, firms in more educated and dense areas will be able to internalise these positive externalities of peers' R&D better. We suggest that in areas with a more valuable (more dense) human capital the positive effect of technology spillovers on knowledge stock measured by patents will be higher, for the given level of R&D expenses.

H1: In areas with a higher value of human capital (higher density of human capital) the positive relationship between patenting and technological spillovers will be larger.

In turn, we suggest that in the areas with a more valuable (more dense human capital), due to a higher ability of employees to assimilate and implement new knowledge, the positive (negative) effect of technology spillovers on R&D expense will be greater (lower) when R&D of technological peers shows strategic complementarity (substitutability).

H2: In areas with a higher value of human capital (higher density of human capital) the positive (negative) relationship between R&D effort and technological spillovers will be larger (smaller).

The second spillover effect identified by Bloom, Schankerman and Van Reenen (2013), product market rivalry effect of R&D, has a negative effect on a firm's value due to business stealing. Theoretically, R&D by product market competitors (excluding any effects of technological similarity of rivals) does not affect the firm's knowledge production and therefore patenting activity. However, this theoretical prediction will not hold, if patents are costly and the decision to patent is endogenously taken by the firm considering this cost (Bloom, Schankerman and Van Reenen, 2013). In this case, firms will patent more (less) if the knowledge of rivals is a strategic complement (substitute) to its own knowledge. Bloom, Schankerman and Van Reenen (2013) found no statistically significant relationship between product market spillovers and the citation-weighted number of patents in their study of 1981-2001 period. At the same time, Lucking, Bloom and Van Reenen (2018) find a negative relationship between the variables after 2000 as the evidence that competitors' R&D decreases the marginal benefit from R&D effort of a given firm, and this firm's propensity to patent decreases.

High product market spillovers increase the firm's risk of market stealing – when competitors innovate more, there is a higher chance that they patent the product first and obtain monopoly rights and corresponding rents from this invention. When firms are located in areas with a higher value of human capital or its higher density, the ideas exchange is likely to increase, because in such areas, the pool of available knowledge is larger, and inventors have a higher chance of face-to-face interaction and switching jobs (Almeida and Kogut, 1999). Combined with the availability of significant R&D stock created by product market rivals, the threats to the competitive position of the firm are likely to increase, as well as the opportunities to mitigate them. In his model, Romer (1990) explained that it is unlikely that firms will undertake R&D expenses if they cannot capture its result. Thus, the owner of knowledge will protect the invention via patenting or trade secrets. Therefore, in order to protect firms' ideas and gain the market share, we suggest that firms will attempt to patent more.

H3: In areas with a higher value of human capital (higher density of human capital) the positive (negative) relationship between patenting and product market spillovers will be larger (smaller).

According to Bloom, Schankerman and Van Reenen (2013), if there is strategic substitution between rivals' R&D efforts, high spillovers will be negatively related to R&D expenses of a given firm. Strategic complementarity of R&D spending by the firm's product market rivals results in a positive effect of rivals' R&D on firms' own R&D expense; this effect is explained by patent race models. The enhanced competition increasing the stakes for the competing firms may motivate greater investment of resources in innovation (e.g., Loury, 1979)[1]. Lucking, Bloom and Van Reenen (2018) find a negative relationship between product market spillovers and R&D expenses before 1990 and a positive relationship after that, suggesting that the strategic complementarity of rivals' R&D efforts increased over time. Therefore, we suggest that firms will increase their R&D expenses when the firm locates in the area with valuable and concentrated human capital in response to product market threats. Based on the patent races idea, when there is a higher risk of losing market to innovative competitors, firms will try to patent more and therefore will increase R&D expenses.

H4: In areas with a higher value of human capital (higher density of human capital) the positive (negative) relationship between R&D effort and product market spillovers will be larger (smaller).

The exact mechanism allowing firms surrounded by high-quality human capital and located in dense areas increase their productivity is still debated. Duranton and Puga (2004) and Carlino and Kerr (2015) explain three possible mechanisms leading to the change in firms' productivity and innovation output in the result of agglomeration – learning[2], sharing, and

[1] Alternative explanation for the positive relationship of own and rivals' R&D expenses is the common shock to investment opportunities (Bloom, Schankerman and Van Reenen, 2013).

[2] Called *knowledge spillovers* in Carlino and Kerr (2015). We call it following Duranton and Puga (2004) in order to avoid confusion with the measure of technology spillovers (also called knowledge spillovers) from Bloom, Schankerman and Van Reenen (2013).

matching. Learning mechanism relates to the ability of geographically concentrated individuals to exchange knowledge more effectively. Literature relying on this mechanism has mostly focused on the passive exchange of knowledge from close proximity of innovators without elaborating specific mechanisms of knowledge exchange (Carlino and Kerr, 2015). Sharing mechanism is responsible for the economies of scale in the result of sharing locally available specialised inputs of production. Sharing is likely to relate to the human capital qualities to the extent that availability of high-quality human capital can be correlated with the availability of local amenities generating higher returns on scale due to cheaper inputs or easier access to the necessary services or specialists (e.g., venture capital financiers, patent attorneys, advertising agencies can be considered such shared inputs). Matching mechanism is responsible for a better match of firms and employees and occurs due to a more active labour market. The process of matching, however, involves two opposite effects: while the availability of a larger pool of workers increases the chance of a more productive match, there is also a higher competition for the productive workers and the risk of losing a valuable employee.

Prior literature found it challenging to disentangle the mechanisms behind the agglomeration effects on firms' innovation (e.g., see review of literature by Audretsch and Feldman (2004) and Carlino and Kerr (2015)). Nevertheless, in our empirical tests discussed in additional tests we control for some of the effects that give a hint on the existing mechanisms. We control for the overall level of the area's economic activity, measured as in Glaeser and Hausman (2020) using the number of business establishments' growth rate. Another control we use is the presence in the area of an actively patenting university to control for the presence of another important user and generator of knowledge other than local human capital. Carlino and Kerr (2015) state that the presence of universities is different from the effect of education and skills discussed above and can be considered a specific natural advantage around which innovative clusters are likely to form. Lastly, we control for the presence of non-compete provisions in the state of the firm's MSA to check whether a legislative mechanism allowing for more employees' freedom in the choice of workplace explains the identified effects. Instrumental variables approach also sheds light on the existence of the mechanisms we are hypothesising about and is described in Section 4.

3 Data and Variables Construction

3.1 Firm-level data

Firm-level data is obtained from Compustat/CRSP merged dataset. We drop firms with negative and/or missing values on sales and total assets in Compustat, as well as firms from financial services (SIC codes between 6000 and 6999) and utilities (SIC codes between 4900 and 4999) sectors. All accounting variables in Compustat and ratios computed using Compustat data were winsorized at 1% level. For the purpose of the analysis, we identify firm location based on zip code or state of the company's corporate headquarters or home office available in Compustat (ADDZIP and STATE[3] variables). Corporate headquarters is a principal centre of decision-making for major corporate decisions, including capital investments and R&D. For example, Dougal, Parsons and Titman (2015) identified peer effects on investment at firms headquarter locations and emphasised the importance of top management communication in shaping the firm's investment strategy. We consider firms headquarter location to be a suitable basis for the analysis of firms' innovation activities. However, we perform additional tests using firms' research centres' location in Section 3.4.2.

3.2 Innovation

Firms' innovation activity is measured by two sets of variables capturing inputs and outputs of innovation. The input is measured as the logarithm of one plus R&D expenses scaled

[3] STATE variable in Compustat shows the abbreviation of the state where headquarters of the firm are located. It is different from variable INCORP that for US firms shows the state of incorporation. While most firms in our sample are incorporated in Delaware (INCORP variable), very few observations have their headquarters there (ADDZIP and STATE). For example, Intel Corp. is incorporated in Delaware but has its "principal executive offices" in California, as shown in the 10-K report: https://www.sec.gov/Archives/edgar/data/50863/000005086316000105/a10kdocument12262015q4.htm.

by Sales from Compustat (*L(RD/Sales)*) and as a logarithm of R&D expenses deflated by the Consumer Price Index (CPI) (*L(RD)*). XRD variable containing information on R&D expenses in Compustat has many missing values, thus, to address the issue of possible incorrect and missing data, all negative values of R&D expense in Compustat are replaced by zero and missing values are replaced by zero if the firm had non-missing R&D expenses at least in one year in Compustat.

Output of firms' innovation is measured by the firms' patenting activity, as it is a standard practice in the literature (e.g., Aghion and Jaravel, 2015; Kogan et al., 2017; Brav et al., 2018). Three measures of patenting activity that we use are borrowed from Kogan et al. (2017). The first measure, *L(Tcw)*, is the logarithm of one plus citation-weighted patent count, a widely used measure of innovation output in the literature. The second measure, *L(Tsm)*, is the logarithm of one plus the total dollar value of innovation produced by a given firm in a given year, calculated based on stock market value of patents. *L(fNpats)* is the logarithm of one plus unweighted count of patents granted to the firm in a given year. We employ three different measures of patenting activity to capture three different dimensions of innovation output. Unweighted patent count (*L(fNpats)*) reflects the quantity, while two other measures reflect the quality of invention: scientific value of produced patents (*L(Tcw)*) and a private economic value of patents reflecting the potential to its commercialization and rent extraction (*L(Tsm)*) (Kogan et al., 2017).

The key explanatory variables include the measures of R&D spillovers from Lucking, Bloom and Van Reenen (2018) and MSA's socio-economic characteristics from U.S. Census Bureau described below. R&D spillovers from Lucking, Bloom and Van Reenen (2018) is an updated measurement of spillovers from Bloom, Schankerman and Van Reenen (2013)[4]. The authors measure two conceptually different spillover effects resulting from R&D efforts of firms. First variable, *SPILLTECH*, measures the pool of technology spillovers available to a given firm as

[4]We borrow the updated technological and product market spillover measures from Nicholas Bloom's website: https://nbloom.people.stanford.edu/research.

the stock of R&D of all firms interacting with the analysed firm in technology space, weighted by the measure of technological proximity between firms proposed by Jaffe (1986). Second variable, *SPILLSIC*, measures the pool of product market spillovers as the stock of R&D of all firms interacting with the analysed firm in product market space, weighted by the measure of product market proximity between firms. The latter measure acts as a proxy for the market stealing effect by competitors with which the firm interacts in the same SIC industries.

We use a range of firm–level controls that include standard variables influencing the firm's innovation efforts and results. Firm size, *log(MV)*, is measured as a logarithm of the firm's market value deflated using the CPI; market value in turn is a sum of market value of the firm's equity (PRCC_F*CSHO) and book value of its debt (LT – TXDITC + max(PSTKL, PSTKRV, PSTK)). Capital-labour ratio, *K/L*, is measured as a logarithm of 1 + ratio of firm's net capital assets (PPENT) to the number of employees (EMP). Firm's age, *log(Age)*, is measured as a logarithm of 1 + the number of years since the firm appeared in Compustat. *Bleverage* is the ratio of the book value of debt to the market value of the firm's assets calculated as above. Asset growth rate, *Atgrow*, is the change in the book value of assets (AT) between current and lagged values divided by the lagged value of assets. *Hiring rate* is the relative change in the number of employees between periods. Profitability measured by *ROA* is the earnings before interest and taxes (EBIT) divided by the book value of total assets. *Tobin's q* is the market value of the firm divided by the book value of assets. *Log(HHI)* is a logarithm of the Herfindahl-Hirschman Index of market concentration defined as the sum of the squares of the firms' market shares; market shares are computed using sales deflated by the CPI at the 4-digit SIC industry-level.

In additional tests, we use a non-weighted patent count obtained from an updated patent data available up 2018 on the USPTO Patentsview website[5]. This data is not merged with any common identifier of databases containing firms' financial information and used in research. Thus, we undertake a challenge to merge these data with Compustat's GVKEY by name. We edit companies' names in each database to bring them to low case, remove punctuation, special

[5]USPTO Patentsview: http://www.patentsview.org/download/.

symbols, and common words (e.g., "incorporated", "limited", "company", "co", etc.) and use Stata's *matchit* algorithm to obtain the closest name match from Compustat for each name of the patent assignee in the patent database. We only keep matches that have a sufficiently high name similarity score to avoid false matches (minimum score that we allowed is 0.85, we keep a few observations with lower scores adding additional controls for names similarity, such observations are normally misspellings). Then, we counted all patents of all assignees that matched with each Compustat firm. We compared our count with the patent count data from Kogan et al. (2017) and identified firms for which our count differs significantly from their data. For top 70 such firms ranked on the total number of patents we performed a manual match, searching for the Compustat name in the patent data and assigning GVKEY manually. We concentrated on large firms because those are the ones that usually have many research divisions or subsidiaries with names that may significantly differ from the name of the parent firm.

Based on this newly merged patent data, we created a dataset that contains the patent count in each of the firm's research facility's MSA. To construct these data, for each patent we identified the location from where the majority of the inventors listed in the patent comes from[6]. When the patent was created by the equal number of scientists from two or more MSAs, we take the location of the scientist with the highest sequence on the patent, assuming that a higher listed inventor is a more important contributor to the patent[7].

3.3 Local human capital characteristics

We test the effect of interaction of technology and product market spillovers with the human capital characteristics at firms' location using data on socio-economic characteristics of metropolitan areas from the United States Census Bureau and the measure of the potential

[6]Patent location data only contains the city and state, or the coordinates of the inventor. We linked the inventor's location city with a city-zipcode crosswalk by city name and its state. Via zipcode we linked the city to the corresponding CBSA. Zipcode-CBSA link is also described in the next subsection.

[7]We however note that it is not always the case that the primary inventor is the most important contributor, since the order may be simply alphabetical.

density increase (*PDI*) from Memarian and Vergara-Alert (2018). Using Census-based variables, we attempt to measure the value and density of the human capital available in the area and thus their productivity and the propensity to exchange ideas and skills. *PDI* measures the expected further construction development of the metropolitan area, and consequently, a potential for human capital growth.

Census data is obtained using the Census Factfinder website. We download these data selecting core-based statistical areas (CBSA) geographical category. CBSA data includes data on metropolitan statistical areas (MSA) and micropolitan areas. For the current analysis, we keep data only at the MSA level. To aid the interpretation of results in regressions with interactions, we demean the MSA-level measures of local human capital characteristics.

We measure educational attainment (*Bachelor_perc*) as the ratio of population with bachelor's or higher degree (masters, professional degree, and doctoral degree) to the total population at least 25 years old. The second measure of the human capital value that we use is income level, which is calculated as a logarithm of median household income in the MSA (*Log(Med_inc)*)[8]. Population density (*Log(Density)*) is measured as the logarithm of annual MSA's population estimate divided by the MSA land area in square miles. Data on the MSA land area is available only in 2010, so the change in population density, as we calculate it, reflects the change of population size. Because the MSA land area is not available on annual basis, Knudsen et al. (2008) construct it aggregating land areas of smaller geographical units into corresponding MSAs. However, they notice that the MSA land area changes little over time and their measure of population density reflects the population growth. Therefore, we believe, our population density measure calculated using a constant land area in 2010 will not generate significant bias. *Log(Bus_density)*, the second measure of density, is the ratio of the number of business establishments in the MSA divided by the MSA land area.

[8]Gentrification literature (e.g., Brummet and Reed, 2018) uses additional measures of local area quality: poverty rate (proxy for neighbourhood amenities – exposure to public goods, e.g. safety and school quality), commute distance and employment (characterises nearby work opportunities), change in rent and house values (e.g., when successful firms attract new employees and drive house prices up).

The measure of the *PDI* was developed by Memarian and Vergara-Alert (2018). It quantifies the amount of land with considerable opportunities for further fast construction growth. The measure is based on the idea that available lands in developed and relatively dense urban areas have more opportunities for fast construction growth due to the existing infrastructure and services. Classification of the MSA areas by the potential for further development was conducted by authors using Google Maps images and a computer script that assigned lands into categories based on the maps' colour codes. PDI measure is calculated as the ratio of size (in square meters) of land that can quickly increase its density (developed land) to the total size of land available for construction (the sum of developed and less developed lands which are expected to grow its density more slowly).

3.4 Sample Overview

We matched zip codes from Compustat with the core-based statistical areas (CBSA) codes from Census via CBSA-zip code crosswalk files provided by the Office of Policy Development and Research[9]. For several CBSA codes existing in Census but not in the crosswalk files, we used web scrapping to obtain the missing zip codes. We also used CBSA names to match Compustat and Census data with the PDI measure. We keep only observations that have necessary Compustat data, spillovers data, and at least one of the analysed MSA characteristics matched via company zip code. The period of analysis differs between the regressions due to varying data availability. We analyse the impact of Census-based human capital characteristic interacted with spillover measures on innovation inputs for the period 2005-2015 and have 4,812 observations, and the impact of PDI – for 2010-2015 with 1,969 observations. *PDI* was estimated in Memarian and Vergara-Alert (2018) for 2010 and, by its logic, this is a forward-looking measure. Therefore, we use *PDI* only in the analysis of investment inputs measured by R&D

[9]Due to differences in geographical and administrative classifications of territories, crosswalk files sometimes assign one zip code to a few (usually two) different CBSAs. These files also report the proportion of businesses with a given zip code registered in a given CBSA. To avoid duplicated data, we only keep one CBSA with the largest proportion of businesses having a given zip code from all businesses with this zip code. Therefore, a small proportion of firms registered in the other CBSA but with the same zip code will be classified to a nearby CBSA.

expenses available in Compustat after 2010. However, because the patent data matched with CRSP identifiers from Kogan et al. (2017) is available up to 2010, only Census-based measures (and not *PDI*) can be used for the analysis of innovation output in 2005-2010 period with 1,862 observations. An additional analysis uses our originally matched patent data for the period from 2005 to 2015 and includes all explanatory variables of interest.

4 Empirical Tests

4.1 Baseline Empirical Methodology

The baseline tests examine the relationship between human capital characteristics in the region of firm location, technological and product market spillovers, and the innovation inputs and outputs of the firms. We estimate the following baseline regression model:

$$\begin{aligned} Innovation_{it} &= \beta_1 MSAchar_{it} + \beta_2 SPILLTECH_{it} + \beta_3 SPILLSIC_{it} \\ &+ \beta_4 MSAchar{*}SPILLTECH_{it} + \beta_5 MSAchar{*}SPILLSIC_{it} + \beta_6 X + \Lambda + \epsilon_{it} \end{aligned} \tag{1}$$

In the equation, i is the index of the firm and t is the index of time. Dependent variable $Innovation_{i,t}$ takes the form of each of the five variables measuring innovation inputs and outputs: $L(RD/Sales)_{it}$, $L(RD)_{it}$, $L(fNpats)_{it}$, $L(Tcw)_{it}$, $L(Tsm)_{it}$. $MSAchar_{it}$ is the regional attribute of interest: proportion of population with at least a bachelor's degree, logarithm of median income, density, or PDI. X is a vector of firm-level controls, Λ represents fixed effects, ϵ_{it} is a random error.

In all regressions we include year and industry fixed effects to account for an economy-wide time trend and time-invariant differences across industries. We control for a wide set of firm-level characteristics described in Section 3 to minimize the chance that the identified effects are driven by omitted variables. In addition to nine controls included in all regressions, a lagged

R&D scaled by sales is included in the regressions where the number of patents is a dependent variable. Because regions across the U.S. states vary significantly (MSAs within Arkansas are significantly different from MSAs within New York state), in a separate set of regressions we also include U.S. state fixed effects to exploit variation characteristics of MSAs located in the same state. Standard errors in all regressions are clustered at the MSA level.

Table 1 presents the summary statistics and description of variables used in the analysis. As mentioned above, the number of observations differs due to the availability of data. Therefore, our sample for analysis of innovation inputs differs from the sample used for the analysis of innovation outputs – the former covers a twice longer period. Panel A of Table 1 shows firms' characteristics. We can see from the table that the sample of firms is rather heterogeneous in terms of size and is skewed to the right – median firm market value is 0.85 billion USD, while the average is 9.71 billion USD, meaning there are many small and a few very large firms in the sample. We use logarithms of monetary values and some ratios to limit the effect of outliers. Beforehand, we winsorize Compustat accounting data and ratios at 1%.

Table 1 Panel B shows summary statistics for the MSA data used in the analysis. Average MSA has population of nearly 2 million people, the proportion of population with bachelor's or higher degree of 30%, average annual (deflated by CPI) income of 38 thousand USD, and population density of 529 people per square mile. Panel B of Table A2 in Appendix presents the descriptive statistics for all MSA in the United States for which there is information on variables we are analysing. The same indicators as above for the average MSA in the United States: population is 0.7 million people, the proportion of population with at least bachelor's degree is 26%, average income is 34 thousand USD, and population density is 286 people per square mile. Based on comparison of the two tables, in our analysis we are considering larger and wealthier MSAs than the average across the United States.

4.2 Baseline Results

We first report and interpret results from the regressions analysing the relationship between human capital value, R&D spillovers, and firms' innovation inputs and outputs. Then we describe results of regressions with human capital density and PDI and their interaction with R&D spillovers as the main independent variables of interest. We conclude the analysis looking at the joint effect of density and human capital value rerunning regressions on two subsamples obtained from partitioning the main sample by the median density.

4.3 Human capital value and spillovers

Table 2 presents results for regressions where independent variables of interest are *Bachelor_perc* and *log(Med_inc)*. We first include each of the two variables in the regression along with *log(SPILLTECH)* and *log(SPILLSIC)* without interactions. If the variable measuring a local human capital characteristic is significant, we add the interactions of this variable with spillover measures. We do not report regressions with interactions if the corresponding variable measuring a human capital characteristic is insignificant in the regression without interactions.

Table 2 shows that in the regression with *L(RD/Sales)* independent variables *Bachelor_perc* and *log(Med_inc)* are both significant and have positive coefficients (columns (1) and (7)). Thus, with the increase in *Bachelor_perc* and *log(Med_inc)*, R&D intensity is increasing on average. These independent variables are insignificant in the rest of the regressions with the three measures of patenting activity and a logarithm of R&D expenses *L(RD)* as dependent variables. Thus, we report the regression with interactions only for *L(RD/Sales)* in columns (2) and (8). In equation (2) of Table 2, both interaction effects are statistically significant. The coefficient at *Bachelor_perc* ceases being significant. This coefficient represents the relationship between educational attainment and R&D intensity when R&D spillovers equal zero, a point which lies outside the empirical distribution of spillover measures in our sample. Therefore, we are not interpreting this coefficient. We can see from equation (2) of Table 2 that the coefficient at the measure of technology spillovers at the mean level of educational attainment (zero value of the demeaned *Bachelor_perc* variable) is significant and equals 0.019, meaning that the increase in *SPILLTECH* by 1% increases R&D intensity of the firm by 0.02% when educational attainment is at the average level. Our measure of *SPILLTECH* differs from the original measure of R&D stock in Bloom, Schankerman and Van Reenen (2013) by the factor of 100 (we divide the original measure by 100 before taking a logarithm). Therefore, to interpret the result using the measure of R&D stock as in Bloom, Schankerman and Van Reenen (2013), we must multiply the result by 100. Therefore, the increase of 1% in the R&D stock produced by technological peers that the given firm can build on is associated approximately with 2% increase in the ratio of R&D-to-sales. However, as column (2) shows, when educational attainment increases by 10 percentage points, the positive effect of technology spillovers on R&D intensity decreases. So, holding other variables constant, the increase of 1% in the R&D stock produced by technological peers where educational attainment in the area is 10 percentage points above the mean, is associated approximately with 1% increase in the ratio of R&D-to-sales. Thus, the positive association between technology spillovers and R&D-to-sales ratio will be smaller in areas with a more valuable human capital and larger in areas with a less valuable human capital. This result is contradictory to the proposed relationship in *H2*.

At the same time, the interaction of *Bachelor_perc* and *log(SPILLSIC)* is positive and significant, but the coefficient at *log(SPILLSIC)* without interaction is insignificant. Thus, the effect of increasing the R&D stock by product market rivals on R&D intensity is increasing with educational attainment (effect would become larger if the individual effect of *log(SPILLSIC)* was positive and statistically significant and would become smaller if the individual effect of *log(SPILLSIC)* was negative and statistically significant). Because the coefficient at *log(SPILLSIC)* is not significant, we cannot say if the overall effect of product market spillovers on R&D intensity is positive or negative. This result supports *H4* hypothesis.

Column (8) of Table 2 shows that the interaction effect of *log(Med_inc)* and *log(SPILLTECH)* is insignificant. The interaction of *log(Med_inc)* and *log(SPILLSIC)* is significant and positive, while the individual effect *log(SPILLSIC)* is insignificant. The interpretation is similar to the one of the results from column (2) discussed above.

Figure A1 also illustrates how the effect of *log(SPILLTECH)* and *log(SPILLSIC)* on the dependent variables differs at various levels of educational attainment and income in the MSA. For example, Graphs E and F show that there is no significant variation in the effects of *log(SPILLTECH)* and *log(SPILLSIC)* in patent regressions depending on *Bachelor_perc* and *log(Med_inc)*.

In sum, local human capital value significantly relates to R&D intensity but not R&D level or output. R&D intensity has a positive association with the stock of technology spillovers, but this association is decreasing with the growth in educational attainment. The effect of product market spillovers on R&D intensity becomes more positive with the growth of education, but the overall sign of the relationship between R&D intensity and product market spillovers could not be identified. Thus, we find some support of hypothesis *H4* and a result contradicting our prediction in *H2*. Results are discussed in Section 4.6.

4.4 Human capital density and spillovers

Table 3 shows the results of regressing the five dependent variables on the density characteristics of the MSA (i.e., population density *log(Density)* and business density *log(Bus _density)*. Density characteristics have a statistically significant positive relationship with the logarithm of R&D expenses, *L(RD)* (columns (2) and (8)). Thus, with the increase in population and business density in the area, firms tend to spend more on R&D in absolute amount. We can also observe this effect in Table A3 of Appendix where we present descriptive statistics for two subsamples obtained by partitioning the whole sample by median population density. In the two subsamples, firms are similar for all characteristics except for average size and R&D spending. In the high-density subsample, the average firm invests 40% more in R&D.

Table 3 shows that *log(SPILLTECH)* has a positive significant relationship with the dependent variables, but the interaction with density measures is insignificant (columns (3) and (9)). Thus, density level does not significantly affect the positive relationship between technology spillovers and the measures of innovation. At the same time, the interaction of density and *log(SPILLSIC)* is positive and significant, while the coefficient of individual effect of *log(SPILLSIC)* is insignificant. Thus, the effect of increasing the R&D stock by product market rivals on R&D expense level is increasing with density (effect would become larger if the individual effect of *log(SPILLSIC)* was positive and statistically significant and would become smaller in magnitude if the individual effect of *log(SPILLSIC)* was negative and statistically significant). Again, this is consistent with *H4*.

Graphs A and B in Figure A2 also present the predictive margins analysis based on the regressions in columns (3) and (9). Graphs C and D show an example of the marginal effects of spillovers for various levels of density in regressions where dependent variables are the number of patents (columns (5) and (11), for example) – density does not affect significantly the association between spillover measures and innovation output.

Table 4 presents the result of testing the association between the potential density growth of the area measured by *PDI*, R&D spillovers, and innovation inputs. As mentioned before, due to the lack of innovation output data for the period after 2010 but the availability of *PDI* measure only in 2010, we cannot test the association between *PDI* and patenting activity of firms (since *PDI* is a forward-looking measure, it could be used to analyse patents only for 2010 with few observations). *PDI* is insignificant in both regressions of innovation inputs, therefore, we do not present regressions with interactions.

To shortly summarize this subsection, density relates to the level of R&D expenses but not to R&D intensity or innovation output. Density does not affect the positive association between R&D expenses and the stock of technology spillovers. The effect of product market spillovers on R&D expenses becomes more positive with higher density, but the sign of the relationship between R&D expenses and product market spillovers could not be identified. Thus, we only find some empirical support to *H4*.

4.5 Human capital value, density, and spillovers

Table 5 shows regression results based on the sample partitioning by the median population density. Results in columns (2) and (3), regressions in low-density subsample with *L(RD/Sales)* dependent variable, are qualitatively similar to the ones we obtained in Table 2. However, in contrast to Table 2, the effect of *log(SPILLSIC)* on R&D intensity, when education is at the mean, is significant and positive. With the increase of *Bachelor_perc*, this positive effect is increasing; but when Bachelor_perc decreases by 10 percentage points, the total effect of *log(SPILLSIC)* on R&D intensity becomes zero, with further decrease of educational attainment, the effect becomes negative. The individual effect of *log(SPILLTECH)* on R&D intensity is positive and significant when educational attainment is at the mean, and the effect decreases with the increase in education. However, because the magnitude of interaction coefficients is similar, the change in education will create a small change in the predicted R&D intensity – knowledge spillover and market rivalry effects of R&D will almost offset each other in the low-density subsample (holding other variables constant).

In column (16) of Table 5, coefficient at *log(SPILLTECH)* without interaction is positive and significant, while *log(SPILLTECH)* and *log(Med_inc)* interaction is insignificant. Coefficient at *log(SPILLSIC)* without interaction and its interaction with *log(Med_inc)* are positive and significant. Therefore, with the increase in median income, R&D intensity increases in the low-density subsample via interaction with product market spillovers. Interestingly, in the high-density subsample, we find a significant negative relationship between the average educational attainment (and also median income) and the number of patents (columns (6), (9), (19), (22), and (25)) in the high-density subsample. Column (10) shows a significant positive interaction effect of *log(SPILLTECH)* and *Bachelor_perc*, individual effect of *log(SPILLTECH)* is insignificant. Thus, with the growth of educational attainment the effect of technology spillovers on patenting is becoming more positive, but the total effect of *log(SPILLTECH)* on patenting can be positive or negative. The sign of interaction term corresponds to the proposed in *H1*, but coefficient at *log(SPILLTECH)* in patent regressions is rarely significant.

Column (26) shows a significant negative *log(SPILLSIC)* and *log(Med_inc)* interaction term, coefficient at individual effect of *log(SPILLSIC)* is significant and negative. Thus, with the growth of income level, the negative effect of product market spillovers on patenting is increasing in magnitude. This result shows the effect that is opposite from the one we proposed in *H3*. Interaction terms, however, are only occasionally significant showing no robust relationship.

We perform a similar analysis splitting the sample by the *PDI*, the potential for a fast future growth of MSA's density in Table 6. Interestingly, we find significant coefficients for education and income only in regressions for the high-PDI subsample. In this subsample, both education and income level have positive association with R&D expenses. The effect of *log(SPILLSIC)* is negative but becomes less negative with the increase in educational attainment, as proposed in *H4*. In column (8), when the *L(fNpats)* is a dependent variable, we find a positive coefficient at *log(SPILLTECH)* and *Bachelor_perc* interaction term and a negative coefficient at *log(SPILLSIC)* and *Bachelor_perc* interaction term in high-PDI subsample. This result is again consistent with *H1* and contradicts predictions in *H3*.

4.6 Discussion of baseline result

We find some support to *H1* hypothesis: in high-density subsample, the growth of educational attainment is associated with a more positive effect of technology spillovers on patenting. However, the total effect of technology spillovers on patenting can be positive or negative, because the coefficient at the *log(SPILLTECH)* without interaction is not significant. Thus, we find support to the view that the productivity of innovation is rising with the increasing value of human capital in dense areas.

We find contradictory evidence for *H2*: we identify that a positive association between technology spillovers and R&D-to-sales ratio will be smaller when human capital is more valuable. On average, in areas with a high educational attainment, the firm will be spending less on R&D to build on the equal stock of available knowledge than a comparable firm in the area with a low educational attainment. This result is also consistent with the possible differences in complementarity/substitution of R&D efforts explained by Bloom, Schankerman and Van Reenen (2013). In particular, the theory predicts a negative relationship between technology spillovers and R&D expense when R&D efforts of technological peers are substitute to the firm's own R&D. Therefore, based on the currently obtained evidence, in areas with a higher educational attainment, firms can show a lower degree of peers' knowledge complementarity.

Regarding *H3*, we find that, in the high-density subsample, with the growth of income level, the negative effect of product market spillovers on patenting is increasing in magnitude. This effect is opposite to what we proposed. We based out hypothesis on the idea that in dense areas with high-value human capital, inventors have a higher chance of face-to-face interaction and switching jobs. Thus, since the ideas exchange is likely to increase, firms will patent more to protect innovation ideas. However, we find that in high-density MSAs, the same stock of R&D generated by product market rivals is associated with a lower patenting when the educational attainment in the area increases. The identified result can be driven by a higher competition for patenting and a higher difficulty to patent the idea in dense and high-education level areas where the idea flow is large, especially for firms with many competitors performing R&D (high *SPILLSIC*). More analysis should be performed to understand the mechanism in action driving this result (e.g., there may be intellectual property protection differences among MSAs, firms from industries that patent less on average locate in areas with high education levels, etc.).

H4 is supported by the empirical evidence: the effect of increasing the R&D stock by product market rivals on R&D intensity is increasing with both, educational attainment and density. Overall, the results are consistent with the patent races effect. In areas with a more valuable or dense human capital, the stock of available knowledge and the competition for ideas can be stronger. Combined with product market spillovers, in such areas, the potential cost of losing market share will be high and firms will try to innovate more and therefore will increase R&D expenses. Bloom, Schankerman and Van Reenen (2013) explain the positive relationship between *SPILLSIC* and R&D expenses by the complementarity between R&D efforts of product market competitors. Thus, alternatively, R&D of product market competitors in dense areas and areas with a higher level of educational attainment can show a higher complementarity.

4.7 Addressing endogeneity issues

Simultaneous Effects. The problem of analysing the relationships between innovation and local human capital characteristics is the simultaneity of the effects we are trying to identify. Firms can innovate more because there is the supply of valuable human capital, and human capital value/density can rise because individuals with considerable schooling move to areas with successful innovative companies.

The case of Amazon and Seattle provides a suitable illustration of simultaneity problem. The stock of human capital in Seattle grew significantly after the founding of Amazon. Human capital was attracted by the prospects to work in one of the most innovative firms in the world, as well as Amazon could continue innovating due to the availability of valuable human capital. The dynamics in changes of socio-economic characteristics of Seattle can be seen in Table A1 in Appendix. According to the U.S. Census, population of Seattle increased by 19% between 2005 and 2015. For comparison, population of San Francisco increased by 14% in the same period. Dougal, Parsons and Titman (2015) discuss another endogenous channel responsible for city growth due to existing consumption externalities (based on idea in Glaeser and Mare (2001)) that arise from economies of scale in the production of some public goods. In particular, when one firm becomes more prosperous, it can improve consumption opportunities for the employees of other firms, making it easier for these firms to attract new employees. Continuing the example of Seattle, in the last decade, Facebook, Google, Apple, Uber, and many other technology companies opened units in Seattle to benefit from the reach stock of knowledge and capital accumulated in the city.

We are addressing the simultaneity issues using instrumental variables approach. Moreover, instrumental variables help identification if we omitted unobserved variables for which we cannot control.

Lagged explanatory variables as instruments. As a first strategy of dealing with endogeneity, we repeat the analysis using lagged explanatory variables measuring the local human capital characteristics as instruments for contemporaneous human capital characteristics. This strategy assumes that the lagged MSA characteristics do not directly affect firms' current R&D expenditure and patenting and have impact on the innovation activities only via correlation with the current MSA characteristics. In all instrumental variables test, we instrument interaction effects between spillover measures and human capital characteristics using interactions between the instruments for *log(SPILLTECH)* and *log(SPILLSIC)* based on R&D tax credits and constructed by Lucking, Bloom and Van Reenen (2018) and our instruments for human capital characteristics. Thus, in regressions with interactions we have five endogenous variables (e.g., *log(SPILLTECH)*, *log(SPILLSIC)*, *Bachelor_perc*, *log(SPILLTECH)*Bachelor_perc*, and *log(SPILLSIC)*Bachelor_perc)* and five instruments, respectively.

There may be a concern with using this strategy, because the effect of human capital on innovation, especially on patenting, is likely to be delayed. According to the USPTO website, the average length of the patent application process is currently around two years[10]. The effect on R&D expenses is expected to be seen sooner; usually R&D budget is approved one year in advance during the budgeting process and then is partially adjusted during the year depending on the research's need in additional funds. Thus, lagged local characteristics may not only affect current characteristics but also be correlated with the efforts and outputs of R&D that was started or planned a few years ago. To mitigate this effect, we run the analysis using explanatory variables lagged by two years and using MSA characteristics lagged by additional two years as instruments. However, because our sample is 10 years long for R&D expenses and only 5 years long for the number of patents, using four-years lagged data leads for a rather small sample in patenting regressions.

Table 7 presents the results of the test with two-period lagged explanatory variables and four-period lagged instruments. Regressions using contemporaneous explanatory variables

[10]USPTO. June 2019 Patents Data, at a glance, available at: https://www.uspto.gov/dashboards/patents/main.dashxml

and instruments lagged by two years deliver similar results and are not tabulated. We still find a positive significant relationship between educational attainment and income and the measure of R&D intensity (columns (1) and (7)). Individually, in these regressions *log(SPILLTECH)* is still significant and positive, the coefficient's magnitude has not changed; *log(SPILLSIC)* becomes significant (column (1)) and has positive coefficient. Coefficients are only slightly lower in magnitude. Interaction effect of technological spillovers and education is not significant (column (2)) in contrast to not instrumented regressions in Table 2. Interaction between product market spillovers and human capital value measures is still positive and significant. Thus, instrumental variables regressions do not provide the same evidence contradicting *H2* but supports *H4*. In regressions using various measures of patent count as dependent variables, coefficients of spillover measures become twice or triple of the magnitude in non-instrumented regressions, technological spillovers have a positive impact on the number of patents, while product market spillovers have a negative effect. *Log(SPILLSIC)* loses its significance in the regression using the number of patents weighted by their economic value while is still strongly significant and has a negative coefficient in regressions using other patenting measures. This evidence suggests that ability to commercialize invention can be an important mitigator of product market stealing effect. At the same time, the loss of statistical power may be caused by the sample decrease, so the loss of significance should be interpreted with caution.

Table 8 presents results of regressions with instrumented density and spillover measures. A principal difference from Table 3 is the significance at 10% level of density measures in regressions with R&D intensity as dependent variable (insignificant in Table 3). Other results are similar to Table 3, with coefficients magnitude slightly decreasing in R&D effort regressions and increasing in patenting regressions.

However, lagged variables are likely to violate the exclusion restriction needed for the valid instrument if both dependent and independent variables are persistent over time. Human capital characteristics are in fact rather persistent, especially outside some fast-growing MSAs (see Table A1). Patenting behaviour is also persistent (e.g., Bloom, Schankerman and Van Reenen,

2013) and R&D investment, even though easily adjustable in theory, may bare significant sunk costs and thus be history dependent (Manez et al., 2009).

5 Conclusion

Building on predictions of two literature steams, agglomeration literature and studies analysing the impact of different types of innovation spillovers, we provide empirical evidence for the existence of differences in firms' R&D sensitivity to spillovers generated by technological peers and product market rivals. Sensitivities vary with the variation in the local human capital characteristics. These differences can explain why otherwise similar firms located in different areas can benefit from the R&D efforts of their technological peers and be affected by the R&D efforts of their product market rivals differently.

Co-located firms can exchange knowledge via learning, sharing, and matching. While we are not able to identify an exact mechanism underlying our results, learning seems to play an important role for the firms' R&D investment decisions. Controlling for the presence of a patenting university, growth rate of business establishments' number, and the existence of non-compete provisions in the MSA of the firm's headquarters, we find a robust positive effect of educational attainment in the MSA on R&D intensity of firms and the increasing effect of product market spillovers on R&D intensity with the growth in education. In high-density areas, with the growth of educational attainment the negative effect of the R&D stock produced by product market on patenting is increasing in magnitude. This result is consistent with the existence of the patent races effect. When human capital is more valuable or dense, ideas flow faster, and competition for ideas can be stronger. Combined with substantial amount of R&D produced by product market rivals, in such areas, the potential cost of losing market share is high and firms try to innovate more and thus increase R&D expenses. Instrumental variables analysis using lagged characteristics of human capital as instruments point to a potential causal nature of the identified effects.

The analysis using firms' inventor location instead of headquarters location shows that local human capital characteristics are important for the R&D output, but they do not affect the magnitude of the spillovers impact on firms' patenting. This result shows a different mechanism of spillover influence through the headquarters where strategic decisions about R&D are made and through research laboratories where scientists implement these decisions and accumulated knowledge.

Finally, we identify that local legislation favouring employees' freedom to change jobs, as measured by the presence of non-compete provisions, plays an important role and is associated with higher R&D investments and more patenting. In turn, the presence of a patenting university in the MSA of the firm's research facility is associated with a higher number of patents.

The study provides some empirical evidence on the effects omitted by the literature so far. There is an effect of local human capital on the benefits from knowledge spillovers and threats from the R&D of competitors. The total effect of these two sometimes opposite effects can determine the success of the firm's innovation activity. Thus, we provide a first analysis for the future investigation of the knowledge spillovers versus rival's R&D and their impact on firms' innovativeness depending on local factors.

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Table 1: Summary statistics.

Variable name	Median	Mean	Std dev.	Obs.	GVKEYs	Variable description
Panel A.						
L(RD/Sales)	0.03	0.07	0.11	5,025	664	Logarithm of 1 plus R&D expense scaled by Sales
L(RD)	2.79	2.91	1.97	5,025	664	Logarithm of R&D expenses deflated by the CPI
L(fNpat)	2.20	2.52	1.64	1,961	664	Logarithm of 1 the number of patents (from Kogan et al., 2017)
L(Npat_new)	2.20	2.66	1.77	2,323	664	Logarithm of 1 the number of patents (our own merge of USPTO data with Compustat)
L(Tcw)	2.77	3.07	1.81	1,961	664	Logarithm of 1 the sum of citation-weighted patents (from Kogan et al., 2017)
L(Tsm)	3.22	3.75	2.59	1,961	664	Logarithm of 1 the sum of value-weighted patents (from Kogan et al., 2017)
MV	854.24	9,707.82	31,011.42	5,074	664	Market value of Equity plus book value of debt deflated by the CPI (million $)
Assets	527.59	5,222.20	16,786.51	5,074	664	Book value of Total Assets deflated by the CPI (million $)
Age	29.00	33.76	16.24	5,074	664	Number of years since the first appearance of firm in Compustat until the year of analysis
R&D	15.32	143.41	401.19	5,025	664	R&D expenses deflated by the CPI (million $)
Bleverage	0.43	0.47	0.55	5,074	664	Book leverage (book value of debt divided by the book value of assets)
Emp	2.71	13.88	29.98	5,074	664	Number of employees (in thousands)
Mleverage	0.25	0.29	0.20	5,074	664	Market leverage (book value of debt divided by the market value of assets)
Atgrow	0.02	0.05	0.29	5,074	664	Relative change in the book value of assets between two years
Hiring rate	0.01	0.03	0.17	5,074	664	(Total Assets - Lagged Total Assets)/Lagged Total Assets
ROA	0.05	0.01	0.26	5,074	664	Earnings before interest and taxes (EBIT) divided by the book value of assets
Tobin's q	1.65	1.97	1.29	5,074	664	Market value of assets divided by the book value of assets
K/L	3.74	3.79	0.96	5,074	664	Net value of PPE divided by the number of employees (Capital-labour ratio)
log(MV)	6.75	6.75	2.39	5,074	664	Logarithm of MV (see above)
log(Age)	3.37	3.40	0.51	5,074	664	Logarithm of Age (see above)
log(HHI)	0.22	0.26	0.16	5,074	664	Logarithm of HHI (based on market share of deflated sales in 4-digit SIC industry)
log(SPILLTECH)	11.38	11.25	0.91	5,074	664	Logarithm of SPILLTECH from Bloom et al. (2013) divided by 100. SPILLTECH measures the pool of technology spillovers available to a given firm as the stock of R&D of all firms interacting with the analysed firm in technology space, weighted by the measure of technological proximity proposed by Jaffe (1986)
log(SPILLSIC)	10.62	10.30	1.57	5,074	664	Logarithm of SPILLSIC from Bloom et al. (2013) divided by 100. SPILLSIC measures the pool of product market spillovers as the stock of R&D of all firms interacting with the analysed firm in product market space, weighted by the measure of product market proximity
Panel B.						
Population	928	1,899	2,697	985	110	Population, '000 People
Bachelor_perc	30.0%	30.7%	7.2%	985	110	Percent of population of 25 years old and above with at least a bachelor's degree
Med_inc	37,436	38,152	6,922	985	110	Median household income (deflated by CPI)
Poverty_perc	13.1%	13.3%	3.2%	985	110	Percent of population below poverty line
Density	342	529	491	985	110	Population density (Number of people per square mile)
Bus_density	8.43	13.37	13.46	984	110	Business density (Number of establishments per square mile)

Table 2: Human capital value and firm innovation.

This table shows the effect of two measures of human capital value (in the MSA of the firm location) on firms' RD expenses and innovation output. The dependent variables *L(RD/Sales)*, the logarithm of 1 plus RD expense scaled by Sales, and *L(RD)*, the logarithm of RD expenses deflated by the CPI, measure innovation effort of firms; *L(fNpat)*, the logarithm of 1 the number of patents, *L(Tcw)*, the logarithm of 1 plus the sum of citation-weighted patents, and *L(Tsm)*, the logarithm of 1 plus the sum of value-weighted patents, measure innovation output. The main explanatory variables are *Bachelor_perc*, the proportion of population of 25 years old and above with at least a bachelor's degree in MSA (demeaned), *log(Med_inc)*, the logarithm of median household income in MSA (deflated by CPI, demeaned), *log(SPILLTECH)*, the measure of technology spillovers, and *log(SPILLSIC)*, the measure of product market rivalry effect of RD (detailed description in Table 1). Regressions with interaction of human capital characteristics and spillovers are reported only if the effect of human capital characteristics is significant in the regression without interaction. All regressions include control variables described in Section 3, year fixed effects, and industry fixed effects. Standard errors are clustered at the MSA level. Robust t-statistics is reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	L(RD/Sales) (1)	L(RD/Sales) (2)	L(RD) (3)	L(fNpat) (4)	L(Tcw) (5)	L(Tsm) (6)	L(RD/Sales) (7)	L(RD/Sales) (8)	L(RD) (9)	L(fNpat) (10)	L(Tcw) (11)	L(Tsm) (12)
log(SPILLTECH)	0.020***	0.019***	0.213***	0.190***	0.154**	0.115*	0.021***	0.020***	0.214***	0.194***	0.159**	0.120**
	(4.330)	(4.176)	(4.075)	(3.545)	(2.232)	(1.937)	(4.276)	(4.117)	(4.069)	(3.601)	(2.287)	(2.007)
log(SPILLSIC)	0.002	0.005	0.022	-0.183***	-0.203***	-0.143**	0.003	0.004	0.022	-0.185***	-0.204***	-0.143**
	(0.670)	(1.395)	(0.508)	(-2.758)	(-2.849)	(-2.011)	(0.835)	(1.251)	(0.513)	(-2.822)	(-2.897)	(-2.021)
Bachelor_perc	0.192***	-0.066	0.702	-0.499	-0.284	0.045						
	(2.905)	(-0.102)	(1.027)	(-0.523)	(-0.277)	(0.055)						
c.Bachelor_perc#c.log(SPILLTECH)		-0.103*										
		(-1.663)										
c.Bachelor_perc#c.log(SPILLSIC)		0.133***										
		(3.436)										
log(Med_inc)							0.060***	-0.228	0.280	-0.296	-0.248	-0.147
							(2.777)	(-1.123)	(1.154)	(-0.951)	(-0.723)	(-0.559)
c.log(Med_inc)#c.log(SPILLTECH)								-0.018				
								(-0.925)				
c.log(Med_inc)#c.log(SPILLSIC)								0.046***				
								(3.953)				
Observations	4,812	4,812	4,812	1,862	1,862	1,862	4,812	4,812	4,812	1,862	1,862	1,862
R-squared	0.603	0.608	0.879	0.766	0.748	0.910	0.603	0.606	0.879	0.766	0.748	0.910
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Table 3: Human capital density and firm innovation.
This table shows the effect of two measures of human capital density (in the MSA of the firm location) on firms' RD expenses and innovation output. The dependent variables *L(RD/Sales)*, the logarithm of 1 plus RD expense scaled by Sales, and *L(RD)*, the logarithm of RD expenses deflated by the CPI, measure innovation effort of firms; *L(fNpat)*, the logarithm of 1 the number of patents, *L(Tcw)*, the logarithm of 1 plus the sum of citation-weighted patents, and *L(Tsm)*, the logarithm of 1 plus the sum of value-weighted patents, measure innovation output. The main explanatory variables are *log(Density)*, the logarithm of the number of people per square mile in MSA (demeaned), *log(Bus_density)*, the logarithm of the number of establishments per square mile in MSA (demeaned), *log(SPILLTECH)*, the measure of technology spillovers, and *log(SPILLSIC)*, the measure of product market rivalry effect of RD (detailed description in Table 1). Regressions with interaction of human capital characteristics and spillovers are reported only if the effect of human capital characteristics is significant in the regression without interaction. All regressions include control variables described in Section 3, year fixed effects, and industry fixed effects. Standard errors are clustered at the MSA level. Robust t-statistics is reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	L(RD/Sales) (1)	L(RD) (2)	L(RD) (3)	L(fNpat) (4)	L(Tcw) (5)	L(Tsm) (6)	L(RD/Sales) (7)	L(RD) (8)	L(RD) (9)	L(fNpat) (10)	L(Tcw) (11)	L(Tsm) (12)
log(SPILLTECH)	0.022***	0.208***	0.219***	0.178***	0.140**	0.107*	0.022***	0.208***	0.217***	0.180***	0.142**	0.109*
	(4.516)	(3.964)	(4.320)	(3.391)	(2.082)	(1.816)	(4.543)	(3.958)	(4.298)	(3.395)	(2.091)	(1.834)
log(SPILLSIC)	0.004	0.030	0.015	-0.184***	-0.202***	-0.142**	0.004	0.028	0.019	-0.185***	-0.203***	-0.143**
	(1.278)	(0.697)	(0.342)	(-2.813)	(-2.874)	(-2.014)	(1.243)	(0.642)	(0.416)	(-2.824)	(-2.890)	(-2.023)
log(Density)	0.004	0.119**	-1.142*	0.035	0.056	0.040						
	(0.768)	(2.148)	(-1.671)	(0.602)	(0.835)	(0.696)						
c.log(Density)#c.log(SPILLTECH)			0.021									
			(0.331)									
c.log(Density)#c.log(SPILLSIC)			0.094**									
			(2.145)									
log(Bus_density)							0.004	0.113**	-1.057	0.026	0.044	0.031
							(0.823)	(2.149)	(-1.654)	(0.467)	(0.678)	(0.549)
c.log(Bus_density)#c.log(SPILLTECH)									0.018			
									(0.299)			
c.log(Bus_density)#c.log(SPILLSIC)									0.088**			
									(2.222)			
Observations	4,812	4,812	4,812	1,862	1,862	1,862	4,811	4,811	4,811	1,862	1,862	1,862
R-squared	0.598	0.880	0.882	0.770	0.752	0.911	0.598	0.880	0.882	0.770	0.752	0.911
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Table 4: PDI and firm innovation. This table shows the effect of the PDI measure (in the MSA of the firm location) on firms' RD expenses. The dependent variables *L(RD/Sales)*, the logarithm of 1 plus RD expense scaled by Sales, and *L(RD)*, the logarithm of RD expenses deflated by the CPI, measure innovation effort of firms. The main explanatory variable is PDI (potential density increase) is PDI measure is calculated as the ratio of size (in square meters) of land that can quickly increase its density (developed land) to the total size of land available for construction, meaning the sum of developed and less developed lands which are expected to grow its density more slowly (from Memarian and Vergara-Alert (2018)). Other explanatory variables are *log(SPILLTECH)*, the measure of technology spillovers, and *log(SPILLSIC)*, the measure of product market rivalry effect of RD (detailed description in Table 1). Due to the insignificance of the PDI measure in regressions without interactions, regressions with interactions are not included. All regressions include control variables described in Section 3., plus an additional control, the logarithm of the population density *log(Density)*, is included to isolate the effect of potential density increase not related to the current population density of the MSA. Year fixed effects, and industry fixed effects are also included in regressions. Standard errors are clustered at the MSA level. Robust t-statistics is reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	L(RD/Sales)	L(RD)
	(1)	(2)
	2010-2015	2010-2015
log(SPILLTECH)	0.015***	0.257***
	(6.336)	(4.956)
log(SPILLSIC)	0.006	0.101
	(1.447)	(1.418)
PDI	0.001	0.005
	(0.091)	(0.023)
log(Density)	0.007	0.179**
	(0.998)	(2.159)
Observations	1,969	1,969
R-squared	0.762	0.917
Controls	YES	YES
Year FE	YES	YES
Industry FE	YES	YES

Table 5: Human capital value and firm innovation – sample partitioning by population density.

This table shows the effect of the human capital characteristics in the area on firms' RD expenses in two subsamples of firms obtained by partitioning the main sample by the median population density. The dependent variables *L(RD/Sales)*, the logarithm of 1 plus RD expense scaled by Sales, and *L(RD)*, the logarithm of RD expenses deflated by the CPI, measure innovation effort of firms; L(fNpat), the logarithm of 1 the number of patents, *L(Tcw)*, the logarithm of 1 plus the sum of citation-weighted patents, and *L(Tsm)*, the logarithm of 1 plus the sum of value-weighted patents, measure innovation output. **Panel A** shows regression results for the explanatory variables *Bachelor_perc*, the proportion of population of 25 years old and above with at least a bachelor's degree in MSA (demeaned), log(SPILLTECH), the measure of technology spillovers, and *log(SPILLSIC)*, the measure of product market rivalry effect of RD (detailed description in Table 1). **Panel B** shows regression results for *log(Med_inc)*, the logarithm of median household income in MSA (deflated by CPI, demeaned), *log(SPILLTECH)*, and *log(SPILLSIC)*. Regressions with interaction of human capital characteristics and spillovers are reported only if the effect of human capital characteristics is significant in the regression without interaction. All results are shown for the demeaned variables *Bachelor_perc* and *log(Med_inc)*. All regressions include control variables described in Section 3, year fixed effects, and industry fixed effects. Standard errors are clustered at the MSA level. Robust t-statistics is reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

(a) Panel A.

	L(RD/Sales) (1)	L(RD/Sales) (2)	L(RD/Sales) (3)	L(RD) (4)	L(RD) (5)	L(fNpat) (6)	L(fNpat) (7)	L(fNpat) (8)	L(Tcw) (9)	L(Tcw) (10)	L(Tcw) (11)	L(Tsm) (12)	L(Tsm) (13)
Subsample	high	low	low	high	low	high	high	low	high	high	low	high	low
log(SPILLTECH)	0.019**	0.028***	0.025***	0.222**	0.330***	0.132	0.133	0.118	0.068	0.073	0.030	0.109	0.099
	(2.502)	(5.791)	(5.696)	(2.592)	(4.777)	(1.625)	(1.685)	(1.646)	(0.712)	(0.797)	(0.312)	(1.367)	(1.295)
log(SPILLSIC)	0.001	0.008	0.014***	-0.020	0.072	-0.236*	-0.252*	-0.135	-0.276*	-0.300**	-0.119	-0.259*	-0.065
	(0.267)	(1.496)	(2.862)	(-0.398)	(0.624)	(-1.735)	(-1.931)	(-1.295)	(-1.863)	(-2.094)	(-0.999)	(-2.006)	(-0.615)
Bachelor_perc	0.251	0.123**	0.114	-0.047	0.647	-3.609*	-9.734	1.143	-3.565*	-10.174	1.405	-1.858	1.398
	(1.631)	(2.304)	(0.203)	(-0.047)	(0.741)	(-2.073)	(-0.858)	(0.802)	(-1.859)	(-0.835)	(0.864)	(-1.334)	(1.083)
c.Bachelor_perc#c.log(SPILLTECH)			-0.126**				1.751			2.377*			
			(-2.465)				(1.525)			(1.770)			
c.Bachelor_perc#c.log(SPILLSIC)			0.133***				-1.328			-1.961			
			(3.672)				(-1.035)			(-1.409)			
Observations	2,467	2,344	2,344	2,467	2,344	948	948	906	948	948	906	948	906
R-squared	0.606	0.679	0.684	0.920	0.875	0.807	0.808	0.817	0.781	0.783	0.809	0.929	0.920
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

(b) Panel B.

	L(RD/Sales) (14)	L(RD/Sales) (15)	L(RD/Sales) (16)	L(RD) (17)	L(RD) (18)	L(fNpat) (19)	L(fNpat) (20)	L(fNpat) (21)	L(Tcw) (22)	L(Tcw) (23)	L(Tcw) (24)	L(Tsm) (25)	L(Tsm) (26)	L(Tsm) (27)
Subsample	high	low	low	high	low	high	high	low	high	high	low	high	high	low
log(SPILLTECH)	0.019**	0.028***	0.027***	0.223**	0.329***	0.131*	0.119	0.139*	0.065	0.058	0.057	0.108	0.095	0.125
	(2.446)	(5.873)	(5.658)	(2.596)	(4.888)	(1.750)	(1.558)	(1.980)	(0.741)	(0.652)	(0.617)	(1.398)	(1.062)	(1.654)
log(SPILLSIC)	0.002	0.008	0.010**	-0.013	0.074	-0.228	-0.232*	-0.135	-0.267*	-0.270*	-0.120	-0.254*	-0.259*	-0.065
	(0.357)	(1.642)	(2.207)	(-0.255)	(0.662)	(-1.720)	(-1.760)	(-1.330)	(-1.850)	(-1.876)	(-1.036)	(-2.007)	(-2.008)	(-0.625)
log(Med_inc)	0.087	0.039*	-0.138	-0.246	0.280	-1.965***	-4.457	-0.065	-2.008**	-4.198	-0.099	-1.038*	-4.009	-0.078
	(1.555)	(1.890)	(-0.632)	(-0.559)	(1.074)	(-2.864)	(-0.810)	(-0.231)	(-2.770)	(-0.762)	(-0.300)	(-1.817)	(-0.766)	(-0.264)
c.log(Med_inc)#c.log(SPILLTECH)			-0.024				0.666			0.864			0.878	
			(-1.194)				(1.196)			(1.491)			(1.704)	
c.log(Med_inc)#c.log(SPILLSIC)			0.041***				-0.495			-0.742			-0.683*	
			(3.793)				(-1.130)			(-1.601)			(-1.750)	
Observations	2,467	2,344	2,344	2,467	2,344	948	948	906	948	948	906	948	948	906
R-squared	0.604	0.679	0.682	0.920	0.875	0.811	0.812	0.816	0.785	0.787	0.808	0.930	0.931	0.920
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Table 6: Human capital value and firm innovation – sample partitioning by PDI.
This table shows the effect of the human capital characteristics in the area on firms' RD expenses in two subsamples of firms obtained by partitioning the main sample by the median of the PDI measure. The dependent variables *L(RD/Sales)*, the logarithm of 1 plus RD expense scaled by Sales, and *L(RD)*, the logarithm of RD expenses deflated by the CPI, measure innovation effort of firms; *L(fNpat)*, the logarithm of 1 the number of patents, *L(Tcw)*, the logarithm of 1 plus the sum of citation-weighted patents, and *L(Tsm)*, the logarithm of 1 plus the sum of value-weighted patents, measure innovation output. **Panel A** shows regression results for the explanatory variables *Bachelor_perc*, the proportion of population of 25 years old and above with at least a bachelor's degree in MSA (demeaned), *log(SPILLTECH)*, the measure of technology spillovers, and *log(SPILLSIC)*, the measure of product market rivalry effect of RD (detailed description in Table 1). **Panel B** shows regression results for *log(Med_inc)*, the logarithm of median household income in MSA (deflated by CPI, demeaned), *log(SPILLTECH)*, and *log(SPILLSIC)*. Regressions with interaction of human capital characteristics and spillovers are reported only if the effect of human capital characteristics is significant in the regression without interaction. All results are shown for the demeaned variables *Bachelor_perc* and *log(Med_inc)*. All regressions include control variables described in Section 3, year fixed effects, and industry fixed effects. Standard errors are clustered at the MSA level. Robust t-statistics is reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

(a) Panel A.

	L(RD/Sales) (1)	L(RD/Sales) (2)	L(RD/Sales) (3)	L(RD) (4)	L(RD) (5)	L(RD) (6)	L(fNpat) (7)	L(fNpat) (8)	L(fNpat) (9)	L(Tcw) (10)	L(Tcw) (11)	L(Tsm) (12)	L(Tsm) (13)
Subsample	high	high	low	high	high	low	high	high	low	high	low	high	low
log(SPILLTECH)	0.012	0.014	0.017***	0.037	0.128	0.336***	0.281***	-0.436	0.103	0.258**	-0.010	0.163	0.054
	(1.500)	(0.419)	(4.883)	(0.409)	(0.281)	(4.933)	(2.948)	(-1.457)	(1.172)	(2.607)	(-0.076)	(1.377)	(0.591)
log(SPILLSIC)	0.002	-0.037**	0.005	-0.081	-0.358	0.142	-0.394***	0.074	-0.004	-0.369***	-0.068	-0.233**	-0.045
	(0.369)	(-2.217)	(0.924)	(-1.186)	(-1.575)	(1.564)	(-4.191)	(0.284)	(-0.035)	(-3.514)	(-0.540)	(-2.511)	(-0.385)
Bachelor_perc	0.304***	-0.988	0.093	2.098***	-4.389	-0.183	1.479*	-6.678	-1.293	1.002	-0.199	1.420	-0.983
	(2.942)	(-0.928)	(1.445)	(2.767)	(-0.376)	(-0.226)	(1.751)	(-0.708)	(-0.934)	(1.144)	(-0.110)	(1.513)	(-0.710)
c.Bachelor_perc#c.log(SPILLTECH)		-0.003			-0.229			2.045**					
		(-0.026)			(-0.182)			(2.168)					
c.Bachelor_perc#c.log(SPILLSIC)		0.122**			0.835			-1.381**					
		(2.630)			(1.416)			(-2.125)					
Observations	2,589	2,589	2,215	2,589	2,589	2,215	1,028	1,028	824	1,028	824	1,028	824
R-squared	0.616	0.620	0.651	0.920	0.921	0.879	0.837	0.840	0.768	0.819	0.743	0.938	0.905
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

(b) Panel B.

	L(RD/Sales) (14)	L(RD/Sales) (15)	L(RD/Sales) (16)	L(RD) (17)	L(RD) (18)	L(RD) (19)	L(fNpat) (20)	L(fNpat) (21)	L(Tcw) (22)	L(Tcw) (23)	L(Tsm) (24)	L(Tsm) (25)
Subsample	high	high	low	high	high	low	high	low	high	low	high	low
log(SPILLTECH)	0.013	-0.022	0.018***	0.049	-2.793	0.341***	0.281***	0.110	0.258**	0.002	0.162	0.055
	(1.579)	(-0.070)	(4.857)	(0.524)	(-0.751)	(5.007)	(2.947)	(1.334)	(2.549)	(0.014)	(1.351)	(0.610)
log(SPILLSIC)	0.004	-0.693***	0.005	-0.074	-3.676*	0.142	-0.377***	-0.009	-0.355***	-0.072	-0.216**	-0.048
	(0.605)	(-4.511)	(1.051)	(-1.180)	(-1.834)	(1.594)	(-3.888)	(-0.088)	(-3.288)	(-0.582)	(-2.313)	(-0.417)
log(Med_inc)	0.094***	-0.665**	0.015	0.703***	-6.056*	-0.228	0.113	-0.707	-0.050	-0.462	0.040	-0.373
	(3.166)	(-2.081)	(0.654)	(2.969)	(-1.797)	(-0.704)	(0.435)	(-1.327)	(-0.181)	(-0.727)	(0.127)	(-0.830)
c.log(Med_inc)#c.log(SPILLTECH)		0.004			0.268							
		(0.123)			(0.771)							
c.log(Med_inc)#c.log(SPILLSIC)		0.065***			0.337*							
		(4.566)			(1.787)							
Observations	2,589	2,589	2,215	2,589	2,589	2,215	1,028	824	1,028	824	1,028	824
R-squared	0.615	0.621	0.650	0.920	0.921	0.879	0.836	0.769	0.818	0.743	0.938	0.905
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Table 7: Addressing endogeneity issues: Lagged explanatory variables (Human capital value) as instruments.
This table shows the effect of two measures of human capital value (in the MSA of the firm location) on firms' RD expenses and innovation output. Detailed description of dependent and independent variables is presented in Table 1. All explanatory variables are lagged by two years. Lagged by four years *Bachelor_perc* and *log(Med_inc)* are used as instrumental variables for lagged *Bachelor_perc* and *log(Med_inc)*, respectively; the instrument based on the firm-specific tax price of RD from Lucking, Bloom and Van Reenen (2018) is included as instrumental variables for RD spillovers, *log(SPILLTECH)* and *log(SPILLSIC)*; interaction effects between spillover measures and human capital characteristics are instrumented by the corresponding interaction of instrumental variables. Regressions with interaction of human capital characteristics and spillovers are reported only if the effect of human capital characteristics is significant in the regression without interaction. All regressions include control variables described in Section 3, year fixed effects, and industry fixed effects. Standard errors are clustered at the MSA level. Robust t-statistics is reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	L(RD/Sales) (1)	L(RD/Sales) (2)	L(RD) (3)	L(fNpat) (4)	L(Tcw) (5)	L(Tsm) (6)	L(RD/Sales) (7)	L(RD/Sales) (8)	L(RD) (9)	L(fNpat) (10)	L(Tcw) (11)	L(Tsm) (12)
log(SPILLTECH)t-2	0.020***	0.020***	0.185***	0.354***	0.399***	0.232**	0.021***	0.021***	0.186***	0.361***	0.408***	0.238**
	(3.550)	(3.366)	(3.064)	(3.587)	(3.715)	(2.340)	(3.483)	(3.016)	(3.085)	(3.673)	(3.834)	(2.384)
log(SPILLSIC) t-2	0.008*	0.009*	0.032	-0.505***	-0.499**	-0.239	0.008	0.009*	0.031	-0.510***	-0.509***	-0.243
	(1.699)	(1.894)	(0.369)	(-3.082)	(-2.537)	(-1.465)	(1.565)	(1.866)	(0.361)	(-3.153)	(-2.587)	(-1.498)
Bachelor_perc t-2	0.171**	-0.027	0.166	0.646	1.425	0.527						
	(2.195)	(-0.039)	(0.196)	(0.568)	(1.178)	(0.532)						
c.Bachelor_perc t-2#c.log(SPILLTECH) t-2		-0.083										
		(-1.080)										
c.Bachelor_perc t-2#c.log(SPILLSIC) t-2		0.107**										
		(2.379)										
log(Med_inc) t-2							0.063**	-0.297	0.064	-0.055	0.177	-0.078
							(2.418)	(-1.212)	(0.210)	(-0.130)	(0.395)	(-0.203)
c.log(Med_inc) t-2#c.log(SPILLTECH) t-2								-0.010				
								(-0.321)				
c.log(Med_inc) t-2#c.log(SPILLSIC) t-2								0.044**				
1-stage F-test												
log(SPILLTECH) t-2	994.32	726.72	994.32	372.08	372.08	372.08	977.48	712.22	977.48	353.37	353.37	353.37
log(SPILLSIC) t-2	63.93	45.11	63.93	11.84	11.84	11.84	59.81	39.08	59.81	10.92	10.92	10.92
Bachelor_perc t-2	19,163.17	11,901.49	19,163.17	1,548.26	1,548.26	1,548.26						
c.Bachelor_perc t-2#c.log(SPILLTECH) t-2		11,944.25										
c.Bachelor_perc t-2#c.log(SPILLSIC) t-2		11,518.91										
log(Med_inc) t-2							3,825.77	5,142.92	3,825.77	1,982.13	1,982.13	1,982.13
c.log(Med_inc) t-2#c.log(SPILLTECH) t-2								5,320.79				
c.log(Med_inc) t-2#c.log(SPILLSIC) t-2								5,447.82				
Joint significance F-test	698.88	418.98	698.88	57.06	57.06	57.06	698.01	397.26	698.01	56.51	56.51	56.51
Observations	3,209	3,209	3,209	519	519	519	3,209	3,209	3,209	519	519	519
R-squared	0.434	0.436	0.899	0.818	0.794	0.922	0.435	0.436	0.899	0.817	0.793	0.922
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Table 8: Addressing endogeneity issues: Lagged explanatory variables (Density) as Instruments.
This table shows the effect of two measures of human capital value (in the MSA of the firm location) on firms' RD expenses and innovation output. Detailed description of dependent and independent variables is presented in Table 1. All explanatory variables are lagged by two years. Lagged by four years *log(Density)* and *log(Bus_density)* are used as instrumental variables for lagged *log(Density)* and *log(Bus_density)*, respectively; the instrument based on the firm-specific tax price of RD from Lucking, Bloom and Van Reenen (2018) is included as an instrumental variables for RD spillovers, *log(SPILLTECH)* and *log(SPILLSIC)*; interaction effects between spillover measures and human capital characteristics are instrumented by the corresponding interaction of instrumental variables. Regressions with interaction of human capital characteristics and spillovers are reported only if the effect of human capital characteristics is significant in the regression without interaction. All regressions include control variables described in Section 3., year fixed effects, and industry fixed effects. Standard errors are clustered at the MSA level. Robust t-statistics is reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	L(RD/Sales) (1)	L(RD/Sales) (2)	L(RD) (3)	L(RD) (4)	L(fNpat) (5)	L(Tcw) (6)	L(Tsm) (7)	L(RD/Sales) (8)	L(RD/Sales) (9)	L(RD) (10)	L(RD) (11)	L(fNpat) (12)	L(Tcw) (13)	L(Tsm) (14)
log(SPILLTECH) t-2	0.022***	0.023***	0.177***	0.198***	0.371***	0.420***	0.252**	0.022***	0.023***	0.177***	0.197***	0.372***	0.420***	0.253**
	(3.827)	(3.953)	(2.985)	(3.418)	(3.826)	(3.955)	(2.454)	(3.824)	(3.918)	(2.976)	(3.391)	(3.829)	(3.949)	(2.465)
log(SPILLSIC) t-2	0.009*	0.007	0.030	0.007	-0.508***	-0.508***	-0.241	0.009*	0.007	0.029	0.011	-0.510***	-0.509***	-0.243
	(1.842)	(1.341)	(0.347)	(0.074)	(-3.150)	(-2.585)	(-1.486)	(1.822)	(1.426)	(0.335)	(0.113)	(-3.158)	(-2.587)	(-1.496)
log(Density) t-2	0.008*	-0.061	0.107*	-1.196*	-0.051	-0.037	-0.066							
	(1.666)	(-1.161)	(1.781)	(-1.681)	(-0.855)	(-0.489)	(-0.862)							
c.log(Density) t-2#c.log(SPILLTECH) t-2		-0.003		0.026										
		(-0.719)		(0.378)										
c.log(Density) t-2#c.log(SPILLSIC) t-2		0.010***		0.092**										
		(3.089)		(2.145)										
log(Bus_density) t-2								0.008*	-0.049	0.101*	-1.059	-0.054	-0.036	-0.067
								(1.674)	(-0.978)	(1.756)	(-1.580)	(-0.895)	(-0.492)	(-0.883)
c.log(Bus_density) t-2#c.log(SPILLTECH) t-2									-0.003		0.025			
									(-0.662)		(0.373)			
c.log(Bus_density) t-2#c.log(SPILLSIC) t-2									0.008***		0.081**			
									(2.827)		(2.125)			
1-stage F-test														
log(SPILLTECH)	1,000.62	930.27	1,000.62	930.27	343.3	343.3	343.3	999.16	927.3	999.16	927.3	343.16	343.16	343.16
log(SPILLSIC)	55.66	34.47	55.66	34.47	11.22	11.22	11.22	55.66	33.5	55.66	33.5	11.06	11.06	11.06
Log(Density)	67,824.56	47,968.86	67,824.56	47,968.86	38,121.82	38,121.82	38,121.82							
c. log(Density)#c.log(SPILLTECH)		48,482.34		48,482.34										
c. log(Density)#c.log(SPILLSIC)		44,503.13		44,503.13										
log(Bus_density)								1.20e+05	82,134.56	1.20e+05	82,134.56	42,538.82	42,538.82	42,538.82
c. log(Bus_density)#c.log(SPILLTECH)									78,217.00		78,217.00			
c. log(Bus_density)#c.log(SPILLSIC)									78,334.55		78,334.55			
Joint significance F-test	696.30	410.48	696.30	410.48	56.73	56.73	56.73	694.39	415.38	694.39	415.38	56.62	56.62	56.62
Observations	3,209	3,209	3,209	3,209	519	519	519	3,208	3,208	3,208	3,208	519	519	519
R-squared	0.432	0.435	0.900	0.902	0.818	0.793	0.923	0.432	0.435	0.900	0.902	0.818	0.793	0.923
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

A Appendix

A.1 Additional Instrumental Variable Tests

Presence of a land-grant university. Therefore, we supplement this analysis using an instrument for the human capital value characteristics borrowed from Moretti (2004) who uses the presence of land-grant colleges and universities created in the nineteenth century to instrument the share of population with a college degree. The current presence of a college or university in the area can correlate with other characteristics in the area that are likely to affect economic environment. The solution is to use the presence of the land-grant institution that were created more than a century ago. The presence of a land-grant institution in the area predicts the percentage of college graduates (Moretti, 2004) and theoretically is unlikely to be correlated with the economic conditions and investment opportunities in the area today. We borrow the list of land-grant institutions from the National Research Council . The land grant system began in 1862 with legislation that gave states public lands for the purpose of selling, raising funds, and establishing land-grant colleges that would teach agriculture and the mechanical arts. The second part of this legislation was passed in 1890 and granted states cash instead of land, but colleges under that act received the same legal status as after the 1862 Act. In the result, 73 land-grant colleges and universities were founded.

Since we do not include MSA fixed effects in the baseline specification of our regressions, we can use this instrument which is constant over time. The main assumption required for this instrument to be valid is that firms located in MSAs that have a land-grant university are not systematically different in terms of innovation patterns from firms located in MSAs with no land-grant university. Moretti (2004) notes that land-grant institutions were often founded in rural areas and decision about location seems not related to the existence of natural resources or other factors that could make the area wealthier, and the choice of the location seems rather random. The presence of a land-grant college or university was also used by Doms and Lewis

(2006), Shapiro (2006), and Matray (2014).

Despite satisfying the exclusion restriction, the instrument presence of the land-grant university in our sample is weak, since it does not pass the F-tests from the first-stage regressions. Table A10 in Apendix shows the details of the estimation, but we cannot draw conclusions from this analysis.

Sensitivity of housing supply. Additionally, we use the elasticities of housing supply calculated by Saiz (2010) as an instrument for the human capital value and density in the area. According to Saiz (2010), housing prices are higher in land-constrained metropolitan areas; and in order to compensate citizens for higher prices, in such areas, wages or city amenities will be larger. Areas with a low land availability show lower housing supply elasticities. Saiz (2010) estimates elasticities of housing supply as nonlinear combinations of physical and regulatory constraints and the predetermined population levels in the metropolitan area in 2000. These elasticities "prove useful ... in predicting the response of housing markets to future demand shocks" (page 1281). If skilled individuals are attracted to the high amenities available in land-constrained cities, housing supply elasticity will be correlated with the average level of educational attainment and median household income in the MSA. Additionally, population density is likely to be higher in areas characterised by inelastic housing supply. Thus, the instrument is likely to satisfy the relevance condition. To satisfy an exclusion restriction, elasticity of housing supply should not directly affect firms' innovation activities. Being based on the geographical characteristics of the area and regulatory constraints for construction, housing supply is likely to affect innovation only indirectly via the characteristics of human capital or economic conditions in the area.

Tables A11 and A12 in Apendix shows the results of regressions using housing supply elasticity from Saiz (2010) as an instrument for local human capital characteristics. However, again the instruments prove to be weak based on the first-stage F-test. One problem with using this instrument is some differences in the definition of MSAs by Census and Saiz (2010) – Census usually defines MSA as a larger geography than defined by Saiz (2010). For example, one

CBSA "Dallas-Fort Worth-Arlington, TX Metro Area" in Census corresponds to two different metropolitan areas with different housing supply elasticity in Saiz (2010): "Dallas, TX" and "Fort Worth–Arlington, TX". We matched "Dallas-Fort Worth-Arlington, TX Metro Area" with "Dallas, TX" as the largest city in the CBSA, but this match may produce a measurement error and a better merge should be created.

Alternative explanations. So far, however, we cannot exclude the possibility that the effect we capture with our measures of human capital quality and density may in fact come from a different effect (e.g., investment opportunities, favourable legislation, etc.) that correlates with firms' innovation activity in the MSA and is also correlated with the explanatory variables measured at the MSA level (i.e., education, income, and density). Therefore, to check alternative explanations, we add additional MSA-level controls: number of establishments growth rate and the presence of the research university in the MSA, to control for overall economic attractiveness and "natural advantages" Carlino and Kerr (2015) of the MSA. We calculate *Establ_growth* using the U.S. Census Bureau's Business Patterns data as a relative change in the number of establishments in the MSA between two consecutive years. Variable *Patenting_uni* equals 1 if MSA has a university that has a least one patent in the updated USPTO patent database; we define university location as the location of the patent assignee. We do not add multiple other socio-economic MSA-level controls, because due to a high correlation of such variables among each other, adding several socio-economic factors, we risk missing the effect due to multicollinearity.

Table A4 shows the results. Both included controls have a limited statistical power in the regression and do not affect the significance or the magnitude of the coefficients of interest. None of the dependent variables, except for logarithm of R&D expenses, have a statistically significant association with the number of enterprises growth rate and the presence of a patenting university. Firms' R&D expenses are 17% lower in MSAs having a patenting university, compared to firms in MSAs with no such university. From Table A13 of the Appendix presenting a descriptive statistics of the two subsamples partitioned by the presence of a patenting university, we can see that in the areas with no patenting university, firms are on average larger, spend more on R&D, and hold more patents. The results of the regression analysis using density measures are also unchanged after including the two additional controls; both controlling variables are insignificant in all regressions. The results are not tabulated for brevity.

Additionally, we test whether results are changed after accounting for the presence of non-compete legislation in the region. Because in areas with no non-compete agreements , employees can move between companies more freely, innovation spillovers are expected to be higher in such regions (Matray, 2014). Therefore, we test if the presence of non-compete clauses affects R&D expenses and output and include a dummy equal one if the state of the MSA introduced non-compete clauses and zero otherwise. Table A5 presents the results. In fact, the presence of the non-compete provisions is significantly related to the amount of R&D expenses and some measures of patenting activity. Variable Non-compete is significant at 5% and 10% level and has negative coefficient in regressions for R&D intensity (column (1), (2), and (7)), for the amount of R&D expenses (column (3) and (9)), and for the number of patents weighted by their citations and economic value (columns (11) and (12)). For example, in MSAs characterised by the presence of non-compete provisions, firms' R&D intensity is nearly 3% lower, R&D expenditure is 23-24% lower, and the number of citation-weighted patents (significant only in one out of two regressions) is 24% lower. Importantly, *log(Medinc)* loses its significance after introducing Non-compete variable. *Bachelor_perc* is significant but has a slightly lower coefficient.

Table A6 shows the results of a similar analysis using density characteristics as explanatory variables of interest. After introducing Non-compete, both density measures lose their significance in regressions. However, Non-compete is only significant in regressions with R&D intensity and R&D expenditure as dependent variables, it has no significant association with the number of patents. Additional control variables do not change the results in regressions using *PDI* as explanatory variable presented in Table 4 (not tabulated).

Results of the analysis in Tables A5 and A6 show that our measures of income and density in the MSA can correlate with other characteristics important for innovation and spillovers, in particular, the legislation favouring or prohibiting the exchange of knowledge through employees. We ran regressions using *Non_compete* and its interactions with spillover measures instead of density or income characteristics in the MSA (not tabulated). None of the interaction terms is significant in the regressions. Thus, while correlated with local human capital characteristics and innovation of firms, it does not seem to affect the sensitivity of firms' R&D to the available spillovers. Importantly, the level of educational attainment affects firms' R&D intensity and their sensitivity to product market spillovers even controlling for the presence of non-compete provisions, the presence of a patenting university, and the growth rate of the number of businesses.

A.2 Robustness Check

Selection of Industries. The overall sample used in the baseline analysis consists of all industries that patented at least once since 1963, as required by Bloom, Schankerman and Van Reenen (2013) for the construction of their original R&D spillover measures, and that have data on R&D expenses and patent data from Kogan et al. (2017). The range of industries in our sample, compared to the sample of Bloom, Schankerman and Van Reenen (2013), only excludes utilities and financial services sectors, as discussed in Section 3.1. However, it can be well argued that, in many industries, firms tend not to patent their inventions. Based on a survey of almost 1.5 thousand R&D labs in the U.S. manufacturing sector, Cohen, Nelson and Walsh (2000) showed that firms in the chemicals, drugs, mineral products, and medical equipment sectors applied for patents for two-thirds of their inventions, while firms from textile, food, glass, steel, and other metals industries applied for patents for less than 15% of inventions. This fact obviously affects our ability to generalize the results obtained in the analysis using patents as dependent variable, the conclusions are likely to be relevant only for firms patenting their inventions regularly.

To verify that our results are not biased by the presence of industries where patenting is more an exception than a rule, we repeat the analysis for three subsamples of firms from regularly patenting industries. The first subsample includes manufacturing firms (SIC codes from 2000 to 3990) as in Lychagin et al. (2016) plus Computer Related Services (SIC codes from 7370 to 7379) and Conglomerates (SIC code 9997) because these sectors are characterised by active patenting; the second subsample only contains manufacturing firms; the third subsample excludes rarely patenting industries mentioned in Cohen, Nelson and Walsh (2000) from the second subsample. The results obtained from repeating the analysis on all three subsamples shows similar results as the full-sample analysis. In Table A7, we only present results for the subsample of manufacturing firms excluding rarely patenting industries as the most conservative subsample. The subsample is only 10% smaller than the complete data. The magnitude of the coefficients is similar to the full-sample analysis, but interaction term of *SPILLTECH* and *Bachelor_perc* loses its significance. The results for the density measures and *PDI* as main independent variables are close in terms of coefficients' magnitude and the same in terms of their significance. We do not present these results in separate tables for brevity.

Thus, our results are not substantially biased by the inclusion of rarely patenting industries because initially there are few observations from such industries in our data. However, we have to be cautious generalising our results – they will be applicable to those industries where patents represent a valid measure of innovation output. In further analysis of the R&D output we eliminate firms from outside Manufacturing industry and rarely patenting SIC codes following Cohen, Nelson and Walsh (2000) but keep Computer Related Services (e.g., includes Microsoft Corporation with SIC 7372) and Conglomerates (e.g., includes General Electric with SIC 9997) that patent substantially.

Effect of Inventor Location. The choice of firms' headquarters location in the analysis of firms' innovation activities may be challenged. Research laboratories are traditionally considered the locations where scientists communicate and exchange knowledge (e.g., Cohen, Nelson and Walsh, 2000; Bloom, Schankerman and Van Reenen, 2013; Lychagin et al., 2016), generate and absorb spillovers; but R&D labs are often located far from the company's headquarters. Nevertheless, the location of the firm's headquarters is likely to be relevant for the innovation activities. First, R&D budget is normally decided at the headquarters during the annual budgeting process. Research centers are likely to provide their estimates of the R&D funding need, but the decisions about funds allocation are normally taken centrally. Dougal, Parsons and Titman (2015) use headquarters' location in the analysis of peer effect on the firms' investment decisions, the mechanism of the knowledge exchange in their study is top management communications across firms. Multi-subsidiary firms may be an exception from central decision-making. Firms like General Electric have many non-related business and corresponding decision-making centers. In such companies, R&D budgeting decisions is likely to be taken in the headquarters of each subsidiary.

Second, even for the patenting activity, headquarters can be an important location. Menz, Kunisch and Collis (2015) review the literature on the role of corporate headquarters, including their role in subsidiaries' innovation process. Overall, the studies support the notion that corporate headquarters are important for innovation via provision of funds, encouraging risky projects, establishing networks, and providing employees with a platform for formal and informal communication. Nevertheless, an extensive research in innovation, and in particular studies using patent citations, shows the role of the research lab as the center of spillover generation and capture. Thus, we perform an additional analysis to test whether the role of research laboratories' location on innovation is different from the role of headquarters location. Using a newly assembled patent data described in Section 3.2., we first repeat the baseline analysis to ensure that our data is comparable with the patenting data we use in prior analysis and then perform a supplementary analysis of the patenting activities of firms in each research location depending on the local characteristics of this location. We use the inventors' locations from patents as a proxy for the research lab location, as in Lychagin et al. (2016), for instance.

Figure A3 shows the distribution of observations across the MSAs. Figure A3.A. shows that most observations in our sample are headquartered in four major MSAs: New York (10%), Chicago (8%), San Jose (7.7%), and Boston (7%). Importantly, the baseline results are sensitive to the exclusion of these four MSAs from the sample – variables measuring quality and density of human capital lose their significance, even though keeping their sings. Figure A3.B. shows the distribution of firms' inventors across MSAs in our newly merged patent data. The figure shows that the concentration of research facilities across MSAs is significantly lower than headquarters' concentration. Specifically, 60% of observations come from firms headquartered in 15 most represented MSA in the sample; and only around 40% of observations come from research facilities located in 15 most represented MSAs.

According to Table A14 of Appendix, the number of patents counted using the newly merged patent data shows relationships similar to the ones identified using the data from Kogan et al. (2017). There is a positive relationship with *log(SPILLTECH)* and a negative relationship with *log(SPILLSIC)*, however, the coefficients occasionally become insignificant. There is the same lack of statistically significant relationship between the local human capital characteristics and the number of patents. Only *PDI* variable becomes significant at 10% level and has a positive sign; interaction of *PDI* and *log(SPILLTECH)* is also significant and has positive coefficient. Overall, we conclude that the newly merged data does not generate a substantially different results from the baseline analysis and can be used in the analysis of the effect of inventors' location on firms' patenting.

Table A8 shows the results of the analysis of the number of patents and the local human capital characteristics at the location of firms' research facilities. We can perform this analysis only for the number of patents because the patent data allows us to count the firm's patents in each MSA. At the same time, the data about R&D expenses is available only for the firm as a whole. The results differ substantially from the results we obtained using headquarters' location. First of all, *log(SPILLTECH)* is not significant and *log(SPILLSIC)* is significant and changes its sign from negative to positive, compared to the baseline analysis. Interestingly, local human characteristics are significant and have positive association with the number of patents. However, only in one regression (column (2)) interaction between *log(SPILLSIC)* and human capital characteristic is significant, therefore, there is no robust effect of the interaction effects with the patenting.

This result is in contrast to the effects found for the headquarters location where both spillover measures had significant coefficients and local human capital characteristics did not affect significantly the number of patents. Thus, human capital quality and density seem to impact firms' patenting activities, but the effect does not interact with the spillover measures anymore. The identified effects may suggest a different way spillovers get absorbed by headquarters and R&D laboratories. We find same signs and similar magnitude of the coefficients when we repeat the analysis using all explanatory variables lagged by one and two years. However, local human capital characteristics, except for density, become insignificant in lagged regressions, though the sample size decreases as well. Adding three additional MSA-level controls, presence of patenting university, number of establishments growth rate, and having passed non-compete provisions, lead to the loss of significance for *Bachelor_perc* and two density measures, *log(Medinc)* stays significant and has a positive sign. Interestingly, in all regressions the presence of patenting university in the MSA is statistically significant and has a positive association with the number of patents. The number of firms' patents in the MSA with a patenting university is 30-45% higher than in MSAs with no such university present. Table A9 shows the results. Using one and two years lagged explanatory variables deliver equivalent results and are not reported.

A.3 Figures

Figure A1.A. Marginal effects of spillovers on *L(RD/Sales)* with respect to *Bachelor_perc*

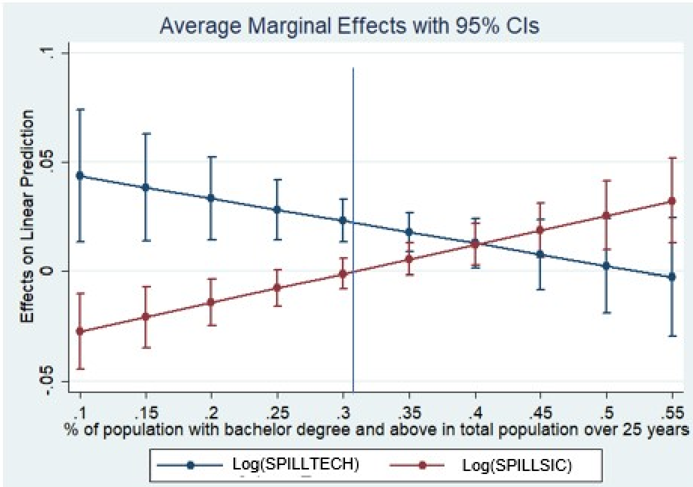

Figure A1.B. Marginal effects of spillovers on *L(RD/Sales)* with respect to *log(Med_inc)*

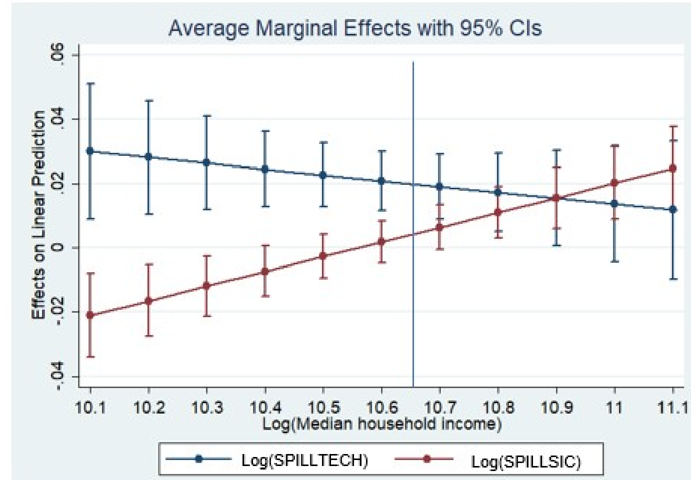

Figure A1.C. Marginal effects of spillovers on *L(RD)* with respect to *Bachelor_perc*

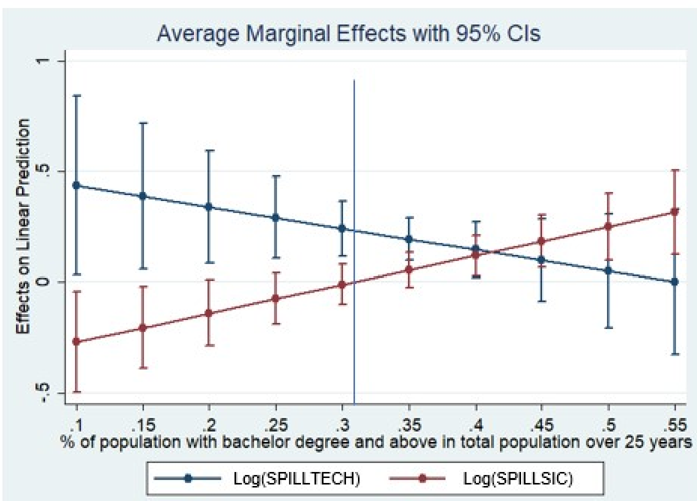

Figure A1.D. Marginal effects of spillovers on *L(RD)* with respect to *log(Med_inc)*

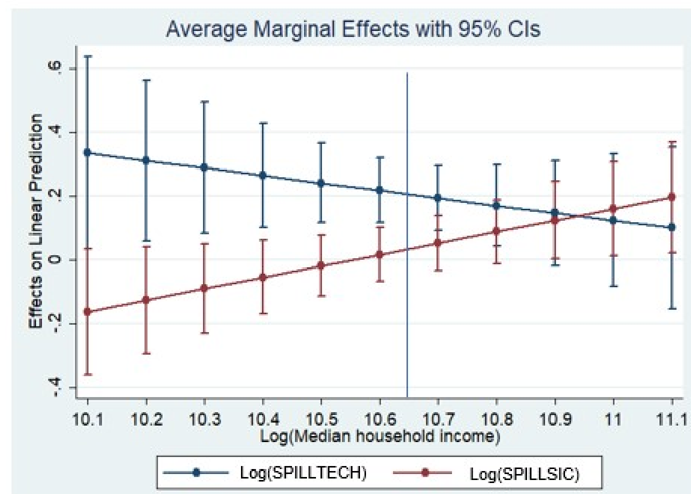

Figure A1: Margins of responses – Human capital value and Innovation. The figures show the predictions of the marginal effect of *log(SPILLTECH)* and *log(SPILLSIC)* from a model with interaction in the result of manipulating the values of the covariates (*Bachelor_perc* and *log(Med_inc)*). The vertical axis shows the predicted magnitude of the spillover variables' marginal effect, horizontal axis shows the values of the covariate interacted with spillover measures. The long vertical line shows the mean value of a variable on horizontal axis.

Figure A2.A. Marginal effects of spillovers on *L(RD)* with respect to *log(Density)*

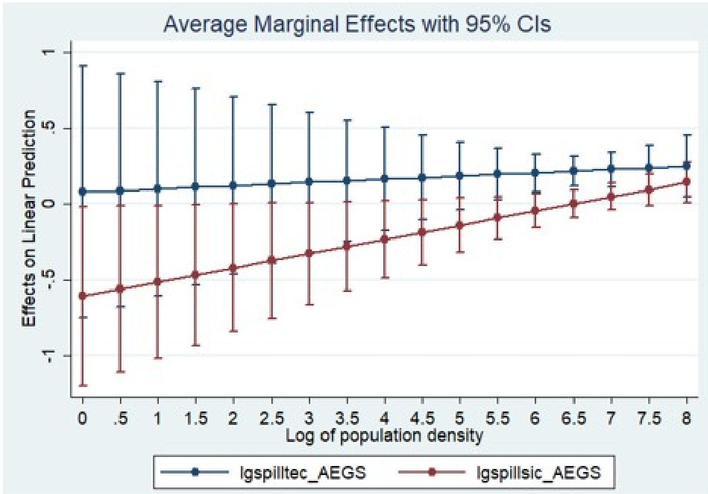

Figure A2.B. Marginal effects of spillovers on *L(RD)* with respect to *log(Bus_density)*

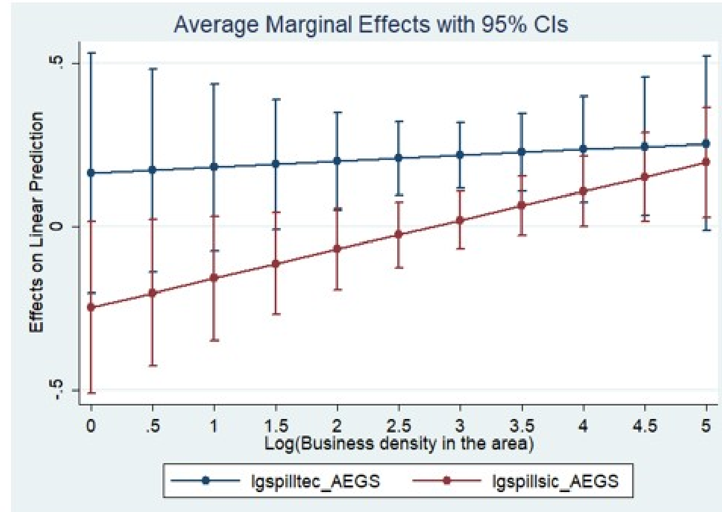

Figure A2.C. Marginal effects of spillovers on *L(Tcw)* with respect to *log(Density)*

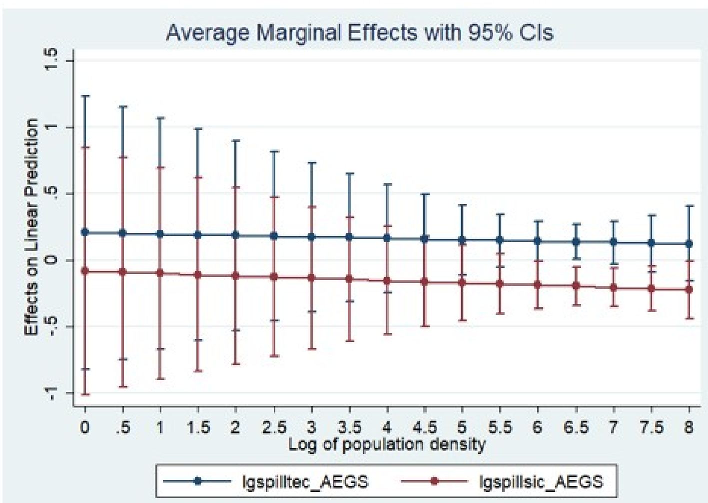

Figure A2.D. Marginal effects of spillovers on *L(Tcw)* with respect to *log(Bus_density)*

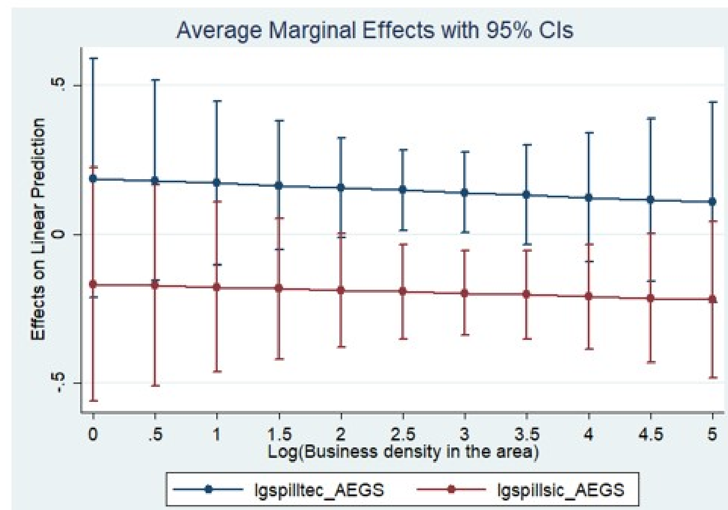

Figure A2: Margins of responses – Human capital density and Innovation. The figures show the predictions of the marginal effect of *log(SPILLTECH)* and *log(SPILLSIC)* from a model with interaction in the result of manipulating the values of the covariates *(Bachelor_perc* and *log(Med_inc)*). The vertical axis shows the predicted magnitude of the spillover variables' marginal effect, horizontal axis shows the values of the covariate interacted with spillover measures. The long vertical line shows the mean value of a variable on horizontal axis.

Figure A3.A. Distribution of observations across MSAs – Headquarters location

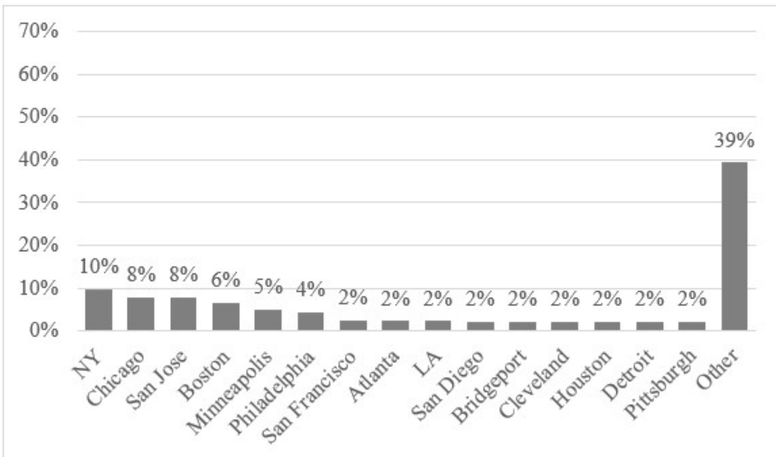

Figure A3.B. Distribution of observations across MSAs – Inventors location

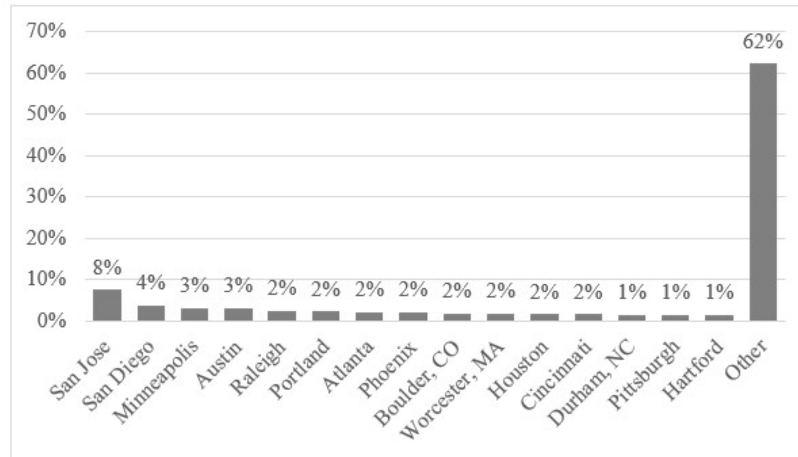

Figure A3: The figures show the frequency of observations across the MSAs. Figure A shows the frequency of observations from the baseline sample where each observation is at the firm-year level, location is the location of firms' headquarters. Figure B shows the frequency of observations from the sample where each observation is at the firm-year-MSA level build from the newly assembled patent data.

Table A1: Socio-economic characteristics of 10 selected MSAs (Source: U.S. Census Bureau).

Name of MSA	Year	Population ('000 People)	% of population of at least 25 years old with bachelor's degree and above	Median household income (deflated by CPI)	% of population below poverty	Population density (People per square mile)	Business density (establishments per square mile)
Atlanta	2005	4,829	34%	42,066	11%	579	16
Atlanta	2015	5,688	37%	39,354	14%	682	16
Change, %		18%	8%	-6%	22%	18%	5%
Austin	2005	1,406	39%	39,279	13%	333	8
Austin	2015	2,003	43%	43,913	12%	475	12
Change, %		42%	9%	12%	-11%	42%	36%
Boston	2005	4,271	41%	48,293	10%	1,225	36
Boston	2015	4,780	46%	51,498	10%	1,371	36
Change, %		12%	13%	7%	7%	12%	2%
Chicago	2005	9,272	32%	42,567	12%	1,288	33
Chicago	2015	9,558	36%	41,272	13%	1,328	34
Change, %		3%	12%	-3%	13%	3%	2%
Detroit	2005	4,429	26%	39,515	13%	1,139	27
Detroit	2015	4,310	30%	35,047	16%	1,108	25
Change, %		-3%	12%	-11%	27%	-3%	-7%
New York	2005	18,351	35%	43,665	13%	2,744	80
New York	2015	20,000	38%	44,925	14%	2,991	86
Change, %		9%	10%	3%	12%	9%	7%
Pittsburgh	2005	2,315	27%	32,460	11%	438	12
Pittsburgh	2015	2,348	33%	35,342	12%	445	11
Change, %		1%	22%	9%	8%	1%	-3%
San Francisco	2005	4,072	43%	50,871	10%	1,648	48
San Francisco	2015	4,650	47%	57,848	11%	1,882	51
Change, %		14%	9%	14%	7%	14%	6%
Santa Fe	2005	138	41%	35,249	13%	72	3
Santa Fe	2015	148	41%	36,386	13%	78	2
Change, %		8%	0%	3%	0%	8%	-8%
Seattle	2005	3,134	36%	42,764	10%	534	16
Seattle	2015	3,738	41%	49,230	10%	637	17
Change, %		19%	15%	15%	6%	19%	6%

Table A2: Averages of MSA characteristics in 2005-2015 by year (Source: U.S. Census Bureau).

Panel A.

Year	Population (N of People)	% of population of at least 25 years old with bachelor's degree and above	Median household income (deflated by CPI)	% of population below poverty	Population density (People per square mile)	Business density (establishments per square mile)	Number of MSAs
2005	675,142	25%	34,101	14%	273	7.1	354
2006	696,960	25%	34,511	14%	283	7.1	356
2007	700,492	25%	34,698	14%	284	7.2	358
2008	706,856	25%	36,240	14%	286	7.1	358
2009	706,200	25%	34,135	15%	286	6.9	363
2010	698,798	26%	32,735	16%	285	6.7	350
2011	704,927	26%	32,519	17%	287	6.6	350
2012	711,241	26%	32,671	17%	289	6.7	350
2013	717,246	27%	32,809	17%	291	6.8	350
2014	723,703	27%	33,534	16%	292	6.8	350
2015	730,210	28%	34,242	16%	294	6.9	350

Panel B.

Variable name	Median	Mean	Std dev.	Obs.	MSAs	Variable description
Population	250	706	1,554	3,889	363	Population, '000 People
Bachelor_perc	25.0%	25.9%	8.1%	3,886	363	Percent of population of 25 years old and above with at least a bachelor's degree
Med_inc	32,866	33,845	6,140	3,888	363	Median household income (deflated by CPI)
Poverty_perc	15.0%	15.4%	4.5%	3,889	363	Percent of population below poverty line
Density	191	286	317	3,889	363	Population density (Number of people per square mile)
Bus_density	4.4	6.9	8.4	3,876	363	Business density (Number of establishments per square mile)

Table A3: Descriptive statistics of subsamples obtained by partitioning the main sample by median population density.

	High density					Low density				
Variable name	Median	Mean	Std dev.	Obs.	MSAs	Median	Mean	Std dev.	Obs.	MSAs
log(1+R&D/Sales)	0.04	0.07	0.11	2484	664	0.03	0.08	0.11	2187	664
log(1+R&D)	2.90	3.01	2.02	2484	664	2.58	2.76	1.89	2187	664
log(1+fMpats)	2.20	2.56	1.63	1027	664	1.95	2.49	1.65	934	664
log(1+Tcw)	2.84	3.09	1.76	1027	664	2.64	3.06	1.85	934	664
log(1+Tsm)	3.22	3.76	2.63	1027	664	3.25	3.74	2.54	934	664
MV	774.73	10,485.24	33,211.23	2493	664	854.21	8,169.70	26,641.56	2227	664
Assets	502.63	5,975.33	19,291.72	2493	664	521.89	4,057.54	12,492.47	2227	664
Age	33.00	35.30	16.49	2493	664	26.00	30.94	15.36	2227	664
R&D	17.14	162.68	433.35	2484	664	12.26	114.73	344.73	2187	664
Blev	0.44	0.48	0.36	2493	664	0.41	0.46	0.68	2227	664
Emp	2.70	14.89	31.82	2493	664	2.52	12.00	26.25	2227	664
Mlev	0.27	0.31	0.21	2493	664	0.22	0.27	0.20	2227	664
Atgrow	0.02	0.05	0.31	2493	664	0.02	0.05	0.27	2227	664
Hiring	0.01	0.03	0.17	2493	664	0.02	0.03	0.18	2227	664
ROA	0.05	0.00	0.26	2493	664	0.05	0.02	0.27	2227	664
Q	1.60	1.90	1.29	2493	664	1.70	2.03	1.32	2227	664
K/L	3.67	3.74	0.95	2493	664	3.78	3.82	0.97	2227	664
log(MV)	6.65	6.70	2.47	2493	664	6.75	6.73	2.28	2227	664
log(Age)	3.50	3.44	0.51	2493	664	3.26	3.31	0.50	2227	664
log(HHI)	0.22	0.26	0.16	2493	664	0.21	0.25	0.15	2227	664
log(SPILLTECH)	11.40	11.32	0.88	2493	664	11.35	11.17	0.95	2227	664
log(SPILLSIC)	10.67	10.38	1.48	2493	664	10.59	10.21	1.66	2227	664

Table A4: Addressing endogeneity issues: additional controls.

This table shows the effect of two measures of human capital value (in the MSA of the firm location) on firms' RD expenses and innovation output. The dependent variables *L(RD/Sales)*, the logarithm of 1 plus RD expense scaled by Sales, and *L(RD)*, the logarithm of RD expenses deflated by the CPI, measure innovation effort of firms; *L(fNpat)*, the logarithm of 1 the number of patents, *L(Tcw)*, the logarithm of 1 plus the sum of citation-weighted patents, and *L(Tsm)*, the logarithm of 1 plus the sum of value-weighted patents, measure innovation output. The main explanatory variables are *Bachelor_perc*, the proportion of population of 25 years old and above with at least a bachelor's degree in MSA (demeaned), *log(Density)*, the logarithm of the number of people per square mile in MSA (demeaned), *log(SPILLTECH)*, the measure of technology spillovers, and *log(SPILLSIC)*, the measure of product market rivalry effect of RD (detailed description in Table 1). **Two additional controls at the MSA level are added** to the baseline specification: *Patenting_uni* equals one if MSA has a least one university with patents reported in the USPTO database; *Establ_growth* is the growth rate in the number of establishments in the MSA. Regressions with interaction of human capital characteristics and spillovers are reported only if the effect of human capital characteristics is significant in the regression without interaction. All regressions include control variables described in Section 3, year fixed effects, and industry fixed effects. Standard errors are clustered at the MSA level. Robust t-statistics is reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	L(RD/Sales) (1)	L(RD/Sales) (2)	L(RD) (3)	L(fNpat) (4)	L(Tcw) (5)	L(Tsm) (6)	L(RD/Sales) (7)	L(RD/Sales) (8)	L(RD) (9)	L(fNpat) (10)	L(Tcw) (11)	L(Tsm) (12)
log(SPILLTECH)	0.020***	0.018***	0.213***	0.205***	0.183**	0.139**	0.021***	0.020***	0.215***	0.209***	0.187**	0.145**
	(4.357)	(4.238)	(3.755)	(3.577)	(2.498)	(2.239)	(4.329)	(4.176)	(3.755)	(3.636)	(2.564)	(2.309)
log(SPILLSIC)	0.002	0.004	0.010	-0.195***	-0.208***	-0.149*	0.002	0.004	0.010	-0.196***	-0.208***	-0.147*
	(0.441)	(1.142)	(0.206)	(-2.786)	(-2.756)	(-1.942)	(0.601)	(1.087)	(0.220)	(-2.838)	(-2.794)	(-1.931)
Bachelor_perc	0.196***	0.111	0.670	-0.286	-0.083	0.340						
	(2.841)	(0.166)	(0.822)	(-0.269)	(-0.072)	(0.362)						
c.Bachelor_perc#c.log(SPILLTECH)		-0.116*										
		(-1.805)										
c.Bachelor_perc#c.log(SPILLSIC)		0.131***										
		(3.278)										
log(Med_inc)							0.061***	-0.181	0.248	-0.225	-0.175	-0.058
							(2.808)	(-0.914)	(0.836)	(-0.643)	(-0.453)	(-0.196)
c.log(Med_inc)#c.log(SPILLTECH)								-0.023				
								(-1.244)				
c.log(Med_inc)#c.log(SPILLSIC)								0.047***				
								(3.943)				
Patenting_uni	0.004	0.002	-0.172**	0.029	0.046	0.024	0.005	0.003	-0.167**	0.029	0.048	0.028
	(0.434)	(0.268)	(-2.154)	(0.270)	(0.375)	(0.273)	(0.577)	(0.404)	(-2.120)	(0.262)	(0.380)	(0.313)
Establ_growth	-0.039	-0.003	-0.958	-0.930	1.418	2.904	-0.025	0.005	-0.920	-1.022	1.350	2.888
	(-0.319)	(-0.025)	(-0.723)	(-0.241)	(0.312)	(0.735)	(-0.209)	(0.045)	(-0.697)	(-0.265)	(0.298)	(0.731)
Observations	4,127	4,127	4,127	1,460	1,460	1,460	4,127	4,127	4,127	1,460	1,460	1,460
R-squared	0.613	0.617	0.882	0.781	0.759	0.915	0.612	0.616	0.882	0.781	0.759	0.915
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Table A5: Addressing endogeneity issues: additional controls.
This table shows the effect of two measures of human capital value (in the MSA of the firm location) on firms' RD expenses and innovation output. The dependent variables *L(RD/Sales)*, the logarithm of 1 plus RD expense scaled by Sales, and *L(RD)*, the logarithm of RD expenses deflated by the CPI, measure innovation effort of firms; *L(fNpat)*, the logarithm of 1 the number of patents, *L(Tcw)*, the logarithm of 1 plus the sum of citation-weighted patents, and *L(Tsm)*, the logarithm of 1 plus the sum of value-weighted patents, measure innovation output. The main explanatory variables are *Bachelor_perc*, the proportion of population of 25 years old and above with at least a bachelor's degree in MSA (demeaned), *log(Density)*, the logarithm of the number of people per square mile in MSA (demeaned), *log(SPILLTECH)*, the measure of technology spillovers, and *log(SPILLSIC)*, the measure of product market rivalry effect of RD (detailed description in Table 1). **Three additional controls at the MSA level are added** to the baseline specification: *Patenting_uni* equals one if MSA has a least one university with patents reported in the USPTO database; *Establ_growth* is the growth rate in the number of establishments in the MSA; *Non_compete* is a dummy variable equal 1 if the state of the firms' headquarter location introduced non-compete provisions, and zero otherwise. Regressions with interaction of human capital characteristics and spillovers are reported only if the effect of human capital characteristics is significant in the regression without interaction. All regressions include control variables described in Section 3, year fixed effects, and industry fixed effects. Standard errors are clustered at the MSA level. Robust t-statistics is reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	L(RD/Sales) (1)	L(RD/Sales) (2)	L(RD) (3)	L(fNpat) (4)	L(Tcw) (5)	L(Tsm) (6)	L(RD/Sales) (7)	L(RD) (8)	L(fNpat) (9)	L(Tcw) (10)	L(Tsm) (11)
log(SPILLTECH)	0.019***	0.018***	0.203***	0.198***	0.174**	0.133**	0.020***	0.206***	0.204***	0.180**	0.140**
	(4.409)	(4.284)	(3.421)	(3.325)	(2.336)	(2.066)	(4.484)	(3.506)	(3.445)	(2.447)	(2.182)
log(SPILLSIC)	0.002	0.004	0.017	-0.187**	-0.200**	-0.150*	0.003	0.020	-0.188**	-0.199**	-0.148*
	(0.580)	(1.173)	(0.363)	(-2.601)	(-2.581)	(-1.974)	(0.859)	(0.428)	(-2.623)	(-2.591)	(-1.951)
Bachelor_perc	0.140**	0.136	0.278	-0.573	-0.433	0.015					
	(2.129)	(0.206)	(0.356)	(-0.510)	(-0.356)	(0.016)					
c.Bachelor_perc#c.log(SPILLTECH)		-0.104									
		(-1.637)									
c.Bachelor_perc#c.log(SPILLSIC)		0.111***									
		(2.920)									
log(Med_inc)							0.028	-0.006	-0.490	-0.483	-0.342
							(1.111)	(-0.018)	(-1.159)	(-1.061)	(-1.030)
Patenting_uni	0.000	-0.001	-0.188**	0.034	0.055	0.038	0.001	-0.189**	0.027	0.048	0.035
	(0.047)	(-0.079)	(-2.515)	(0.316)	(0.435)	(0.431)	(0.110)	(-2.409)	(0.237)	(0.374)	(0.393)
Establ_growth	-0.051	-0.019	-1.018	-0.400	2.149	3.668	-0.037	-0.979	-0.611	1.941	3.523
	(-0.432)	(-0.162)	(-0.779)	(-0.102)	(0.469)	(0.922)	(-0.320)	(-0.752)	(-0.159)	(0.430)	(0.897)
Non-compete	-0.034**	-0.030**	-0.230*	-0.129	-0.156	-0.135	-0.033*	-0.243*	-0.212	-0.244*	-0.211*
	(-2.339)	(-2.006)	(-1.925)	(-1.096)	(-1.272)	(-1.257)	(-1.888)	(-1.695)	(-1.495)	(-1.709)	(-1.803)
Observations	4,099	4,099	4,099	1,448	1,448	1,448	4,099	4,099	1,448	1,448	1,448
R-squared	0.618	0.621	0.884	0.782	0.760	0.916	0.616	0.884	0.783	0.761	0.916
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Table A6: Addressing endogeneity issues: additional controls.
This table shows the effect of two measures of human capital density (in the MSA of the firm location) on firms' RD expenses and innovation output. The dependent variables *L(RD/Sales)*, the logarithm of 1 plus RD expense scaled by Sales, and *L(RD)*, the logarithm of RD expenses deflated by the CPI, measure innovation effort of firms; *L(fNpat)*, the logarithm of 1 the number of patents, *L(Tcw)*, the logarithm of 1 plus the sum of citation-weighted patents, and *L(Tsm)*, the logarithm of 1 plus the sum of value-weighted patents, measure innovation output. The main explanatory variables are *Bachelor_perc*, the proportion of population of 25 years old and above with at least a bachelor's degree in MSA (demeaned), log(Density), the logarithm of the number of people per square mile in MSA (demeaned), *log(SPILLTECH)*, the measure of technology spillovers, and *log(SPILLSIC)*, the measure of product market rivalry effect of RD (detailed description in Table 1). Three additional controls at the MSA level are added to the baseline specification: *Patenting_uni* equals one if MSA has a least one university with patents reported in the USPTO database; *Establ_growth* is the growth rate in the number of establishments in the MSA; *Non_compete* is a dummy variable equal 1 if the state of the firms' headquarter location introduced non-compete provisions, and zero otherwise. Regressions with interaction of human capital characteristics and spillovers are reported only if the effect of human capital characteristics is significant in the regression without interaction. All regressions include control variables described in Section 3, year fixed effects, and industry fixed effects. Standard errors are clustered at the MSA level. Robust t-statistics is reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	L(RD/Sales) (1)	L(RD) (2)	L(fNpat) (3)	L(Tcw) (4)	L(Tsm) (5)	L(RD/Sales) (6)	L(RD) (7)	L(fNpat) (8)	L(Tcw) (9)	L(Tsm) (10)
log(SPILLTECH)	0.020***	0.201***	0.188***	0.159**	0.127*	0.020***	0.200***	0.189***	0.161**	0.127*
	(4.502)	(3.457)	(3.122)	(2.144)	(1.939)	(4.511)	(3.447)	(3.128)	(2.149)	(1.948)
log(SPILLSIC)	0.004	0.021	-0.189***	-0.198**	-0.148*	0.003	0.019	-0.190***	-0.200***	-0.149**
	(1.058)	(0.435)	(-2.683)	(-2.620)	(-1.984)	(1.027)	(0.404)	(-2.699)	(-2.648)	(-1.994)
log(Density)	0.006	0.085	0.048	0.098	0.058					
	(1.226)	(1.075)	(0.567)	(1.023)	(0.729)					
log(Bus_density)						0.006	0.083	0.036	0.080	0.048
						(1.394)	(1.098)	(0.442)	(0.862)	(0.624)
Patenting_uni	0.006	-0.108	0.076	0.143	0.092	0.006	-0.108	0.066	0.128	0.084
	(0.520)	(-1.131)	(0.516)	(0.868)	(0.782)	(0.562)	(-1.107)	(0.445)	(0.774)	(0.713)
Establ_growth	-0.013	-0.713	0.034	3.035	4.196	-0.013	-0.722	-0.066	2.888	4.117
	(-0.121)	(-0.579)	(0.009)	(0.670)	(1.062)	(-0.119)	(-0.590)	(-0.017)	(0.637)	(1.041)
Non-compete	-0.038**	-0.216*	-0.087	-0.103	-0.115	-0.038**	-0.217*	-0.091	-0.110	-0.119
	(-2.466)	(-1.902)	(-0.738)	(-0.806)	(-1.044)	(-2.471)	(-1.903)	(-0.784)	(-0.870)	(-1.098)
Observations	4,099	4,099	1,448	1,448	1,448	4,099	4,099	1,448	1,448	1,448
R-squared	0.616	0.884	0.782	0.761	0.916	0.616	0.884	0.782	0.761	0.916
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Table A7: Robustness check: Human capital value, density, and firm innovation (subsample of patenting industries).
This table shows the effect of two measures of human capital value (in the MSA of the firm location) on firms' RD expenses and innovation output. Subsample contains the following industries: Manufacturing (SIC 2000-3990), excluding Glass and Steel productions. The dependent variables *L(RD/Sales)*, the logarithm of 1 plus RD expense scaled by Sales, and *L(RD)*, the logarithm of RD expenses deflated by the CPI, measure innovation effort of firms; *L(fNpat)*, the logarithm of 1 the number of patents, *L(Tcw)*, the logarithm of 1 plus the sum of citation-weighted patents, and *L(Tsm)*, the logarithm of 1 plus the sum of value-weighted patents, measure innovation output. The main explanatory variables are *Bachelor_perc*, the proportion of population of 25 years old and above with at least a bachelor's degree in MSA (demeaned), *log(Density)*, the logarithm of the number of people per square mile in MSA (demeaned), *log(SPILLTECH)*, the measure of technology spillovers, and *log(SPILLSIC)*, the measure of product market rivalry effect of RD (detailed description in Table 1). Regressions with interaction of human capital characteristics and spillovers are reported only if the effect of human capital characteristics is significant in the regression without interaction. All regressions include control variables described in Section 3, year fixed effects, and industry fixed effects. Standard errors are clustered at the MSA level. Robust t-statistics is reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	L(RD/Sales) (1)	L(RD/Sales) (2)	L(RD) (3)	L(fNpat) (4)	L(Tcw) (5)	L(Tsm) (6)	L(RD/Sales) (7)	L(RD/Sales) (8)	L(RD) (9)	L(fNpat) (10)	L(Tcw) (11)	L(Tsm) (12)
log(SPILLTECH)	0.019***	0.017***	0.184***	0.127*	0.101	0.079	0.020***	0.019***	0.185***	0.133**	0.108	0.086
	(3.790)	(3.391)	(3.330)	(1.975)	(1.276)	(1.291)	(3.748)	(3.363)	(3.355)	(2.052)	(1.360)	(1.396)
log(SPILLSIC)	0.002	0.005	0.016	-0.154**	-0.176**	-0.125*	0.003	0.005	0.018	-0.156**	-0.178**	-0.126*
	(0.697)	(1.589)	(0.343)	(-2.360)	(-2.473)	(-1.679)	(0.919)	(1.513)	(0.393)	(-2.441)	(-2.537)	(-1.706)
Bachelor_perc	0.196***	-0.028	0.975	-0.218	-0.048	0.007						
	(2.869)	(-0.036)	(1.344)	(-0.214)	(-0.044)	(0.009)						
c.Bachelor_perc#c.log(SPILLTECH)		-0.109										
		(-1.547)										
c.Bachelor_perc#c.log(SPILLSIC)		0.137***										
		(3.806)										
log(Med_inc)							0.059***	-0.238	0.342	-0.244	-0.216	-0.181
							(2.690)	(-1.080)	(1.272)	(-0.693)	(-0.568)	(-0.669)
c.log(Med_inc)#c.log(SPILLTECH)								-0.020				
								(-0.939)				
c.log(Med_inc)#c.log(SPILLSIC)								0.049***				
								(4.106)				
Observations	4,324	4,324	4,324	1,691	1,691	1,691	4,324	4,324	4,324	1,691	1,691	1,691
R-squared	0.594	0.599	0.876	0.746	0.723	0.904	0.593	0.597	0.876	0.747	0.724	0.904
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Table A8: Human capital value, density, and firm innovation – updated patent count.
This table shows the effect of the human capital characteristics in the area on firms' patenting. The dependent variables *L(Npat_new)*, the logarithm of 1 plus the number of patents based on our own merge of USPTO updated patent data with Compustat. Detailed description of dependent and independent variables is in Table 1. **Each observation is at the firm – year – MSA level.** In these regressions, MSA characteristics vary for the firm-year when its patents' inventors are located in various MSAs; firm-level controls are the same for all firm – year - MSAs. All regressions include control variables described in Section 3, year fixed effects, and industry fixed effects. Standard errors are clustered at the MSA level. Robust t-statistics is reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	L(Npat_new) (1)	L(Npat_new) (2)	L(Npat_new) (3)	L(Npat_new) (4)	L(Npat_new) (5)	L(Npat_new) (6)	L(Npat_new) (7)	L(Npat_new) (8)	L(Npat_new) (9)
log(SPILLTECH)	0.046	0.060	0.079	0.071	0.054	0.066	0.054	0.067	0.072
	(0.307)	(0.420)	(0.578)	(0.494)	(0.358)	(0.453)	(0.358)	(0.455)	(0.295)
log(SPILLSIC)	0.167**	0.177**	0.172**	0.179**	0.171**	0.161**	0.173**	0.162**	0.166
	(2.184)	(2.300)	(2.200)	(2.281)	(2.228)	(2.089)	(2.243)	(2.098)	(1.177)
Bachelor_perc	1.907*	-5.242							
	(1.864)	(-0.725)							
c.Bachelor_perc#c.log(SPILLTECH)		-0.082							
		(-0.122)							
c.Bachelor_perc#c.log(SPILLSIC)		0.721*							
		(1.698)							
log(Med_inc)			1.177***	-3.070					
			(2.975)	(-1.009)					
c.log(Med_inc)#c.log(SPILLTECH)				0.169					
				(0.608)					
c.log(Med_inc)#c.log(SPILLSIC)				0.195					
				(1.012)					
log(Density)					0.151*	-0.532			0.185*
					(1.704)	(-0.563)			(1.879)
c.log(Density)#c.log(SPILLTECH)						0.003			
						(0.026)			
c.log(Density)#c.log(SPILLSIC)						0.058			
						(1.042)			
log(Bus_density)							0.143*	-0.409	
							(1.697)	(-0.449)	
c.log(Bus_density)#c.log(SPILLTECH)								-0.004	
								(-0.039)	
c.log(Bus_density)#c.log(SPILLSIC)								0.053	
								(1.017)	
PDI									-0.393
									(-1.273)
Observations	6,943	6,943	6,943	6,943	6,943	6,943	6,940	6,940	3,275
R-squared	0.099	0.101	0.115	0.116	0.093	0.094	0.093	0.094	0.093
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES	YES

Table A9: Human capital value, density, and firm innovation – updated patent count.

This table shows the effect of the human capital characteristics in the area on firms' patenting. The dependent variables *L(Npat_new)*, the logarithm of 1 plus the number of patents based on our own merge of USPTO updated patent data with Compustat. Detailed description of dependent and independent variables is in Table 1. **Each observation is at the firm – year – MSA level.** Three additional controls at the MSA level are added to the baseline specification: *Patenting_uni* equals one if MSA has a least one university with patents reported in the USPTO database; *Establ_growth* is the growth rate in the number of establishments in the MSA; *Non_compete* is a dummy variable equal 1 if the state of the firms' headquarter location introduced non-compete provisions, and zero otherwise. In these regressions, MSA characteristics vary for the firm-year when its patents' inventors are located in various MSAs; firm-level controls are the same for all firm – year - MSAs. All regressions include control variables described in Section 3, year fixed effects, and industry fixed effects. Standard errors are clustered at the MSA level. Robust t-statistics is reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	L(Npat_new) (1)	L(Npat_new) (2)	L(Npat_new) (3)	L(Npat_new) (4)	L(Npat_new) (5)	L(Npat_new) (6)	L(Npat_new) (7)
log(SPILLTECH)	0.023	0.068	0.071	0.028	0.027	0.189	0.290
	(0.142)	(0.477)	(0.465)	(0.180)	(0.174)	(0.766)	(1.103)
log(SPILLSIC)	0.370**	0.382**	0.376**	0.369**	0.370**	0.331	0.345
	(2.357)	(2.423)	(2.306)	(2.366)	(2.365)	(1.339)	(1.422)
Bachelor_perc	1.258						
	(1.035)						
log(Med_inc)		1.166***	-2.660				
		(2.666)	(-0.651)				
c.log(Med_inc)#c.log(SPILLTECH)			0.050				
			(0.126)				
c.log(Med_inc)#c.log(SPILLSIC)			0.283				
			(1.472)				
log(Density)				0.108		0.105	0.110
				(1.008)		(0.874)	(0.885)
log(Bus_density)					0.096		
					(0.934)		
PDI						-1.027**	-26.300**
						(-2.142)	(-2.591)
c.PDI#c.log(SPILLTECH)							2.043*
							(1.777)
c.PDI#c.log(SPILLSIC)							0.040
							(0.080)
Patenting_uni	0.294**	0.326**	0.331**	0.325**	0.331**	0.451***	0.444***
	(2.131)	(2.398)	(2.410)	(2.373)	(2.394)	(2.923)	(2.874)
Establ_growth	1.380	1.360	1.357	1.835	1.807	1.544	1.475
	(0.991)	(0.944)	(0.946)	(1.307)	(1.285)	(1.030)	(0.985)
Non-compete	-0.172	-0.097	-0.101	-0.203	-0.202	-0.554**	-0.575**
	(-0.992)	(-0.639)	(-0.632)	(-1.067)	(-1.058)	(-2.502)	(-2.106)
Observations	4,527	4,527	4,527	4,527	4,527	2,425	2,425
R-squared	0.124	0.144	0.145	0.123	0.122	0.129	0.132
Controls	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES	YES

Table A10: Addressing endogeneity issues: Presence of a land-grant university as instrument.
This table shows the effect of two measures of human capital value (in the MSA of the firm location) on firms' RD expenses and innovation output. Detailed description of dependent and independent variables is presented in Table 1. The presence of a land-grant university in the MSA is used as an instrumental variable for *Bachelor_perc* and *log(Med_inc)*; the instrument based on the firm-specific tax price of RD from Lucking, Bloom and Van Reenen (2018) is included as an instrumental variables for RD spillovers, *log(SPILLTECH)* and *log(SPILLSIC)*. Regressions with interaction of human capital characteristics and spillovers are reported only if the effect of human capital characteristics is significant in the regression without interaction. All regressions include control variables described in Section 3, year fixed effects, and industry fixed effects. Standard errors are clustered at the MSA level. Robust t-statistics is reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	L(RD/Sales) (1)	L(RD) (2)	L(fNpat) (3)	L(Tcw) (4)	L(Tsm) (5)	L(RD/Sales) (6)	L(RD) (7)	L(fNpat) (8)	L(Tcw) (9)	L(Tsm) (10)
log(SPILLTECH)	0.038	0.436	0.215	0.195	0.027	0.004	-0.146	0.250	0.340	0.316
	(1.416)	(0.992)	(1.054)	(0.823)	(0.115)	(0.047)	(-0.111)	(0.744)	(0.629)	(0.399)
log(SPILLSIC)	0.017	0.206	-0.420***	-0.472***	-0.180	-0.010	-0.256	-0.418***	-0.466**	-0.170
	(0.958)	(0.682)	(-2.959)	(-2.828)	(-1.121)	(-0.131)	(-0.219)	(-2.832)	(-2.531)	(-0.794)
Bachelor_perc	-1.078	-18.259	1.181	4.942	9.842					
	(-0.533)	(-0.512)	(0.073)	(0.269)	(0.566)					
log(Med_inc)						0.697	11.812	-1.006	-4.208	-8.381
						(0.253)	(0.272)	(-0.069)	(-0.188)	(-0.273)
1-stage F-test (weak identification)										
log(SPILLTECH)	1,057.21	1,057.21	521.50	521.50	521.50	1057.21	1057.21	521.50	521.50	521.50
log(SPILLSIC)	57.59	57.59	17.57	17.57	17.57	57.59	57.59	17.57	17.57	17.57
Bachelor_perc	6.69	6.69	1.28	1.28	1.28	6.63	6.63	1.15	1.15	1.15
log(Med_inc)										
Joint significance F-test	2.79	2.79	1.23	1.23	1.23	0.75	0.75	0.19	0.19	0.19
Observations	4,296	4,296	1,150	1,150	1,150	4,296	4,296	1,150	1,150	1,150
R-squared	0.281	0.727	0.791	0.759	0.889	0.061	0.333	0.791	0.700	0.765
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Table A11: Addressing endogeneity issues: elasticity of housing supply as instrument.
This table shows the effect of two measures of human capital value (in the MSA of the firm location) on firms' RD expenses and innovation output. Detailed description of dependent and independent variables is presented in Table 1. Elasticity of housing supply in the metropolitan area estimated by Saiz (2010) is used as instrument for *Bachelor_perc* and *log(Med_inc)*; the instrument based on the firm-specific tax price of RD from Lucking, Bloom and Van Reenen (2018) is included as an instrumental variables for RD spillovers, *log(SPILLTECH)* and *log(SPILLSIC)*. Regressions with interaction of human capital characteristics and spillovers are reported only if the effect of human capital characteristics is significant in the regression without interaction. All regressions include control variables described in Section 3, year fixed effects, and industry fixed effects. Standard errors are clustered at the MSA level. Robust t-statistics is reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	L(RD/Sales) (1)	L(RD) (2)	L(fNpat) (3)	L(Tcw) (4)	L(Tsm) (5)	L(RD/Sales) (6)	L(RD) (7)	L(fNpat) (8)	L(Tcw) (9)	L(Tsm) (10)
log(SPILLTECH)	0.022***	0.201***	0.223***	0.194**	0.134*	0.023***	0.219***	0.220***	0.190**	0.130*
	(3.530)	(3.237)	(3.176)	(2.302)	(1.931)	(3.890)	(3.670)	(3.386)	(2.430)	(1.954)
log(SPILLSIC)	0.011**	0.119	-0.332***	-0.464***	-0.247**	0.010**	0.107	-0.325***	-0.456***	-0.240**
	(2.257)	(1.597)	(-2.903)	(-3.310)	(-2.189)	(2.105)	(1.387)	(-2.856)	(-3.283)	(-2.063)
Bachelor_perc	0.243	4.239	-0.913	-1.078	-1.059					
	(1.016)	(1.614)	(-0.314)	(-0.282)	(-0.446)					
log(Med_inc)						0.066	1.148	-0.245	-0.289	-0.284
						(0.957)	(1.576)	(-0.318)	(-0.286)	(-0.459)
1-stage F-test (weak identification)										
log(SPILLTECH)	1048.76	1048.76	570.62	570.62	570.62	1048.76	1048.76	570.62	570.62	570.62
log(SPILLSIC)	42.53	42.53	20.60	20.60	20.60	42.53	42.53	20.60	20.60	20.60
Bachelor_perc	9.26	9.26	4.45	4.45	4.45					
log(Med_inc)						15.76	15.76	7.12	7.12	7.12
Joint significance F-test	116.46	116.46	41.50	41.50	41.50	199.27	199.27	75.38	75.38	75.38
Observations	4,184	4,184	1,667	1,667	1,667	4,184	4,184	1,667	1,667	1,667
R-squared	0.613	0.895	0.776	0.752	0.916	0.611	0.897	0.777	0.753	0.916
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Table A12: Addressing endogeneity issues: elasticity of housing supply as instrument.
This table shows the effect of two measures of human capital density (in the MSA of the firm location) on firms' RD expenses and innovation output. Detailed description of dependent and independent variables is presented in Table 1. Elasticity of housing supply in the metropolitan area estimated by Saiz (2010) is used as instrument for *log(Density)* and *log(Bus_density)*; the instrument based on the firm-specific tax price of RD from Lucking, Bloom and Van Reenen (2018) is included as an instrumental variables for RD spillovers, *log(SPILLTECH)* and *log(SPILLSIC)*. Regressions with interaction of human capital characteristics and spillovers are reported only if the effect of human capital characteristics is significant in the regression without interaction. All regressions include control variables described in Section 3, year fixed effects, and industry fixed effects. Standard errors are clustered at the MSA level. Robust t-statistics is reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	L(RD/Sales) (1)	L(RD) (2)	L(RD) (3)	L(fNpat) (4)	L(Tcw) (5)	L(Tsm) (6)	L(RD/Sales) (7)	L(RD) (8)	L(RD) (9)	L(fNpat) (10)	L(Tcw) (11)	L(Tsm) (12)
log(SPILLTECH)	0.024***	0.237***	0.230***	0.221***	0.191**	0.131*	0.024***	0.237***	0.231***	0.221***	0.191**	0.131*
	(4.222)	(4.133)	(4.278)	(3.282)	(2.394)	(1.955)	(4.219)	(4.124)	(4.270)	(3.289)	(2.399)	(1.959)
log(SPILLSIC)	0.011**	0.123	0.142**	-0.322***	-0.452***	-0.236**	0.011**	0.123	0.139**	-0.323***	-0.453***	-0.237**
	(2.053)	(1.608)	(2.284)	(-2.836)	(-3.280)	(-2.009)	(2.057)	(1.627)	(2.259)	(-2.852)	(-3.297)	(-2.031)
Log(Density)	0.010	0.172*	1.685	-0.040	-0.047	-0.046						
	(0.934)	(1.787)	(1.055)	(-0.303)	(-0.277)	(-0.429)						
c. log(Density)#c.log(SPILLTECH)			-0.075									
			(-0.626)									
c. log(Density)#c.log(SPILLSIC)			-0.062									
			(-0.392)									
log(Bus_density)							0.009	0.158*	1.529	-0.037	-0.044	-0.043
							(0.934)	(1.776)	(1.052)	(-0.304)	(-0.278)	(-0.430)
c. log(Bus_density)#c.log(SPILLTECH)									-0.072			
									(-0.661)			
c. log(Bus_density)#c.log(SPILLSIC)									-0.053			
									(-0.373)			
1-stage F-test (weak identification)												
log(SPILLTECH)	1048.76	1048.76	1162.77	570.62	570.62	570.62	1048.76	1048.76	1162.77	570.62	570.62	570.62
log(SPILLSIC)	42.53	42.53	115.43	20.60	20.60	20.60	42.53	42.53	115.43	20.60	20.60	20.60
Log(Density)	10.50	10.50	6.92	12.86	12.86	12.86						
c. log(Density)#c.log(SPILLTECH)			6.55									
c. log(Density)#c.log(SPILLSIC)			6.33									
log(Bus_density)							12.31	12.31	8.33	15.39	15.39	15.39
c. log(Bus_density)#c.log(SPILLTECH)									7.80			
c. log(Bus_density)#c.log(SPILLSIC)									7.54			
Joint significance F-test	577.00	577.00	76.47	194.78	194.78	194.78	658.13	658.13	87.12	215.26	215.26	215.26
Observations	4,184	4,184	4,184	1,667	1,667	1,667	4,184	4,184	4,184	1,667	1,667	1,667
R-squared	0.605	0.899	0.899	0.776	0.753	0.916	0.605	0.900	0.899	0.776	0.753	0.916
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Table A13: Descriptive statistics of subsamples obtained by partitioning the main sample by the presence of patenting university.

	MSA has patenting university					No patenting university				
Variable name	Median	Mean	Std dev.	Obs.	MSAs	Median	Mean	Std dev.	Obs.	MSAs
log(1+R&D/Sales)	0.03	0.08	0.13	2,622	664	0.04	0.07	0.10	2,403	664
log(1+R&D)	2.61	2.71	1.82	2,622	664	2.95	3.14	2.10	2,403	664
log(1+fNpats)	2.08	2.43	1.54	1,021	664	2.20	2.62	1.73	940	664
log(1+Tcw)	2.73	3.00	1.74	1,021	664	2.82	3.16	1.88	940	664
log(1+Tsm)	3.25	3.60	2.37	1,021	664	3.22	3.91	2.80	940	664
log(Npat_new)	2.20	2.53	1.64	1,206	664	2.30	2.81	1.89	1,117	664
Npat_new	8.00	74.86	258.78	1,206	664	9.00	153.73	614.68	1,117	664
MV	830.77	6,118.39	19,618.18	2,655	664	902.65	13,647.43	39,567.25	2,419	664
Assets	521.76	3,172.91	9,823.10	2,655	664	543.83	7,471.43	21,808.47	2,419	664
Age	28.00	32.55	15.95	2,655	664	31.00	35.09	16.46	2,419	664
R&D	12.65	95.06	300.66	2,622	664	18.10	196.18	482.37	2,403	664
Blev	0.41	0.47	0.68	2,655	664	0.44	0.48	0.36	2,419	664
Emp	2.50	10.33	23.51	2,655	664	3.10	17.76	35.37	2,419	664
Mlev	0.23	0.28	0.20	2,655	664	0.28	0.31	0.21	2,419	664
Atgrow	0.02	0.05	0.27	2,655	664	0.02	0.05	0.31	2,419	664
Hiring	0.02	0.03	0.18	2,655	664	0.01	0.03	0.17	2,419	664
ROA	0.05	0.01	0.26	2,655	664	0.05	0.00	0.26	2,419	664
Q	1.68	2.01	1.31	2,655	664	1.62	1.92	1.27	2,419	664
K/L	3.77	3.81	0.97	2,655	664	3.69	3.76	0.95	2,419	664
log(MV)	6.72	6.64	2.20	2,655	664	6.81	6.88	2.58	2,419	664
log(Age)	3.33	3.36	0.50	2,655	664	3.43	3.44	0.51	2,419	664
log(HHI)	0.23	0.26	0.16	2,655	664	0.21	0.25	0.16	2,419	664
log(SPILLTECH)	11.39	11.19	0.96	2,655	664	11.38	11.32	0.85	2,419	664
log(SPILLSIC)	10.58	10.30	1.52	2,655	664	10.66	10.30	1.62	2,419	664

Table A14: Human capital value, density, and firm innovation – updated patent count. This table shows the effect of the human capital characteristics in the area on firms' patenting for the purpose of comparing with baseline analysis of patenting using patent data from Kogan et al. (2017) in Table 2-4

	L(Npat_new) (1)	L(Npat_new) (2)	L(Npat_new) (3)	L(Npat_new) (4)	L(Npat_new) (5)	L(Npat_new) (6)
log(SPILLTECH)	0.157	0.166*	0.165*	0.166*	0.060	0.184
	(1.583)	(1.681)	(1.674)	(1.681)	(0.355)	(1.291)
log(SPILLSIC)	-0.205*	-0.199*	-0.195*	-0.196*	-0.202	-0.254**
	(-1.731)	(-1.671)	(-1.667)	(-1.672)	(-1.635)	(-2.072)
Bachelor_perc	1.461					
	(1.148)					
log(Med_inc)		0.193				
		(0.480)				
Log(Density)			0.007		-0.031	-0.036
			(0.101)		(-0.163)	(-0.191)
log(Bus_density)				0.004		
				(0.056)		
PDI					0.921*	-13.063**
					(1.903)	(-2.190)
c.PDI#c. log(SPILLTECH)						1.351***
						(3.258)
c.PDI#c. log(SPILLSIC)						-0.180
						(-0.527)
Observations	2,116	2,116	2,116	2,115	888	888
R-squared	0.774	0.773	0.773	0.773	0.800	0.804
Controls	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES