Human Capital Reallocation and Agglomeration of Innovation: Evidence from Technological Breakthroughs*

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Abstract

This paper identifies the reallocation of human capital as a key channel of agglomeration spillovers for innovative firms. To measure agglomeration spillovers, I study how R&D labs in different local labor markets respond differently to scientific breakthroughs, which create large and unexpected shocks to innovation productivity in certain technology categories. Taking advantage of U.S. Census longitudinal establishment data matched with patent records, I systematically locate R&D labs in all local labor markets for each firm. I document four main findings. First, following scientific breakthroughs, affected labs in thicker local labor markets (i.e., commuting zones with more inventors innovating in a certain field) produce more patents and higher-quality patents, consistent with positive agglomeration spillovers. Second, the increase in patenting is mostly attributed to new hires rather than incumbent inventors. Third, the thick labor market effect is concentrated in states and industries where there is lower enforceability of non-compete agreements and labor is more mobile. Finally, using textual analysis to identify lab-level exposure to scientific breakthroughs, I find that inventors are reallocated to labs that are more favorably affected by shocks, which helps labs in thicker labor markets to more easily bring in inventors working in the same niche fields and having a diverse knowledge base. Taken together, these results point to labor mobility as a key force in explaining why innovative firms cluster, and suggest that the clustering of firms in thick labor markets can foster corporate innovation by facilitating productivity-enhancing reallocation of human capital following scientific breakthroughs.

Keywords: Innovation, Local Labor Market, Human Capital Allocation, Labor Mobility, Noncompete Agreements, Scientific Breakthroughs, Agglomeration Spillovers

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Innovative activity is highly clustered in space. 5% of commuting zones[1] account for over 75% of patent-weighted inventors in the US. Given the important role that human capital plays in producing innovation, existing literature explores channels through which a high concentration of skilled workers could explain the superior performance of a handful of technology hubs. Dating back to Marshall's *The Principles of Economics*, there are two dominant theories. One is that the agglomeration of specialized human capital may generate localized knowledge spillovers based on "ideas in the air." Physical proximity reduces communication costs, under this view, and facilitates the transmission of knowledge.[2] The second is that agglomeration facilitates the allocation of human capital in local labor markets. Thick labor markets (i.e., local markets with a large number of inventors innovating in a certain field) can improve the propensity and quality of matching between firms and workers when heterogeneity exists, and can facilitate the mobility of workers to firms when productivity shocks create an unexpected demand for specific skills.[3]

Compared with a large literature on knowledge spillovers, empirical work investigating the link between innovation clusters and the allocation of human capital in the local labor market is more limited. One potential reason is the challenge of locating the actual places where firms' innovative activities are conducted, which is especially difficult for private and multi-unit firms due to a general lack of large-scale data. More importantly, empirically distinguishing the source of advantages from locating in talent clusters is difficult.

In an attempt to fill the gap, I focus on the labor channel underlying the agglomeration of innovation activity. To measure agglomeration spillovers, I study how R&D labs in different local labor markets ("LLMs" hereinafter) respond differently to scientific breakthroughs that create large and unexpected shocks to innovation productivity in a technology category. I investigate two related questions: (*i*) Do R&D labs in thick LLMs disproportionately benefit from breakthroughs? (*ii*) What is the main mechanism that explains the thick market effects? Using large-scale Census plant-level data, I provide empirical evidence in support of thick market effects. In response to one unit of breakthroughs, a R&D lab's response in patent quantity and quality increases by 25.88% and 45.74% if the associated LLM is thicker than an average LLM by one-standard-deviation. To investigate the role played by labor mobility, I examine whether the productivity gains are

[1]Approximating local labor markets(Autor and Dorn (2013)), commuting zones (CZs) are geographic units of analysis intended to reflect the local economy where people live and work more closely. A commuting zone is a geographic area encompassing urban and rural areas that share a common market.

[2]Marshall (1890) described cities as "having ideas in the air". Theoretical framework has established that direct interactions among workers form the basis for accumulation and diffusion of knowledge, including Glaeser (1999), von Hippel (1994) among others. Recent evidence on knowledge spillovers through social interactions includes Zacchia (2019), Roche et al. (2022) and Atkin et al. (2022)

[3]The ideas are formalized in theoretical work by Helsley and Strange (1990), Krugman (1991a,b), Strange, Hejazi, and Tang (2006), Almazan, De Motta, and Titman (2007), Overman and Puga (2010), among others.

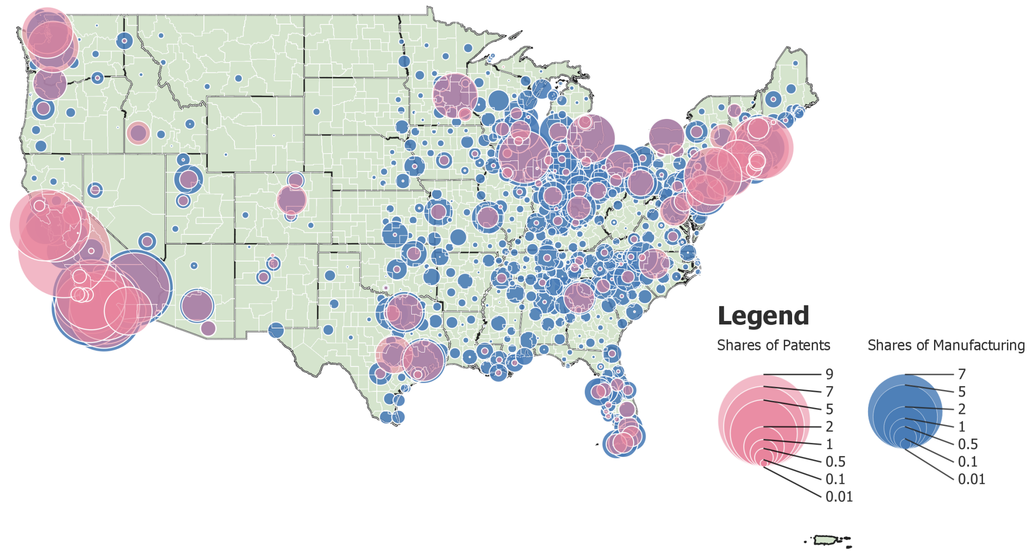

Figure 1: **Geographic Distribution of Patent-Weighted Inventors.** The figure presents the spatial distribution of inventors weighted by shares of patents filed by US companies from 1981 to 2010. The size of the pink circles represents the shares of patent-weighted inventors by commuting zones. I assess innovation hot spots in accordance with inventors' addresses listed on patents. When multiple inventors are associated with one application, each inventor's commuting zone receives a share of the patent. By comparison, the average manufacturing employment shares by commuting zones are plotted with blue circles. Compared with 12% of commuting zones contributing to 75% of manufacturing employment, 5% of commuting zones accounting for over 75% of patent-weighted inventors suggests that economic forces linked to agglomeration of innovation appear even more localized.

more pronounced among new hires or incumbents and whether the gains are concentrated in states and industries in which labor is more mobile because there is lower enforceability of non-compete agreements. I find that a R&D lab in a top 5% thick market could have almost doubled its boost in patent productivity without NCs following a boom of breakthroughs. I also use textual analysis to measure labs with higher and lower marginal productivity, using differences in lab-level exposure to breakthroughs. My results consistently support the explanation that thick labor markets encourage innovation by facilitating the productivity-enhancing reallocation of human capital.

Testing the effect of local labor markets on innovation outcomes and inventor mobility requires locating patenting firms' research labs and matching them with their local inventor employees. I accomplish this by exploiting detailed and comprehensive establishment-level data from the Longitudinal Business Database (LBD) of the Census Bureau and the firm-assignee-inventor-matched patent data. Research labs ("R&D labs" hereinafter) are defined as plants that are located in the same commuting zones ("CZs" hereinafter) as inventors employed by the firm. The large scope of the data, which spans business establishments in all industries across all states, allows me to systematically locate R&D labs of all innovative firms in local labor markets and to track innovation activities at the lab level across time. I define a local labor market as $CZ \times ResearchField$. Thickness is measured as the natural logarithm of the number of inventors in a research field residing in the same commuting zone.

To measure exogenous technological breakthroughs, I use patents generated by universities, federal or state government labs, and other public research institutes. It is important for my empirical strategy that the measurement of breakthroughs in the public sector is separated from the measurement of patenting activities by innovative firms in the private sector, which limits the scope for mechanical relations between breakthroughs and future patenting in my analysis. These scientific breakthroughs create large and unexpected productivity shocks to corporate R&D labs. Following the methodology of Kelly, Papanikolaou, Seru, and Taddy (2021), I apply textual analysis to the high-dimensional technical content in patent descriptions to measure the novelty and impact of inventions and to identify scientific breakthroughs as those that significantly depart from prior technology, opening new paths for subsequent innovation.

Through the lens of patent files, I study the direction and composition of the technological projects taken by corporate R&D labs following the shocks and investigate how their subsequent innovation productivity differs depending on local labor market conditions in the research field. Furthermore, I include local labor market by year fixed effects and industry fixed effects in my main regressions, as well as a broad set of control variables. Essentially, my empirical strategy is to exploit the cross-sectional variation across comparable R&D labs in the same LLM that experienced different technological shocks in the same time window. Comparing such R&D labs helps to minimize selection concerns, as these labs are likely to be very similar, given that they share a common research field and choose to locate in the same location. Also, if there exists any complementarity between the research field and the location that makes the local market particularly attractive for talent in the field, they are identically affected.

In the first part of the empirical analysis, I estimate the effects of scientific breakthroughs and local labor market thickness on the quantity and quality of subsequent patents produced by corporate R&D labs. I consider two measures of patent quality: the number of forward citations received by a patent, and the *importance*. I use textual analysis to measure impact and novelty of each patent and measure *importance* as the product of impact and novelty. I first provide evidence to validate my measure of productivity "shocks" by showing that breakthroughs promote patenting productivity of R&D labs. Then I study labor market effects by investigating the extent to which labs' responses to technological shocks depend on their predetermined local labor market thickness. I find that R&D labs in thick local labor markets produce more and better inventions following scientific breakthroughs. In response to each unit increase in breakthrough intensity, a lab affected by a breakthrough will, on average generate 3.13% more patents, 2.26% more citations and 2.58% higher patent counts weighted by *importance* than a similar lab without shocks. A one-standard-deviation increase (1.744%) in labor market thickness leads to an increase of 0.81%, 0.61% and 1.18% in the quantity, citations and importance of patents, which suggests the boosting effects increase by 25.88%, 27% and 45.74% if the associated LLM is one-standard-deviation above the sample mean in terms of thickness. Next, I study labs' responses in their core and non-core technology areas separately and consider exploratory and exploitative inventions. My results show that labs in thick markets experience boosts in productivity through core technologies. Moreover, their inventions tend to be more exploratory and less exploitative. Finally, because not all innovations are patentable, I examine the effects of labor market thickness on the natural logarithm of annual wages per employee to capture changes in investment in human capital. I show that R&D labs that experience a higher volume of breakthroughs grow to be more human-capital intensive, especially in labs located in thick labor markets.

In the second part of the empirical analysis, I investigate the potential explanations for how R&D labs in thick labor markets disproportionately benefit from breakthroughs. Since the mechanism of human capital allocation relies on labor mobility, while network-based spillovers of knowledge do not, I begin by investigating the contribution made by incumbent and newly-hired inventors to the increases in productivity following breakthroughs. I find that the productivity gains are primarily attributed to new hires. Given one unit of breakthroughs, a one-standard-deviation increase (1.744%) in market thickness leads to a 1.21 (1.09)% increase in the number of patents (citations) produced by newly hired inventors, but only results in a 0.37 (0)% increase in the number of patents (citations) produced by incumbent inventors. The results suggest that, if the associated LLM is one-standard-deviation above the sample mean in terms of thickness, the boosting effects on patents (citations) significantly increase by 56.81 (60.1)% for new hires, while only significantly increase by 22.02 (0)% for incumbents. The small estimated thick market effects among incumbent inventors casts doubt on the "knowledge in the air" channel.

To pin down the role of labor mobility in fostering innovation in thick markets, I leverage state-by-industry variation in the use of non-compete agreements ("non-competes" or "NCs" hereinafter), which impose constraints on inventors switching jobs between competing firms.[4] Using

[4]Prior studies have found a negative relationship between noncompetes and labor mobility(Marx, Strumsky, and Fleming (2009), Fallick et al. (2006), Starr (2019), Jeffers (2019) and Johnson et al. (2020)), especially for skilled labor. Using a natural experiment, Marx, Strumsky, and Fleming (2009) finds causal evidence of a decreased mobility of inventors after the noncompetes became enforceable in Michigan. In a more general setting, Jeffers (2019) shows that stronger enforceability of non-competes leads to a substantial decline in employee mobility, especially in knowledge-intensive occupations, which are particularly relevant in the context of inventors. Similarly, Johnson et al. (2020) finds more significant effects among workers most likely to sign NCs. Starr et al. (2019) find workers, including those unconstrained by noncompetes, receive relatively fewer job offers and have reduced mobility in state-industry combinations with a higher incidence and enforceability of noncompetes. NCs can also make it more difficult for small firms to hire experienced workers(Kang and Fleming (2020)).

strict enforcement of NCs as a plausibly exogenous constraint on labor market mobility following technological shocks, I re-examine the thick market effects on innovative productivity. I find that when non-competes are rigorously enforced, there are substantial declines in the thick market effect on patent quantity and quality, sweeping away almost all of the thick-market benefits. Following a breakthrough with median intensity, an average labor market (in terms of thickness) without NCs can promote local labs' innovation as well as a top 5% thick market with NCs. R&D labs in a top 5% thick market could have enjoyed a 60% larger boost in patent productivity without NCs. The NC-related reduction in patenting outputs is more considerable among new hires. Moreover, the NC-related reduction in inventor turnover is especially large among recent movers after breakthroughs. These results support the theory that thick labor markets promote innovation after technological shocks through labor mobility.

Next, to further demonstrate the link between human capital allocation and productivity gains, I explore the variation in labs' exposure to scientific breakthroughs to study the direction of labor reallocation. The idea is analogous to the efficient allocation of physical assets found in the market for corporate assets (Maksimovic and Phillips (2001, 2002)). Consistent with profit maximization by firms in a neoclassical framework, Maksimovic and Phillips (2001, 2002) find that the market facilitates the reallocation of assets from less productive to more productive users. In addition, transactions are more frequent when the industry experiences positive demand shocks and productivity increases following the transactions.

Applying textual analysis to the high-dimensional technical descriptions in patent files, I measure labs' exposure to a scientific breakthrough by evaluating the extent to which the discovery is relevant to the lab. Labs with high exposure tend to have the necessary knowledge and technological background to understand scientific advances and thus have an advantage in seizing technological opportunities. I find that following breakthroughs, exposure is positively related to inventor onboarding and negatively related to inventor offboarding, the effects of which are further amplified in thick labor markets. This is similar to the redeployment patterns of physical capital in response to shocks in Maksimovic and Phillips (2001, 2002), under the assumption that exposure provides a credible measure of marginal productivity. I also confirm that the ex-ante potential is realized ex-post, and the realization of productivity gains is strongly associated with labor market thickness. Thus, my findings suggest that thick local labor markets promote the productivity-enhancing allocation of human capital.

Finally, I analyze the characteristics of new inventors and show that human capital is deployed to more productive uses. I find evidence of a better match between new hires and firms in thicker labor markets in the sense that inventors work in the same tech niche as the lab. I also find that new hires provide a broader knowledge set in the sense that their previous inventions have less overlap with labs' prior patents, measured by textual similarity.

The results stand up to a range of robustness analyses. I use specifications with various fixed effects on the interaction between lab characteristics and LLM to compare labs in narrower groups in which potential selection issues are minimized. Results are robust when considering geographically-distant breakthroughs. Effects are even stronger when focusing on first-wave breakthroughs and a potentially "cleaner" thickness measure based on historical labor market conditions unaffected by any breakthrough shocks. Finally, using lab fixed effects to allow for different lab-specific baselines, I provide within-lab analysis of the thick market effects and show consistent results. I also find that thick labor markets help labs to streamline the inventor team in technological downturns and to acquire human capital when the demand for talent increases after breakthroughs create new innovation opportunities.

This paper contributes to several strands of literature. First, I build on the extensive literature on agglomeration, particularly on the clustering of innovation activities.[5] My analysis adds to the empirical work that seeks to understand the underlying forces that account for the agglomeration spillovers among innovative firms. I complement this line of research by providing evidence for a specific mechanism through which local agglomeration of human capital explains the superior performance of innovative firms in clusters. And I distinguish between two major channels, market-based allocation of human capital and network-based spillovers of "knowledge in the air." Using US Census micro-level data on establishments matched with patent records that allows me to systematically locate R&D labs in local labor markets, I examine thick labor market effects in a broad context. My analysis extends the studies on labor mobility in specific industries and regions (Fallick, Fleischman, and Rebitzer (2006), Freedman (2008), among others) to firms in all industries across all states. In addition, the paper speaks to the growing literature on local knowledge spillovers. For example, Matray (2021) shows that local innovation spillovers could be explained by localized learning and employees moving across local firms. Providing supporting evidence for the second explanation, my paper emphasizes that the mobility of inventors could not only facilitate spillovers to incumbents through learning from "knowledge embedded in the people," but also directly enhance productivity, providing the main channel through which firms realize the benefits from technological breakthroughs.

[5] Recent work includes but is limited to Moretti (2021), Kerr and Robert-Nicoud (2020), Lerner and Nanda (2020), Gross and Sampat (2020), Buzard, Carlino, Hunt, Carr, and Smith (2017), Golman and Klepper (2016), Kerr and Kominers (2015), Agrawal, Cockburn, Galasso, and Oettl (2014), Belenzon and Schankerman (2013), and Chen, Gompers, Kovner, and Lerner (2010).Carlino and Kerr (2015) provide a review of research on the connections between agglomeration and innovation. Previous reviews include Combes and Gobillon (2015), Rosenthal and Strange (2004) and Duranton and Puga (2003).

Second, this paper contributes to the literature on the reallocation of human capital. The factors affecting the reallocation of human capital have been studied for bank credit (Bai et al. (2018)), hedge fund activism (Brav et al. (2018)), going pubic (Babina et al. (2020), Bernstein (2015)), lending relationships (Hombert and Matray (2016), patent protection (Melero et al. (2020)), corporate R&D (Babina and Howell (2018)) and conglomerate form (Seru (2014). I add to this literature by looking into the productivity dispersion arising from exposure to breakthroughs and its interplay with local labor markets. Focusing on the role of the external market, my paper also sheds light on the conditions under which labor markets help to redeploy labor better in response to changing opportunities, complementing the reallocation that can occur within internal labor markets (Tate and Yang (2015, 2016), Giroud and Mueller (2015)).

The analysis of the reallocation of human capital in this paper also complements the literature on physical capital allocation. Jovanovic and Rousseau (2002) use Q theory to explain that firms with high productivity buy firms with low productivity. They study the role of technology adoption in creating cross-sectional dispersion of Qs and show that assets are reallocated toward more efficient firms through mergers (Jovanovic and Rousseau (2008)). Maksimovic and Phillips (2002) model asset reallocation as firms' responses to aggregate demand shocks and show that the productive segments of conglomerates grow faster. Examining actual productivity changes around the transition of asset ownership, Maksimovic and Phillips (2001) provide evidence of the efficiency of physical capital reallocation, especially through asset sales of plants and divisions. Yang (2008) develops a dynamic neoclassical model of asset sales in the presence of productivity shocks and generates predictions consistent with empirical evidence that firms optimally purchase assets when idiosyncratic shocks raise their productivity relative to industry peers. I complement this literature by investigating human capital allocation in the presence of productivity shocks arising from scientific breakthroughs. By measuring idiosyncratic exposure to shocks, I show that human capital tends to be reallocated to more productive use, consistent with the redeployment patterns of physical capital predicted from the neoclassical models above. Due to the fact that human capital is embedded in workers who are subject to employee-employer relationships, I also provide evidence that labor market frictions matter. The ability to move skilled workers from less to more productive labs largely depends on the effective thickness of the labor market, accounting for constraints such as NCs.

Third, this paper contributes to the literature evaluating the effects of noncompete agreements. Extensive evidence has been found that NCs impede labor mobility, especially for skilled labor in knowledge-intensive occupations. This paper complements this string of research by showing that the enforceability of NCs attenuates inventor mobility during technological advances, as a result of which the use of human capital as an innovation input is not optimal. Existing literature reaches different conclusions on whether NCs negatively affect innovation. On the one hand, enforceable NCs help solve under-investment in human capital due to the holdup problem by prohibiting departures to competitors. For example, Jeffers (2019) and Starr (2019) find firm-sponsored training is more common in states with more stringent NCs enforcement. On the other hand, enforced NCs can hinder the development of fast-growing technological firms and sectors. In particular, they impede firm entry and innovative startup performance (Samila and Sorenson (2011), Jeffers (2019), Starr (2019)). By comparing the innovation outcomes of labs with and without enforced NCs during the period of scientific advances, this paper reveals that the use of noncompete clauses can hurt innovation activities that rely on rapid labor turnover and, thus, limit the scope for technology diffusion. My empirical results provide an estimation of how much research facilities under the legal enforceability of noncompetes can take advantage of technological advances that would otherwise have emerged.

Finally, the paper contributes to the literature studying the relation between scientific advancement in public research institutes and innovation conducted by corporations in the private sector. It has long been known that there is a positive and substantial connection between firm patenting and prior scientific research (Trajtenberg, Henderson, and Jaffe (1997), Adams (2002)), especially in close technological domains (Jaffe (1989)). By providing extensive evidence that scientific advances considerably influence patenting activities by corporate R&D labs, this paper documents that the realization of productivity gains heavily depends on access to specialized talent in local labor markets and emphasizes the crucial role played by human capital mobility. Much of the existing evidence relies on the network of patent-to-patent citations and patent-to-publication citations to detect technological spillovers (Ahmadpoor and Jones (2017)). Methodology-wise, this paper contributes to this literature by providing a text-based approach to systematically study the impact of science on corporate innovation and to quantify idiosyncratic exposure to technological shocks without reliance on citations, in which case the linkage between two inventions heavily depends on inventors' awareness of the existence of prior technology and personal discretion in whether to make a citation.

The remainder of this paper is organized as follows. Section 1 describes my sources of data and the sample construction process. Section 2 outlines the paper's empirical strategy and presents the main effects of breakthroughs as a shock to corporate R&D labs. Section 3 presents the results on how labs in thick labor markets disproportionately benefits from breakthroughs, while Section 4 investigates the mechanisms underlying the thick market effects. Section 5 presents a discussion of additional tests and Section 6 concludes.

1 Data

This section describes data sources and the sample construction process. I discuss the strategy of locating R&D facilities, the definition of the local labor market, and the measure of labor market thickness. I also provide definitions of key variables and present descriptive statistics.

To construct my sample, I use establishment and firm data from the Longitudinal Business Database (LBD) of the Census Bureau and the universe of U.S. patents granted between 1976 and 2019.

1.1 Patents, Inventors and Local Labor Market

The source of patent data is derived from PatentsView, a patent database which provides detailed patent-level records on nearly seven million patents derived from the United States Patent and Trademark Office (USPS) bulk data files.

The dataset provides information on patent application dates, the date when the patent was ultimately granted, patent assignees, patent inventors, other patents cited as prior work, the technology classification of the patent, as well as textual and graphic content of patents content from 1976 to the present. Usually, assignees (a company, university, research lab, or other organization) hold the ownership of a patent invented by one or a team of inventors as a result of an employer-employee relationship. Disambiguation algorithms are applied to provide unique identifiers for patent inventors and assignees, making it possible to follow individuals' inventing activities and employment history (conditional on patenting) over time. Those identifiers are constructed using inventor and assignee information such as name and geography along with co-invention networks.[6] In the meantime, the dataset contains detailed information on the residential address of inventors linked with patents, which allows me to geographically locate inventors and, thus, the local labor market they are associated with.

I use a sample of all U.S. utility patents granted between 1976 and 2019. Cooperative Patent Classification (CPC) code are assigned to patents to define the relevant technology area. In this analysis, I will use the CPC section code to describe the "research field" and the CPC class code to to describe "technology class." There are 8 research fields defined for patents studied in sample. The distribution of R&D labs across fields are shown in Table 2 Panel C.

I then collect information on inventors associated with the patents. Based on the inventors' residential address reported on their patent applications, I construct a sample of inventors with a

[6] The PatentsView disambiguation algorithm yields a very similar groupings of inventor records, according to Akcigit and Goldschlag (2022), as their most recent work, which combines multiple sources of administrative data on firms and individuals to build the bridge between inventor records in the patent data to unique person identifiers in the Census Bureau data, cross-validating the quality of both disambiguation methods.

valid U.S. address. There are roughly 1.7 million unique inventors over 1976-2019 residing in U.S. and filing at least one patent. I use the field in which an inventor filed most patents to determine the main research field of inventors and the main three-digit technology class are determined in the same way. Though it is rare the case, if an inventor has same number of patents in more than one research field or technology class, I use the field and class in which an inventor filed more important patents based on citation received.

Local Labor Markets Following Moretti (2021), I define local labor markets as the combination of location $\times$ research field. The geographical units of analysis I employ are commuting zones. There are 709 commuting zones (2000 version) in the United States, and they cover the entire country.[7] CZs are a useful proxy for estimating the scope of local labor markets since CZs are based on economic geography rather than jurisdictional boundaries. Relying on Census commuting flows with additional information, they are designed as a self-contained economic unit with dense economic activity within its borders and little economic activity crossing its borders. Also, they cover the entire United States, including rural areas where many inventors could live. Thus, there are 709 $\times$ 8 local labor markets specified for each combination of CZ and research field.

The thickness of local labor markets is measured as the natural logarithm of the number of inventors in a specific research field residing in the same commuting zone. Using the panel of inventors, I aggregate the inventor-year-level data to the LLM-year level, yielding a measure of LLM thickness over time. For example, Table 1 shows the top ten thick local labor markets by research field in 2000.

Table 1: [INSERT TABLE HERE]

1.2 R&D labs

Locating the actual places where corporate innovation is conducted has long presented challenges to researchers due to the need for more data, especially for private and multi-unit firms. Although the site of corporate headquarters or patent office can be observed in some cases, using this single location to study local labor markets is wildly misleading for geographically-dispersed firms. In this section, I exploit detailed and comprehensive establishment-level data from the Longitudinal Business Database (LBD) of the Census Bureau and the matched patent data to determine the location of R&D facilities and document their innovative activities at the lab level.

[7] County-CZ crosswalk is obtained from https://www.ers.usda.gov/data-products/commuting-zones-and-labor-market-areas/

The LBD is a census of business establishments and firms in the U.S. with paid employees comprised of survey and administrative records. It contains longitudinal establishment identifiers, data on establishment location, age, industry, employment, annual payroll and firm affiliation, available for nearly every establishment in the U.S. annually. It is worth emphasizing that LBD data covers firms in all industries that cover the whole territory of the U.S., which means that there is less likely to be a selection problem than in analyses that have confined their samples to a portion of states or selective industries. The LBD data used in this paper covers from 1990 to 2019.

Focusing on corporate innovation, my sample only includes patenting firms and excludes non-corporation assignees (individuals, government, universities, etc.). Similar to raw inventor data, the original patent records lack consistent identifiers for firms. To identify LBD firms as patent assignees over time, I rely on large-scale disambiguation efforts on patent assignees made by PatentsView and the patent assignee-LBD firm ID crosswalk built by Dreisigmeyer, Goldschlag, Krylova, Ouyang, and Perlman (2018), which takes a triangulation strategy introduced by Graham et al. (2018) leveraging fuzzy matches of both patent assignees and inventors, in combination with job-level data, to disambiguate and validate matches. The established linkage between patent assignees and LBD firms covers patents granted from 2000 to 2019, with widespread application dates mostly from the 90s to recent years due to the uneven time lag between the time a patent application is submitted and the time it is granted, which usually takes at least one year and can be pending for five years and more. Along the analysis, a year is defined as the year of the patent application, not the year when the patent is granted since the application year has been widely viewed as the timing that can better reflect the actual timing of innovative activities being done. To supplement the patenting firms and the records of their patent that applied in the 1990s, I extend the assignee-firm matching using the disambiguated assignee identifier along with cross-validation of name and address. As a result, I obtain a complete sample of firms that have at least one patent application since 1990. Among U.S. assignees defined by addresses in their patent applications, over 90% of them are well-matched to LBD firms. Linking firms in LBD, which contain information on establishments with patent and inventor data allows me to identify their innovation activities conducted by local research facilities.

To distinguish facilities engaged in R&D activities, I rely on firms' patenting records and track their patent history, which contains the residential address of their inventors. By comparing the location of establishments and the address of inventors, research labs ("R&D labs" hereinafter) are identified as those plants where at least one establishment can be found in the commuting zone where associated inventors reside. If there are multiple establishments in a commuting zone, I group them into one facility. Thus, R&D labs are defined at the firm-CZ level. Table 2 Panel D summarizes the lab characteristics. The variable "su-mkt" indicates the R&D labs that are single-unit firms, which means they have a sole establishment relevant for innovation concerning patenting. About 48% of R&D lab-year are single-unit. More than a half of the sample consist of R&D labs belonging to multi-unit firms and the large standard deviation of the variable implies that a handful of firms have R&D labs across an extensive set of locations. The finding reinforces the necessity of using plant locations rather than the sole address of corporate headquarters or patent office (which is listed as the assignee address on patent applications) to determine the R&D facilities.

I use the technology class in which an R&D lab filed most patents to determine its main technology class and thus the research field (the local labor market) relevant for the lab. Table 1 presents the distribution of R&D labs by research field.

The unit of observation in the paper is a lab-year. My main analysis uses a sample of R&D labs that were established at least when scientific breakthroughs arrived. Also, I dropped the patents co-assigned to private R%D labs and public research institutes, including universities and government labs.

Other Data Sources I identify whether an innovative firm have received any venture capital between 1990 and 2005, based on to the linkage LBD firms with VC-financing information from VentureSource and VentureXpert built by Puri and Zarutskie (2012).

To supplement information on inventor, I match the inventor-patent data from PatentsView with web-scraped database by Kaltenberg et al. (2021) and obtain inventor age.

1.3 Measures of Innovation Productivity

To evaluate the lab-specific productivity of innovation output, I will use several patent-based measures, including widely-adopted measures over the last two decades and novel text-based measures. Patents provide one of the most valuable data that includes rich insights into the types and value of inventions that firms pursue.

The first primary measure of productivity is the quantity of patents that labs applied that were ultimately granted. The year of application is most relevant,since it provides a proxy for determining when inventors began developing the invention.

Patent counts correspond to the quantity of innovation, and patents can be heterogeneous in the number of ideas they contain and exhibit considerable variation in their value, some of which are argued to be useless. The distribution of patent value is highly skewed. I employ three measures to capture the quality of inventions. The first citation-based measure is based on forward citations received by patents adjusted by the fixed effect methodology(Hall et al. (2001)). Forward citations indicate the technological impact of a patent on future inventions. Citation rates vary considerably over time and across technologies. Thus, I adjust patent citations for the changing distribution of patent citations each year by scaling citations by the average number of citations per patent granted in the same year and the same three-digit technology class. This is necessary to solve the patent-level bias problem highlighted in Lerner and Seru (2021) induced by truncation of reported patent awards and citations, which can affect estimates of time trends and patterns across technology classes and regions.

I construct a binary variable, $Top\text{-}CitedPatents$, which is an indicator variable equal to one if a patent ends up in the top 10% of all patents from the same year and technology class in terms of forward citations received (Bernstein, Mcquade, and Townsend (2021)). This variable identifies a subset of highly influential patents granted within a technology class in a given year. The last variable I used to capture the importance associated with patents invented by a lab is the count of important-weighted patents. $Importance$ is a text-based measure that combines both novelty and impact of an invention. The measure is positively related to citation-based quality measure as well as stock return-based value measure(Kogan, Papanikolaou, Seru, and Stoffman (2017)), which estimates the private economic value of patents from stock market response to news about patents and thus is available to patents assigned to public firms only. Kelly et al. (2021) confirms the text-based importance measure is a strong predictor of return-based patent value. The advantage of importance is that the measure is available to all patents. Section 2 includes details on constructing the importance measure from the high-dimensional textual content in patent technical descriptions.

Due to the skewed nature of the distribution of patent counts and citation counts, I use the natural logarithm of the count-based variables.[8] Panel D of Table 2 presents the correlation matrix of my patent-based measures of innovation outputs. Panel E of Table 2 presents the summary statistics of variables used in the paper.

Table 2: [INSERT TABLE HERE]

[8]Since logarithm of zero is undefined, to avoid losing the lab-year observations with zero patents, following the common practice in the literature(Hirshleifer et al. (2012), Bernstein et al. (2021), among others), I add one to the actual values when calculating the natural logarithm. Results remain robust when I estimate Poisson regressions on actual patent-count and citation-count variables.

2 Research Design

2.1 Scientific Breakthroughs

To obtain exogenous technological shocks, I rely on breakthroughs in the public sector including universities and other public research institutes. These scientific breakthroughs create large and unexpected productivity shocks to corporate innovation. The measurement of breakthroughs is separated from the measurement of patenting activities by innovative firms in the private sector, which limits the scope for mechanical relations between technological shocks and future patenting by firms. To identify scientific breakthroughs, I build text-based indicators of breakthroughs following Kelly, Papanikolaou, Seru, and Taddy (2021). The idea is that innovations that greatly influence future technologies and deviate from the status quo are more likely to represent scientific breakthroughs. As a first step to measure the similarity between any two inventions, I rely on technical descriptions extracted from textual contents used in patent abstracts. I apply natural language processing techniques on high-dimensional textual data from over 6 millions patents to obtain a text-based similarity matrix describing pairwise similarities of patents.

2.1.1 Similarity Matrix and Patent Importance

To derive meaning from human-generated free-form technical descriptions of patents, the unstructured text must be converted to a numerical representation. The natural language processing methodology used here is Term Frequency-Inverse Dense Frequency (TF-IDF) technique. TF-IDF analyzes the library of all 6 million patents as a whole. TF measures how often a term appears in a specific patent, and IDF indicates the relative rarity of a term in the collection of all documents. The terms are pre-processed with the removal of stop words and token normalization. The technique is motivated by the view that the importance of a term to a focal patent is positively related to its frequency in the technical description, while the information uniqueness of the term is inversely related to its frequency across the library of all patents. The final TF-IDF value, equal to the product of TF and IDF, is used as the weight for each term in each patent description. Thus, the free-form textual description of a patent can be represented by a vector of TF-IDF weighted terms. I rely on the textual content in the patent abstract to vectorized each invention. The similarity between any two vectorized patents can be calculated as the cosine distance of two vectors, ranging from zero to one. The output is a machine-automated measure of the relation between any two patents. This is an improvement upon on other widely used citation-based measures, in which case the linkage between two patents depends on inventors' awareness of the existence of prior art and her (or patent examiner's) discretion in whether to make a citation.

I measure the linkages between any given invention and the set of existing and subsequent patents based on the similarity matrix. Following the definition used by Kelly et al. (2021), novel patents are those that are conceptually distinct from their predecessors and therefore has a lower similarity score than previous inventions (backward similarity). Impactful patents influence future scientific advances, reflected in their high similarity with subsequent innovations (forward similarity). **Importance** is defined as the ratio of the 5-year forward to the 5-year backward similarity,[9] net of year fixed effects. The measure of patent importance is used extensively in this paper as an overall quality measure of patents. Besides, the similarity matrix that measures technological relevance between any two patents also serves as crucial inputs to construct variables of interest used in the following analysis.

2.1.2 Measures of Scientific Breakthroughs

Breakthroughs are the most important innovations. They reshape the technological frontier and open new paths for considerable future work to build on. I identify breakthroughs as the most important inventions, those in the right tail of the importance measure across all patents, thus being both highly distinctive from previous work but related to subsequent innovations. I use the top 10 percentile as the cutoff following the definition in Kelly et al. (2021).

To build indices of scientific breakthroughs, I focus on breakthrough innovations generated from universities, federal or state government labs, and other public research institutes. Innovations from the public sector are closer to basic research and have potential spillovers to innovations in the private sector, which are more likely to be directed toward commercial use. Public research institutions produce scientific progress that is subsequently transferred into product and process innovations by private businesses, referred to as the public-good nature. Current research has shown inventions filed by public research institutes heavily cites scientific publications and likely represent basic research. These research conducted by universities and other public research institutes can generate substantial spillovers to industrial R&D. It is also shown that the commercial spillover effects come through more clearly within their technical domains (Jaffe (1989), Ahmadpoor and Jones (2017)). A booming technology usually involve multiple breakthrough inventions. For this reason, I aggregate the total number of breakthrough inventions by technology class (also referred as "technology category" in the paper) to obtain indices that describe the arrival intensity of scientific breakthroughs for each technology class. In my sample, examples of booming technologies that experienced strong breakthroughs with high intensity include genetic engineering, computing,

[9] An alternative definition of Importance, based on the ratio of the 10-year forward to the 5-year backward similarity, is employed for robustness tests and generates consistent results.

electric communication technique, optics, and nanotechnology. Using the application year as the timing when a breakthrough innovation arrives, I obtain a measure of the intensity of technology-specific scientific breakthroughs from 1981 to 2010.[10]

2.2 Empirical Strategy

2.2.1 Specifications

My primary interest is to examine how corporate innovation unevenly benefits from unexpected technological opportunities depending on their pre-determined locations, with specific attention the role of the mobility of human capital in the process. Scientific breakthroughs significantly departing from prior conventions can reshape existing technological trajectories and create technological opportunities for private businesses. The arrival timing of a breakthrough is highly random, creating unexpected productivity "shocks" to corporate R&D labs.

First, I establish the validity of productivity shocks on private sector innovation and investigate the magnitude of responses by subsequent corporate inventions to scientific breakthroughs. I estimate regressions of patenting outcomes by R&D labs on the intensity measures of breakthroughs that hit the technological domain of the private lab using a model as follows.

$$Y_{ikcf,t} = \beta_j Bkthr_{k,t-j} + Controls_{ikcf,t} + FEs + \epsilon_{ikcf,t} \tag{2.1}$$

Importantly, to investigate the extent to which labs' responses lean on the thickness of local labor market, I include an interaction term to capture the interplay between scientific breakthroughs and labor market thickness specified below.

$$Y_{ikcf,t} = \beta_1 Bkthr_{k,t-j} + \beta_2 Bkthr_{k,t-j} \times Thickness_{cf,t-j} + Controls_{ikcf,t} + FEs + \epsilon_{ikcf,t} \tag{2.2}$$

The outcome variable is measured for R&D lab i in technology class k and located in a local labor market (defined by commuting zone c × research field f) in year t. $Bkthr_{k,t-j}$ indicates the intensity of scientific breakthroughs in technology class k in year $t-j$, measured by the log number of breakthroughs generated from universities and public research institutes in the period. $Thickness_{cf,t-j}$ represents the thickness of the local labor market at the beginning of year $t-j$.

[10] Although patents granted before 1976 are not in my database and thus not included in the calculation, the resulting index of breakthroughs, using the same definition as Kelly et al. (2021), are highly correlated with their index (correlation coefficient over 0.98) in the overlapping period.

To study the effects of pre-shock local labor market thickness on innovation productivity and human capital reallocation following scientific breakthroughs, I rely on cross-sectional variation in which I compare patent outputs and talent mobility across R&D labs that experienced differential productivity shocks. I focus on pre-determined labor market conditions to exclude the effects from endogenous sorting of labor following the breakthroughs. Still, there remain potential concerns as the location of an R&D lab is not randomly assigned. It may be the case that labs that actively engage in research activities strategically choose to locate in the innovation clusters.

To address these issues, I include $CZ \times research\,field \times year$ fixed effects. With the inclusion of this LLM by year fixed effects, I am identifying off of R&Ds labs that are faced with the same local labor market but conduct research in the tech niche experiencing the differential intensity of breakthroughs during the same time window. The general orientation of their innovation activities is also likely to be similar, given that they share a common research field and choose to locate in the same locality. Also, they are identically affected by any time-invariant or time-varying complementary between a location and a research field that makes the local market particularly attractive for talent in the field.[11] Besides, labs conducting innovation in the same research field might operate a business in different industries. I include industry fixed effects to account for heterogeneity across industries in patenting propensity.

I also include a set of control variables, $Controls_{ikcf,t}$, to account for time-varying lab characteristics. For example, large labs or labs affiliated with large firms may have better access to resources and thus can better take advantage of breakthroughs than smaller labs. I measure lab size using the log employment of the lab and measure firm size using the log employment of the firm. Firms at a different stage of their life cycle can take a different strategy to conduct research. Mature firms may be less incapable of responding to radical technological changes that upset their established technologies. The age is thus controlled using the years since the initial year of the first establishment with positive employment. I calculate the total number of labor markets where a firm has R&D labs to control for the impact of intra-company transfers through internal labor markets on the lab outcomes. I also include an indicator variable to represent the single-unit labs. Labs also differ in their innovation experience, which is controlled by the stock of highly-cited patents owned by the lab in the past. The control variables are included across various specifications unless otherwise specified. Standard errors are clustered at the LLM-year level to account for potential serial correlation across labs in the same LLM in response to a wave of breakthroughs. I standard-

[11]The fixed effects can filter out many other sources of benefit that labs might obtain from locating in the field-specific innovation cluster, including changes in access to finance, such as venture capital that tend to populate in a certain area and "hot" field during certain periods, and proximity to research universities, such as Stanford in Silicon Valley and MIT as well as Harvard in Boston(Saxenian (1994), and Lee and Nicholas (2013)).

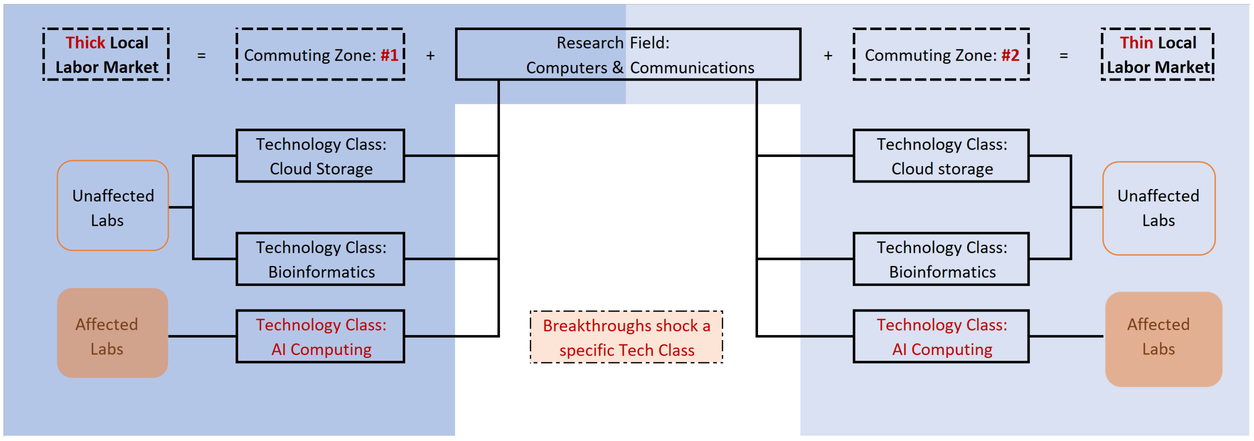

Figure 2: **Empirical Strategy: Exploit Cross-Sectional Variation Within Local Labor Markets**
The figure illustrates the main empirical strategy. A local labor market is defined as $Commuting\,Zone \times Research\,Field$. This figure depicts two LLMs of a research field, $Computers\,\&\,Communications$. Within the field, there are different technology classes, illustrated by three examples, $Cloud\,Storage$, $Bioinformatics$ and $AI\,Computing$. In a given year, a certain technology class, i.e., $AI\,Computing$ can be shocked by scientific breakthroughs. Using $CZ \times research\,field \times year$ fixed effects, the estimation of breakthrough effects relies on the cross-sectional comparison between R&D labs in $AI\,Computing$ and unaffected labs in other classes within the same research field. The thick market effects estimate the extent to which such comparison depends on local labor market thickness (dark blue vs. light blue).

ize all independent variables to have the mean as zero and the standard deviation as one to ease interpretation and magnitude comparison.

To sum up, with the use of a broad set of control variables and fixed effects, my empirical strategy is to focus on cross-sectional comparison across comparable R&D labs in the same LLM that experienced differential productivity shocks during the same time window and investigate whether the comparison depends on the pre-determined local labor market thickness.

2.2.2 Main Effects of Scientific Breakthroughs on Corporate Innovation

To verify the validity of productivity shocks induced by scientific breakthroughs and investigate the magnitude of responses by subsequent corporate innovation, I estimate regressions of innovation outputs produced by R&D labs, the number of patents and the number of core inventions on the intensity of breakthroughs using Model 2.1.

Are R&D labs responding to breakthroughs that have arrived, in which case scientific breakthroughs catalyze corporate innovation? Or are R&D labs are "responding" to future breakthroughs, in which case corporate innovation predicts or affects the arrival of scientific breakthroughs? To answer these questions, I employ a 9-year window for breakthroughs around a given year in which the R&D lab's patenting output is assessed. I estimate the effects of breakthroughs at different timing on corporate innovation responses. The effects of interest are denoted β_j, where $-4 <= j <= 4$. Ideally, I would observe coefficients for the breakthrough terms before year t

to be positive and statistically significant, while coefficients for year t and after to be indifferent from zero. A pattern like this would support the productivity "shock" assumption. In addition, this specification allows me to assess how long it takes for labs to respond after the arrival of technological shocks.

Table 3 Panel A presents the results. All the independent variables are standardized. R&D labs that experienced scientific breakthroughs in their technological domain produce more patents, confirming that breakthroughs have a positive impact on corporate innovation. The estimated coefficient implies that a one-standard-deviation increase in the intensity of scientific breakthroughs in $t-3$ year leads to 1.63% increase in the total patent output, the boost in core inventions is 1.37%.The breakthroughs in $t-2$ year also have a significant positive effect on labs' patents in year t, although the magnitude is more minor. Labs respond to technological opportunities that happened two or three years ago. In other words, the realization of productivity shocks takes about three years. Concurrent and future scientific breakthroughs are irrelevant.

Table 3: [INSERT TABLE HERE]

Given the dynamics of breakthrough effects observed in Panel A, I estimate regressions of various measures of innovation outputs on the cumulative intensity of breakthroughs that happened within a three-year window. I examine the main effects of scientific breakthroughs on the quantity and quality of all patents, separately study the impact on core and non-core inventions, and look into the exploratory nature of patents produced by R&D labs. Table 3 Panel B presents the results. Across all patent outputs, I estimate a positive coefficient that is statistically significant at the 1% level. This result indicates that labs produce more patenting outputs following scientific breakthroughs in their technology domain. Scientific breakthroughs not only lead to more patents in R&D labs, the quality of these patents, measured by forwarding citations received by the inventions, is also higher. The effects are mainly driven by the increase of patents in the core technologies that experienced breakthroughs and meanwhile, there are modest positive spillovers on the patenting in peripheral tech classes. Examining the effects on labs' exploratory and exploitative patents indicates that scientific breakthroughs mainly lead to more exploratory inventions. Besides, lab characteristics also matter in producing patents. I find that large labs and labs that belong to large firms at a younger stage of their life cycle produce patents at a higher rate following scientific breakthroughs. Besides, past experience in producing high quality patents also help in producing more patents. The internal labor market is also positively associated with patent outputs.

3 Thick Labor Market Effects

3.1 Quantity and Quality of Innovation Outputs

In this section, I discuss my main analysis of how corporate innovation unevenly benefits from unexpected scientific breakthroughs depending on the predetermined location.

First, I present initial evidence showing how R&D labs' patenting activities react to scientific breakthroughs and whether local labor markets affect the strength of reactions. Figure 3 shows a binned scatter plot of the relationship between the log number of patents filed by R&D labs in a given year and the intensity of scientific breakthroughs that happened in the past three years, measured by the log number of technology-specific breakthroughs. The binned scatter plot graphs the non-parametric relationship between corporate innovation and scientific breakthroughs for two subgroups, conditioning only on application year effects. Specifically, the relation is plotted separately for labs in the thick and thin LLMs based on a median split. The curve of labs in thick markets is above the curve in thin markets, representing a positive baseline difference in patenting rate between two markets. But the innovative productivity of labs in thick and thin follow similar trajectories in that the difference is slight and stable when few scientific breakthroughs are arriving. As the intensity of breakthroughs increases, both groups produce more patents. In particular, the two groups start to diverge, and the gap becomes wider. To sum up, the upward slope indicates the positive effects of scientific breakthroughs on patent output by R&D labs. The broader gap suggests the additional productivity gain on patenting for labs in a thick market. The pattern is consistent with the hypothesis that R&D labs in thick markets can unevenly benefit more from technological opportunities.

In Table 4, I estimate the effect of thick labor markets on labs' innovation output following scientific breakthroughs in a regression setting using Model 2.2 where the time window I use to measure the intensity of breakthroughs is $(t-3, t-1)$. Model 3.1 is the main specification used extensively in the analysis.

$$
\begin{aligned}
Y_{ikcf,t} =& \beta_1 Bkthr_{k,(t-3,t-1)} + \beta_2 Bkthr_{k,(t-3,t-1)} \times Thickness_{cf,t-3} \\
& + Controls_{ikcf,t} + FEs + \epsilon_{ikcf,t}
\end{aligned} \tag{3.1}
$$

where n denotes industry and s denotes the state. As before, i indexes R&D lab, k technology class, commuting zone $c \times$ research field f represents local labor market. Outcome variables are patent-based measures of innovative outputs. Patent-based quantity measures could be zero for

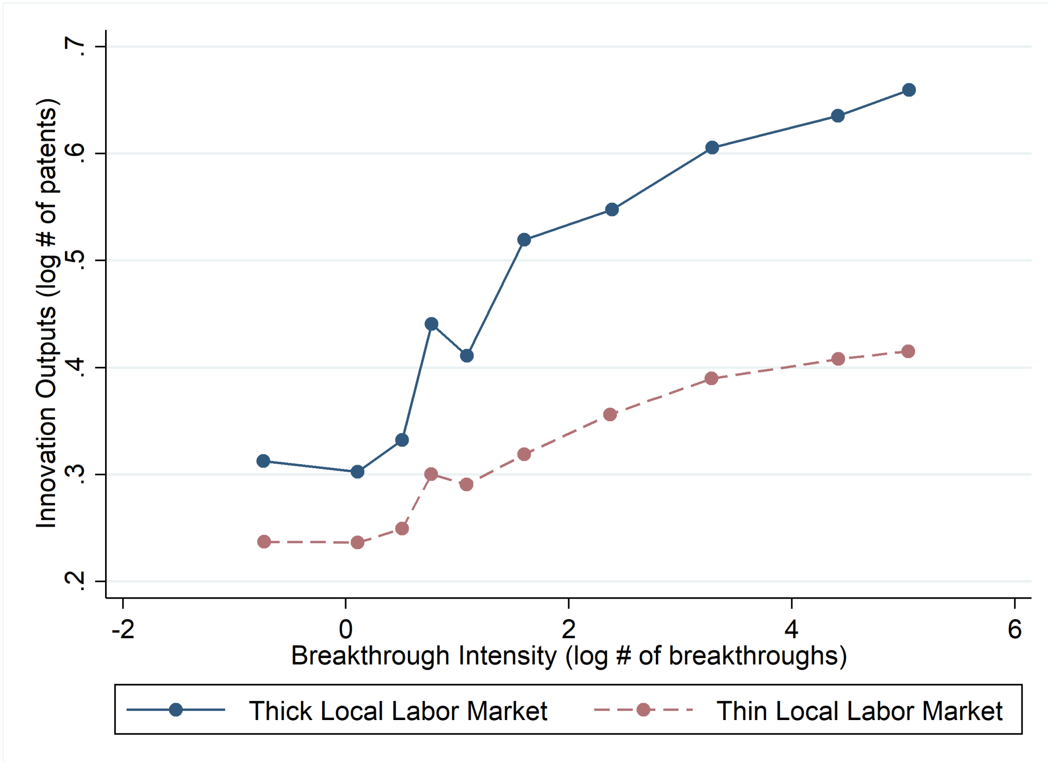

Figure 3: **Innovation of R&D Labs by Thick LLM.** The figure shows the binned plots of innovation outputs (log number of patents) produced by R&D labs in a given year and the intensity of scientific breakthroughs measured by the log number of technology-specific breakthroughs in the past three years, conditioning only on application year effects. This plot corresponds to the regression in Table 4 Column 1: The same sample is used, and variables in the x- and y-axis follow the same definitions. R&D labs are sorted into thick and thin local labor markets based on a median split of the labor market thickness.

some lab x year observations; thus, I take the log patent count plus one as outcome variables and use the linear model as the main specification across the analysis. Table 4 presents my findings.[12]

Table 4 Panel A: [INSERT TABLE HERE]

In column (1), I first examine the effect of thick labor markets on the number of patents a lab produces. By including LLM x year fixed effects, I reply on cross-sectional variation from labs in the same research field and commuting zones, thus facing the same local labor market but encountering different intensities of technology-specific breakthroughs. Comparing such R&D labs helps minimize selection concerns, as these labs are likely to be similar, and the results on the comparison show that R&D labs that experienced a higher intensity of breakthroughs produce more patents, confirming again that breakthroughs have a positive impact on corporate innovation. What's more, the positive coefficient of the interaction term between breakthrough and local labor

[12]The results are consistent when I estimate a Poisson model where the raw number of patents is used as the outcome variable.

market thickness is statistically significant at the 1% level. The result indicates that the strength of reaction to breakthroughs strongly depends on the local labor market. In terms of magnitudes, the estimated coefficient implies that a one-standard-deviation increase in labor market thickness leads to an addition of 0.81% increase in the patent output in response to each unit of breakthrough intensity. This suggests that given a breakthrough with intensity equal to 1 which lies above the mean by exactly one standard deviation, a R&D lab that lies in the technology class hit by breakthroughs on average will produce 3.13% more patents than that of a similar lab whose main technology was not shocked; and the boost will increase by 25.88% (equal to the ratio of 0.81% and 3.13%) if the associated LLM is one-standard-deviation above the average in terms of thickness.

To understand the effect of labor market thickness on the quality of patent output, I move from measuring the quantity of patent output to measuring the quality using patent citations. In column (2), I measure innovative productivity using the annualized sum of adjusted citations received by patents filed in the year of interest (based again on the application year). Column (2) reports the result. The patents filed by corporate R&D labs after scientific breakthroughs tend to receive more citations in the following years. Besides, the magnitude of thick market effects on patent quality is even larger than that of patent quantity. Given the same level of breakthroughs equal to 1, one standard deviation increase in the labor market thickness leads to an addition of 0.61% increase in the citations received, equivalent to 27% (equal to the ratio of 0.61% and 2.26%) more increase relative to a similarly-shocked lab but without the extra thickness. This result means that R&D labs produce not just more patents but also more influential patents compared to otherwise similar labs without breakthroughs and the difference is substantially larger in thick labor markets.

The impact of inventions might not correspond directly to the number of citations received. Influential innovations often disproportionately receive many citations; thus, the patents that ended up in the top percentiles in the citation distribution are more likely to be impactful inventions. Following Bernstein et al. (2021), I define a top patent if it ended up in the top 10% of all patents from the same year and technology class in terms of citations. I also construct a text-based measure developed by Kelly et al. (2021) to identify important inventions based on the textual similarity of a given patent to previous and subsequent work. Important patents are novel relative to their predecessors and influential for subsequent research.

The indicator of top patents can mainly identify impactful patents to which much future research is related based on citations. A patent with many citations can be very novel, create a new trajectory of technology, or be part of a mainstream technology that has been and continues to be popular. While the indicator of important patents speaks to a more comprehensive concept that emphasizes both novelty and impact, which can also be broadly viewed as an extension of two features of a patent, originality and generality. It is a measure of the overall significance of the patent. Column (3) and (4) examines the effects of scientific breakthroughs and thick labor markets on producing top and important patents. Labs that experienced breakthroughs, especially in thick markets, produce more top and important patents. Given the same level of breakthroughs equal to 1, one standard deviation increase in the labor market thickness leads to an addition of 0.35% and 1.18% increase in the top patents and important patents on top of the 0.49% and 2.58% main effects of breakthroughs.

Overall, the results here lend support to the hypothesis that R&D labs in the thick local labor market produce more and better inventions following scientific breakthroughs.

3.2 Core Technologies and Exploratory Nature

Besides the quantity and impact of patenting outputs, the direction of innovation also consist of important features of the innovative activities of R&D labs. In Table 4 Panel B, I investigate the technology class and exploratory nature of innovations.

Core technology defines the main class of labs, representing the area where labs direct the most effort and resources and tend to be closely associated with its innovation strategy. Though given the findings that R&D labs in thick labor markets affected by scientific breakthroughs produce more patents and patents that are more cited than labs in thin markets, it is plausible that labs in the thin markets just focus exclusively on core technologies to make the best use of breakthroughs and may produce equal or more patents in the core technology class. In that case, the less prominent performance on total patent output might only be due to a shift from peripheral to core patents. To explore the thick market on inventions in the core areas and non-core areas directly, I examine the quantity and impact of core and non-core patents separately by constructing the measures of patent count and citations in the same way as previous ones.

Panel B in Table 4 presents the results. I find that R&D labs in thick labor markets abnormally produce an abnormal amount of both core and non-core patents. The coefficients imply that an R&D lab that experienced breakthroughs with an intensity equal to 1 in the previous three years successfully increases the output of core patents by 0.88% and non-core patents by 0.35% with a one-standard-deviation increase in terms of thickness. The overall quality of inventions is also better, especially for the core inventions. Labs in thick markets also experience abnormal growths in non-core patents, however, with much smaller magnitude. The results suggest that the labs in thick markets disproportionately benefit from breakthroughs, and their benefits are concentrated in their core technologies.

Finally, I investigate whether the thick market effects on exploratory and exploitative inventions are similar to one another or not. I distinguish between exploration of new technologies and exploitation of well-known technologies (March (1991)). Exploitation is the refinement or extension of existing technology familiar to the firm. Exploitative projects tend to be incremental innovations built on existing resources and products. In contrast, exploration involves searching and experimentation in unfamiliar knowledge areas, which may require more resource commitment. Therefore, exploratory inventions rely less heavily on the existing knowledge of their firm. To measure exploration and exploitation, I rely on the text-based technological proximity of inventions across time within each lab. This measure captures whether a lab's inventions in a given year stay closely with or deviate from its existing patent portfolio. Specifically, I calculate the textual similarity between patents filed by a lab in a given year and the lab's prior patents based on the pairwise similarity matrix from Section 2. For each patent, if its average similarity with previous inventions is below 0.2, the patent is identified as an exploratory (*new*) invention; otherwise, the patent is identified as an exploitative (*incremental*) invention. An exploitative innovation will contain textual descriptions similar to the contents in previous patents; while an exploratory innovation will look more different.

The results are presented in two last two columns of Table 4. The table shows that labs in the thick market produce more exploratory patents following breakthroughs above the expected level of similar labs in the same research field and location. While labs also make more exploitative patents after breakthroughs, the effect is driven by labs in the thin market. The coefficients imply that for each unit of breakthrough intensity, a lab in the thick market produced 0.71% more exploratory patents if the labor market thickness increases by one standard deviation.

Overall, the results suggest that following a technological shock, R&D labs become productive, particularly concerning projects in core technology that are high impact and tend to be more exploratory.

Table 4 Panel B: [INSERT TABLE HERE]

3.3 Firm Growth and Long Term Success in Innovation

Although patents provide one of the most useful matrices yielding insights into the types and value of inventions being pursued by firms, there is still limitation with patent data. Patentable inventions might provide an incomplete picture of innovation. In light of this, I use the firm growth, specifically, in the overall human capital embedded in the lab measured by annual wage per employment in log form.

Comparing such R&D labs helps minimize selection concerns, as these labs are likely to be similar, and the results on the comparison show that R&D labs that experienced a higher intensity of breakthroughs produce more patents, confirming again that breakthroughs have a positive impact on corporate innovation. What's more, the positive coefficient of the interaction term between breakthrough and local labor market thickness is statistically significant at the 1% level.

Column (1) of Panel B in Table 4 present the result. The positive coefficients indicate that R&D labs that experienced a higher intensity of breakthroughs grow to be more human-capital intensive, especially for labs located in thick labor markets. The finding suggests that the effects of labor market thickness are not limited to patentable innovation but are also associated with increased human capital embedded in the labs. Column (2) examines the effects on growth in size, measured by total employment. It shows the higher intensity of breakthroughs is associated with a growth of employment in labs, but the effect does not differ by where the lab is located in. It confirms that the thick market effect on lab growth in annual pay is not driven by the abnormal change in the size of employment but is more likely to reflect the change in human capital.

While data on patents imperfectly reflect innovation, they may be the best available measure of inventiveness. In the last two columns of Panel C, I examine whether the thick market benefits from scientific breakthroughs are only temporary or can last longer, since long-lasting effects can lead to extraordinary high levels of performance. I calculate the cumulative top-cited patents and important patents filed in the next five years and define a lab as an innovation "star" if it ends up in the top 1% in the cumulative patenting measures across all labs in the same field. Results show that following breakthroughs, labs increase the likelihood of being an innovation star measured by total top-cited inventions by 0.2%; and the probability will increase by additional 0.25% with a one-standard-deviation increase in labor market thickness, equivalent to 8.52% increase relative to the unconditional probability of being an innovation star. The thick market effect on being an innovation star measured by total important inventions is 0.52% improvement, equivalent to 24% increase relative to the unconditional probability. The results suggest that R&D labs can cumulatively benefit from the thickness. The cumulative advantages might explain why the degree of clustering in innovation activities increases over time.

Table 4 Panel C: [INSERT TABLE HERE]

To sum up, the results in this section show that scientific breakthroughs create positive productivity shocks to corporate R&D labs, and labs in thick local labor markets respond stronger and disproportionately benefit more from the technological opportunities.

4 Investigation of Mechanisms Underlying Thick Market Effects

In this section, I investigate the competing mechanisms which might explain how R&D labs in thick labor markets disproportionately benefit from scientific breakthroughs. To shed some light on the channels that may lead to the productivity gains enjoyed by R&D labs in thick labor markets, I begin by investigating the contribution of the incumbent and new inventors to the increase in innovation outputs following breakthroughs relative to the average levels in comparable labs. To establish the role of labor mobility, I then re-examine the thick market effects on innovative productivity when interacting with non-compete agreement enforceability. Next, to further establish the link between human capital reallocation and productivity gains, I explore the variation in labs' exposure to scientific breakthroughs to study the direction of labor mobility. Finally, I analyze the characteristics of new inventors and the research team.

The primary result from Section 3 is that R&D labs in thick markets produce more and better patents following scientific breakthroughs. Although the idea that thick labor markets are beneficial is not novel, the existing empirical evidence distinguishing potential mechanisms underlying the thick market effects is still limited and far from conclusive. Nevertheless, following scientific breakthroughs that create shocks to innovation productivity, two major motivational theories shed light on the channels through which R&D labs can benefit from locating in a thick local labor market.

One potential channel is that the agglomeration of specialized human capital may generate knowledge spillovers. This line of research has roots in the theoretical frameworks that estimate the knowledge production function with a spatial dimension and create the productivity gain as a function of the aggregate human capital in the locality for market participants.[13] The realization of such gains does not necessarily feature labor mobility but relies on interactions among individuals, which are greatly improved when they are close to each other,[14] since physical proximity with skilled neighbors facilitates transmission of ideas and diffusion of knowledge. Thus, timely access to the latest ideas makes the talent clusters particularly attractive in the period with rapid technological advances, which might explain the additional productivity gains for R&D labs in thick labor markets.

An alternative theory emphasizes the role of thick labor markets in improving the propensity and quality of matching between firms and workers. The idea that labor pooling improves the

[13] Influential literature includes, but is not limited to, Lucas (1988), Audretsch and Feldman (1996).

[14] von Hippel (1994) shows that the knowledge needed for innovation-related problem solving is costly to acquire and transfer and such sticky information, by his term, is best transmitted via face-to-face interaction and through frequent and repeated contact. Glaeser (1999) proposed a model in which the direct interactions among workers in cities are the basis for accumulation and diffusion of knowledge.

matching of firms and workers was first formalized by Helsley and Strange (1990), which models resource allocation in a system of cities with heterogeneous workers and firms with differentiated skill requirements. The labor pooling argument is then extended by introducing firms faced with firm-specific productivity shocks, which create an uncertain exogenous demand for specific skills. Krugman (1991a,b), by considering firms and workers in sectors that are subject to idiosyncratic productivity shocks, argues that geographical closeness facilitates the mobility of workers from low to high productivity firms.[15] Scientific breakthroughs that significantly depart from prior art and reshape existing technological trajectories induce productivity shocks to firms. R&D labs might have differential desires for the skills and characteristics of inventors, and the demand might depend on the exposure to breakthroughs. A talent cluster through facilitating labor mobility and the matching process might also explain the thick market effects on innovation productivity.

4.1 Contribution to Productivity Gains by Inventor Type: New Hires vs Incumbents

Although both knowledge spillovers and labor mobility can explain the thick market effects on productivity, these two mechanisms could have different implications for different groups of inventors. If the main mechanism is inventor mobility, in which case the thickness of local labor markets leads to productive worker-firm match and talent reallocation toward labs that have superior innovation potentials and can make better use of the skilled labor, we should see the reallocated human capital, that is, the new-hires, contribute more to labs' productivity gain. On the other hand, the alternative hypothesis that thick market benefits mainly work through knowledge spillovers which are facilitated by better exchanges of ideas and faster diffusion of information with physical proximity to other inventors does not imply differences in innovation productivity gains between new hires and incumbent inventors.

Variable Definition To calculate the contribution to patenting by inventor types, I first define incumbents and new hires. Based on the inventor-assignee linkages in patent records, I define an inventor as an incumbent for a lab in a given year t if the inventor's recent patent(s) was filed with the same lab; otherwise, the inventor is viewed as a new-hire for the lab in the given year. One

[15] Strange et al. (2006) also model uncertainty-driven agglomeration and show firms with higher uncertainty in labor demand for specialized skills benefit more from co-locating. Almazan, De Motta, and Titman (2007) consider firm-specific productivity shocks and human capital creation as well as allocation in a combined framework by integrating the labor pooling model of Krugman (1991a) with industry-specific human capital investments by firms or workers. They show human capital can flow more easily from the less to the more productive firms in clusters, and firms may prefer to locate in close proximity when there is significant firm-specific uncertainty, though it discourages firm investments in human capital. Overman and Puga (2010) provides an empirical investigation on labor pooling as a source of agglomeration and finds that firms with a sizeable idiosyncratic component in labor demand form industrial clusters using establishment-level data from the UK's Annual Census of Production.

concern is that the employment relationship is not observed during the time when the inventor has joined a lab but before she files the first patent with the lab. Due to the data limitation, the new hires could include the inventors that were hired a while ago and just filed the first patent with the lab after the scientific breakthroughs happened. To mitigate the concern, I further define an inventor as a recent new-hire for a lab in year t if the inventor's most recent patent was filed with a different lab between t and $t-3$. That means the inventor's departure from another lab to the focal lab is certainly within recent three years. The average gap between two jobs is about one year, so the timing of job hopping is accurately captured in this group. Thus, the recent new-hires are clearly inventors that are reallocated to the focal lab during or right after the outbreak of radical scientific advancement.

Patent output measures by inventor type, including the number of patents and adjusted citations, are calculated for each lab-year. To account for the fact that some patents are produced in teams that are made up of both new and incumbent inventors, I distinguish their contribution to each patent based on inventor shares in the whole team and then aggregate the patent outputs at lab-year level by inventor type.

Results I study the effects of thickness and breakthroughs on patent outputs by incumbent and new-hire inventors separately. Table 5 presents my findings. Column (1) and (2) examines cross-sectional differences between the breakthrough-shocked labs and similar labs in terms of the number of patents and adjusted citations accordingly, contributed by incumbent inventors and investigate whether the differences vary in the thickness of local labor market; Column (3) and (4) by new-hires and Column (5) and (6) by recent new-hires.

The estimated coefficients for breakthroughs capture systematic differences between more-shocked and less- (or not-) shocked R&D labs in their responses to scientific breakthroughs regardless of location. The coefficients are positive and significant for both incumbent and new-hires, and the magnitudes of the breakthrough effects on the two groups are comparable. This finding means that both incumbent and newly-hired inventors become more productive with higher intensity of breakthroughs. However, the additional productivity gains from thick labor markets differ for two types of inventors. For patent outputs by incumbent inventors, I find that the estimate of interest (Breakthrough x Thickness) is only 0.0037 in Column (1) and 0.0019 without significance in Column (2), which indicates that incumbent inventors in thick market only produce marginally more patents; when considering the quality of their inventions, they perform indifferently from those in thin markets. While for patent outputs by new-hire inventors, the productivity gains in thick labor markets are significantly positive at the 1% level for both quantity and quality measures with sizable effects according to the estimated coefficients (0.0121 and 0.0109, respectively). The coefficients imply that given a breakthrough with an intensity equal to 1, which lies above the mean by precisely one standard deviation, an increase in market thickness by one standard deviation percent (1.744%) leads to a 1.21 (1.09) percent increase in the number of patents (citations) produced by new-hire inventors. That is, a 10% increase in labor market thickness is associated with about 7%(6%) increase in the quantity(quality) of patents produced by newly-hired inventors.

Another way to interpret the relative magnitudes is by comparing the estimated coefficients with the mean values of dependent variables. The estimated coefficient 0.0037 (0) represents a 1.29% (0%) change relative to the benchmark using the mean of the dependent variable, 0.2878 (0.2673), for incumbent inventors. For new-hires, 0.0121 (0.0109) represents a 5.75% (5.54%) change relative to the benchmark using the mean of dependent variable 0.2104 (0.1969). Similar and stronger results are found for recent new-hires. Remarkably, the thick market effects on quantity and quality of patent outputs, 0.0076 and 0.0069, represent 14.53% and 14.34% change relative to their benchmark.[16]

The fact that the estimates are small in magnitude and only marginally significant (or even insignificant) for the patenting productivity by incumbent inventors casts serious doubt on the potential benefits they could have gained if knowledge spillover were the key driving mechanism. The results imply that knowledge isn't so much "in the air." In fact, the boost in patent outputs following breakthroughs is most prominent for new-hire inventors (especially the recent job hoppers), relative to their benchmark contributions, confirming the productivity gains estimated in the previous analysis are attributed to newly-obtained talent and suggesting inventors are allocated to labs that can better use their human capital in the thick market. The results indicate that thick market effects work through human capital mobility and reallocation.

Table 5: [INSERT TABLE HERE]

4.2 Enforceability of Non-Compete Agreements and Labor Market Effects

To evaluate the extent to which inventor mobility explains the superior productivity gains for R&D labs in thick labor markets, I leverage the state-by-industry level variation in the use of non-compete agreements. The measure of non-competes enforceability used in this paper combines the non-competes index capturing state-level variation in enforceability and incidence scores of non-compete clauses by industry.

[16] Another concern is that new-hires may be more likely to select into technologies that have been shocked by scientific breakthroughs in thick markets, which could account for these results. In an unreported table, I separately examine the outputs in core and non-core technologies and find consistent results in both technology categories.

Non-compete agreements, usually specified in employment contracts, require employees to refrain from joining a rival firm or starting a new venture that could compete with their past employer. The ability of a labor market to reallocate workers is constrained by the use of non-compete agreements(Marx, Strumsky, and Fleming (2009), Fallick et al. (2006), Starr (2019), Jeffers (2019) and Johnson et al. (2020)), especially for skilled labor in knowledge-intensive occupations. Thus the mobility of inventors with specialized skills may largely depend on the extent to which non-compete agreements are enforceable.

The enforceability of the non-compete terms is governed by state statutes and case law. In some states, non-competes clauses are viewed as overly restrictive on competition. They are not enforceable or only enforced in limited circumstances. One typical example is California, where non-compete agreements are considered null and void by courts. On the other extreme, Florida allows extraordinary general skills training to be included in the list of protectable interests of NCs and allows enforcement of such contracts even for employees who are laid off. Most states employ reasonableness tests to evaluate the contract to balance the protection needed by the employer and the harm done to the employee and society (Bishara (2011)). Nevertheless, within the reasonableness structure, the approach and tools used by each court vary materially, which creates considerable variation in the scope of NCs that are permitted and enforced.

Building on seven dimensions of non-compete enforceability identified by Bishara (2011),[17] Starr (2019) constructs a cross-sectional index of non-competes for 1991 and 2009. Figure 4 presents a map of the 2009 Noncompete Index by states,[18] based on which the main measure of enforceability of non-competes used in this paper is constructed.

The enforceability of non-competes not only differs from state to state, but the way they are employed differs widely across industries. I use industry scores in the incidence of non-compete agreements that measure the probability of having a non-compete estimated by Starr et al. (2021) using a large-scale nationally representative survey data.[19] Figure 5 presents the incidence table

[17]The seven dimensions include the statute of enforceability, protectable interest, plaintiff's burden of proof, consideration at inception, consideration post-inception, over-broad contracts and quit versus fire.

[18]The index is re-scaled to be non-negative. Table A1 summarizes the non-compete index for each state. There is minimal variation in the index over time. Changes in enforceability NCs are only possible when the legislature alters the statute, or new precedents are set by state supreme courts. Statistically, the correlation coefficient between the 1991 and 2009 index is 0.94 (Starr (2019)), reflecting the fact that the extent to which the state level change in the legal setting regarding non-compete enforcement is very limited during the years.

[19]2014 survey by Starr, Prescott, and Bishara(Starr et al. (2021)) provides comprehensive evidence about labor market prevalence of NCAs. They found that 18% of labor force participants are bound by non-competes, with 38% having agreed to at least one in the past, and the clauses are much more frequently used among professional and scientific workers. Besides, typically NC clauses include the time scope and limitation on geographic boundaries. According to the survey, most non-compete agreements have a duration of 2 years or less, while the geographic scope is more frequent with no geographic limitation then in the entire country and then in the state, the three accounting for the vast majority cases.

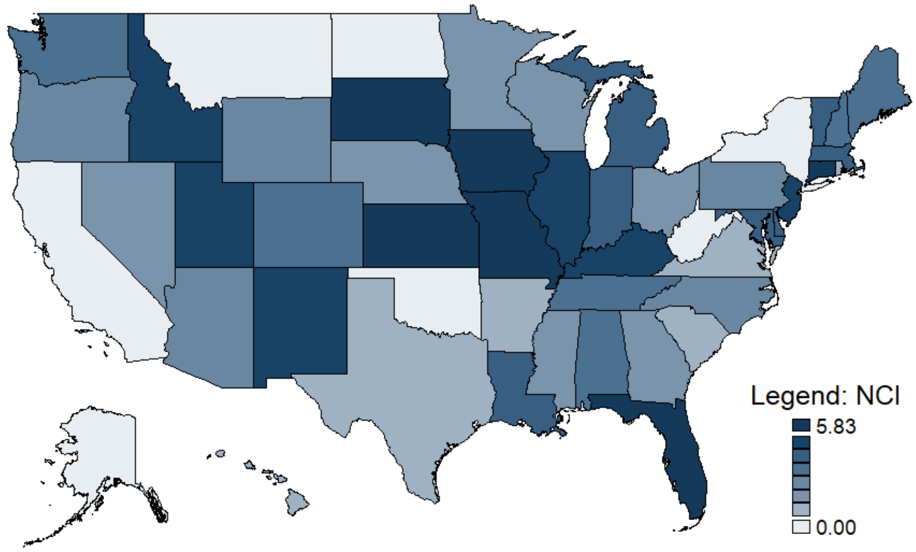

Figure 4: **Noncompete Index by States** The figure presents Noncompete Enforceability Index by Starr (2019). A higher value of NCI indicates stronger enforceability of non-compete agreements in the state. Table A1 summarizes the non-compete index for each state.

by industry. It shows that non-compete clauses are common in most industries and more frequent in certain high-skilled sectors including information, professional and scientific services and mining and extraction.

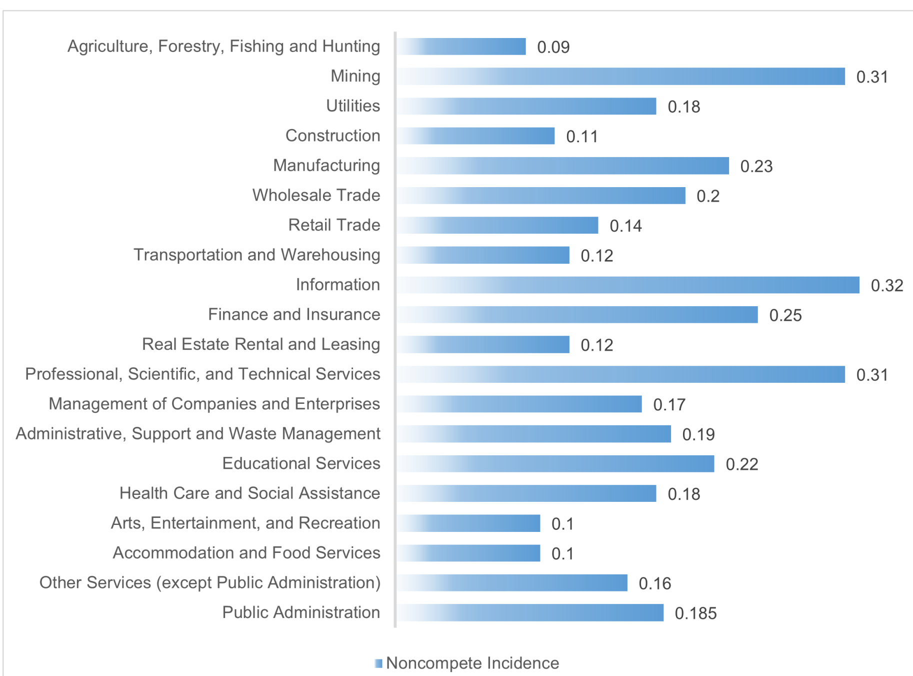

Figure 5: **Noncompete Incidence by Industry** The figure presents incidence of noncompetes by industry based on Starr, Prescott, and Bishara (2021). The incidence of non-competes measures the probability of having a non-compete estimated by Starr et al. (2021) using large-scale nationally representative survey data.

Combining the state-level non-competes index in enforceability and industry-level incidence scores, I take the product as a final measure of non-competes enforceability (NCE). I further define a binary variable, $\mathbf{1}_{\{HighNCE=1\}}$, indicating high enforceability of non-competes when an R&D lab, based on its industry and location, is in the upper quartile in terms of NCE distribution.

4.2.1 Innovation Outputs and Enforceability of Noncompetes

I begin by examining the impact of non-competes on innovation productivity following breakthroughs and the interaction effects with labor market thickness.

First, I revisit the binned scatter plot presented in Figure 3. The graph shows initial evidence that R&D labs in thick labor markets disproportionately produce more disproportionately more patents after scientific breakthroughs. Then, to investigate whether inventor mobility can explain the thick market effects, I further divided labs into two groups based on $\mathbf{1}_{\{HighNCE=1\}}$, the indicator of high non-competes enforceability, shown in Figure 6. In the technology-stable periods in which there are few scientific breakthroughs, the group with high enforceability of non-competes in place shows a higher rate of patenting,[20] though the difference is modest. As the intensity of breakthroughs increases, the group of labs without high NC begins to catch up and quickly surpass the high NE group. When there come above-median breakthroughs, with an intensity larger than 2, the high NE group fails to respond to the technological opportunities, showing a very limited boost in producing inventions. On the other hand, the labs without enforced non-competes are able to keep improving their innovation productivity, indicating the thick market effects found in Figure 3 are virtually driven by the responses from labs enjoying the free movement of labor. Appendix Figure A1 shows the binned scatter plot for the innovation of R&D labs in thin LLM by the enforceability of non-competes. It shows that labs in thin labor markets respond similarly regardless of the non-competes, suggesting that any systematic difference by the use of non-competes in innovation if exists, is very limited in thin markets. This finding suggests that what really matters is the interplay between thick labor markets and the non-competes, not just the use of non-competes in isolation.

In Table 6, I examine the effects of the interplay between labor market thickness and the high enforceability of non-competes on labs' innovation output following scientific breakthroughs in a regression setting specified below.

[20]The pattern is consistent with the positive relationship found in the existing literature between the use of non-competes and knowledge intensity (or skill intensity) of industries (or occupations).

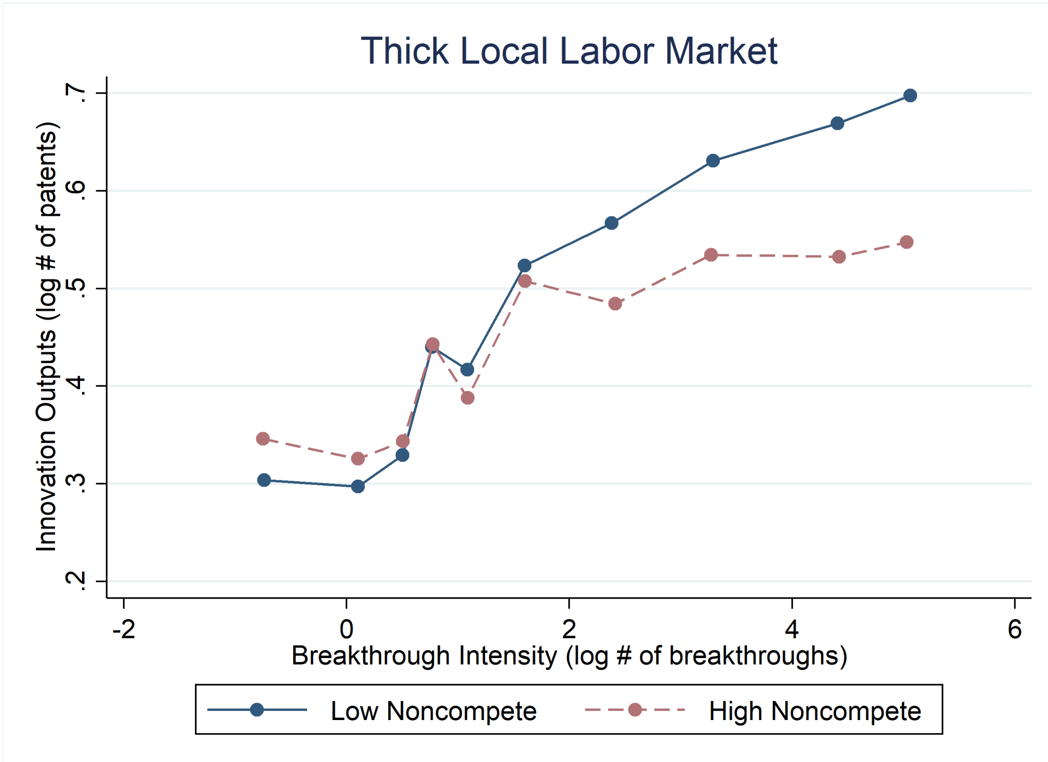

Figure 6: **Innovation of R&D Labs in Thick LLM by Enforceability of Noncompetes.** The figure shows the binned plots of innovation outputs (log number of patents) produced by R&D labs in a given year and the intensity of scientific breakthroughs measured by the log number of technology-specific breakthroughs in the past three years, conditioning only on application year effects. This plot corresponds to the regression in Table 6 Column 1. The same sample is used, and variables in the x- and y-axis follow the same definitions. Focusing on R&D labs in thick labor markets based on a median split of the labor market thickness, the labs are further divided into two groups by $\mathbf{1}_{\{HighNCE=1\}}$, the indicator of high non-competes enforceability.

$$
\begin{aligned}
Y_{ikcf,t} = & \beta_1 Bkthr_{k,(t-3,t-1)} + \beta_2 Bkthr_{k,(t-3,t-1)} \times Thickness_{cf,t-3} \\
& + \beta_3 Bkthr_{k,(t-3,t-1)} \times Thickness_{cf,t-3} \times \mathbf{1}_{\{HighNCE_{ns}=1\}} \\
& + \beta_4 Thickness_{cf,t-3} \times \mathbf{1}_{\{HighNCE_{ns}=1\}} \\
& + \beta_5 Bkthr_{k,(t-3,t-1)} \times \mathbf{1}_{\{HighNCE_{ns}=1\}} \\
& + Controls_{ikcf,t} + FEs + \epsilon_{ikcf,t}
\end{aligned}
\tag{4.1}
$$

By including LLM x year fixed effects, $Breakthrough \times Thickness$ captures cross-sectional variation from labs in the same research field and commuting zones but encountering different intensities of technology-specific breakthroughs. The estimation of $Breakthrough \times Thickness \times \mathbf{1}_{\{HighNCE=1\}}$ and $Thickness \times \mathbf{1}_{\{HighNCE=1\}}$ exploits the variation from labs facing the same local labor market but in industries with various incidence of non-competes clauses, and also the variation from labs in the CZ crossing state borders with different legal treatment for non-competes. Any baseline differences in the patenting rate that may exist across industries are already absorbed by industry fixed effects.

Table 6: [INSERT TABLE HERE]

The results in Columns (1) and (2) correspond to the first two columns in Table 4, in which I examine the effect on the number of patents produced and the number of adjusted citations received. The positive coefficients of the interaction term between breakthrough and local labor market thickness, 0.0122 and 0.0102, indicate the consistency of thick market effects on the quantity and quality of patent outputs. But with the high enforceability of non-competes, the thick market benefits vanish. The magnitudes of the estimated coefficient on $Breakthrough \times Thickness \times \mathbf{1}_{\{HighNCE=1\}}$ are as large as -0.0162 and -0.0164 respectively. Notice that the estimation of $Thickness \times \mathbf{1}_{\{HighNCE=1\}}$ is also negative, indicating an adverse effect of enforced non-competes on innovation productivity of labs in thick labor markets, which are exaggerated in the periods with great technological advances. Although the use of non-competes itself may suggest a higher level of innovation, according to the positive coefficients for $\mathbf{1}_{\{HighNCE=1\}}$, the potential benefits associated with the use of NC, if any, are far from enough to offset the costs for restricting labor mobility in the labor market of some size. The thicker the labor market is, the larger the costs are, which are particularly damaging with the outbreak of scientific advancement.

To trace back the source of the reduction, I re-examine the contribution of the incumbent and new inventors with the use of non-competes in Columns (3) to (8) corresponding to Table 5. The high enforceability of non-competes is consistently associated with significant shrinkage in thick market effects. The NC-related reduction in patenting outputs is larger for new hires. The contribution by new hires is curtailed by having NC in thick markets regardless of breakthroughs; the contribution by recent new hires is further brought down by having NC at the arrival of breakthroughs. Even for incumbents, focusing on Columns (3) and (4), although the use of non-competes may help to retain talent, the outputs by existing inventors can be lower than in the same market without non-competes in the periods with positive scientific breakthroughs.

Across all types, the curtailing effects of high NCs work stronger on the quality of inventions, suggesting that the restriction on human capital mobility not only reduces the likelihood of new inventions but also curbs the otherwise possible synergy between incumbent workers and new hires. Impeding the inspiration and creativity from interactions reduces the invention quality to a greater extent.

To help understand the economic interpretation of the results, I consider a numerical example illustrated in Table 7. A thick labor market has $Thickness$ 1.5 standard deviation above an average market, representing a top 5% local labor market in terms of $Thickness$. Also, I consider one scenario where non-competes are not strictly enforced (Column (1)) and another scenario where non-competes are in place (Column (2)). As a benchmark, an average market without highly enforced non-competes is provided in the Column (3). Each cell value represents the total effect on the quantity of patent produced, calculated as the sum of all main effects and interaction effects based on coefficients estimated in Column (1) of Table 6. Comparing two similarly thick markets, the high enforceability of non-competes is positively associated with a high baseline innovation rate when very few breakthroughs arrive. As the intensity increases, the labs in the thick market without restrictions on labor mobility response very strongly to breakthroughs, while in the market with NCs, the increase in patenting is weaker. In fact, following a median wave breakthroughs, an average market without NCs can promote labs' innovation as good as a top 5% thick market with NCs. R&D labs in the top 5% thick market could have enjoyed 60% (=0.012/0.0196) more boost in patent productivity that would otherwise emerge without NCs.

Table 7: [INSERT TABLE HERE]

4.2.2 Inventor Turnover and Enforceability of Noncompete Agreements

Prior studies have established that non-competes depress mobility, in particular for the high-skilled labor. Since I rely on the enforced non-compete agreements as a barrier to inventor mobility that tends to be especially critical in times of technological breakthroughs, it is also important to establish the validity in this particular setting by showing the scope and magnitude of non-competes effects on turnover of inventors.

Variable Definition To calculate the inventor turnover, I combine two types of inventor moves: onboarding and offboarding. Onboarding inventors follow the definition of new hires used in the previous subsection. Inventor offboarding is defined as the case when the associated assignee documented in patent records has changed, and the timing of the move is proxied by the mid-year between two jobs. Similar to recent new hires, I define recent leaves if the inventor's first patent filed with a different lab is applied within three years of the last patent filed with the current employer. Inventor turnover (recent moves) is then calculated as the sum of inventors onboarding (recent new hires) and recent offboarding. One limitation of this offboarding measure is that the end of an employment relationship is only observed if the inventor moves to another innovative firm and files patents with the new firm. As an alternative measure to define offboarding, I include cases where the inventor has never filed patents with the associated firm for at least ten years. The broadly-defined offboarding consists of both moves to other patenting firms and moves to non-patenting firms (or positions). In these cases, the final invention project filed with a firm is viewed as the last time an employee stays in the firm as an inventor. To determine the timing of the leave, I use several measures, including the application year of the patent (which is closer to the period of conducting R&D work) and the grant year of the patent (which is the time when all the revises and responses to patent examiner are done), and three years after the application year (which is the average timing of patent granting). The reported results are based on the third measure of offboarding but these alternative measures yield consistent empirical findings. Inventor turnover (all moves) is then calculated as the sum of inventors onboarding (new hires) and offboarding.

Table 8 Panel A presents the results on the estimated effects of labor market thickness together with breakthroughs on inventor turnover using Equation 3.1. I look at turnover by all moving inventors, regardless of where they come from and where they eventually depart, and then observe turnover by local inventors, which consist of new-hiring from other local labs and departure to other local labs. Results show that the R&D labs affected by scientific breakthroughs experience higher inventor turnover; the turnover stemming from local mobility is also higher. The effects on inventor turnover are stronger for R&D labs in thick labor markets. In terms of magnitudes, the estimates in Column (1) indicate that a one-standard-deviation increase in breakthrough intensity is associated with a 3.1% turnover increase. Considering labs located in thick labor markets, assuming the increase in breakthrough intensity is coming from 0 (sample mean) to 1, increasing the labor market thickness by one standard deviation percent (1.744%) leads to an additional 1.63 percent increase in the turnover. The change is overwhelmingly driven by local inventor turnover. To address concerns about the ambiguity of mobility timing, I again use the subset of inventors that switched employers within recent three years to identify recent moves and results are reported in Columns (3) and (4). The positive coefficients of the interaction term between thickness and breakthrough are statistically significant at the 1% level with a comparable magnitude as before. To summarize, following scientific breakthroughs, R&D labs in the relevant technology class experience higher inventor turnover, particularly local turnover.

Table 8: [INSERT TABLE HERE]

To examine how labor mobility frictions created by NCs affect inventor mobility in the context of breakthroughs, in Panel B of Table 8, I re-estimate the regressions on inventor turnover with an indicator of high enforceability of non-competes using Equation 4.1. In Columns (3) and (4), I again turn to the turnover resulting from recent moves.

All sorts of turnover for labs in thick labor markets are reduced significantly with high NC enforceability. The additional higher turnover in thick markets following breakthroughs also greatly shrink. The log turnover (local turnover) is 4%(8%) lower relative to a sample mean of 0.4252(0.1415). The results are stronger for recent moves. The reduction in log turnover (local turnover) from recent moves represents 9.77% (10.33%) of the sample mean 0.0901(0.06582) for an R&D lab with strongly enforced NCs, relative to another similar lab in the same market but with low use of NCs. The results show that tighter restrictions on labor mobility lead to insufficient inventor mobility, and the reduction rate is most severe for recent moves within the locality. These results, combined with previous findings of substantial declines in thickness effect on productivity gains when high NCA is in place, support the theories that thick market effects work through inventor mobility.

In an unreported table, I show non-competes reduce inventor turnover, mostly by making it difficult for labs to talent. But noncompetes also prevent the departure of incumbent inventors, who could have been reallocated to another lab making the best use of the human capital without the non-competes restrictions. To sum up, non-competes enforcement indeed attenuates inventor mobility. Moreover, it decreases mobility more sharply for local inventor turnover. The enforcement of non-compete clauses significantly impedes human capital reallocation.

4.3 The Direction of Human Capital Reallocation: Leverage Variation in Exposure to Breakthroughs

To further establish the link between human capital allocation and productivity gains, I explore the cross-sectional variation in labs' exposure to scientific breakthroughs to investigate whether the direction of human capital mobility depends on labs' exposure to technological shocks and how the realization of productivity gains is associated with exposure.

Scientific breakthroughs create productivity shocks to R&D labs. Yet, these scientific discoveries are not randomly distributed. Instead, labs' exposure to a scientific breakthrough is dependent on how relevant a discovery is to their research. A great degree of exposure means that the lab has the necessary knowledge and technological background to understand the scientific advance, to have the capacity to mobilize and apply the new knowledge, and to integrate it into its research path to motivate sequential innovations. Thus, with a relevant knowledge base and even the relevant kind of capital in place, more exposed labs have great potential to successfully pivot off of technological opportunities.

Variable Definition To measure the lab-level exposure to scientific breakthroughs, I explore the extant knowledge base of the R&D lab when breakthroughs occurs, which consists of all its existing patents filed in the past, $\{P_{it}\}$. To quantify the technological relevance of a certain breakthrough to a lab, I select the "closest" past invention as a representative of the most relevant knowledge the lab can rely on. The closeness is measured by the similarity of textual description between any patent of the lab and the breakthrough, according to the text-based similarity score described in Section 1 for each pair of inventions. Thus, the lab i's exposure to the scientific breakthrough, b, is calculated as

$$Exposure_{it,b} = \max_{p_{it} \epsilon\, P_{it}} Similarity(p_{it}, b)$$

To aggregate the exposure measure to the lab-year level, I take the average exposure to all breakthroughs in the given year if the breakthrough wave contains multiple breakthrough inventions $\{B_t\}$. For a focal lab i, the exposure to breakthroughs in a given year is measured as,

$$Exposure_{it} = \frac{1}{B_t} \sum_{b=1}^{B_t} Exposure_{it,b}$$

4.3.1 Exposure to Breakthroughs and Human Capital Reallocation

To study how exposure to breakthroughs affects the direction of human capital allocation, I estimate Equation 4.1 for the inflow of human capital measured by the onboarding and offboarding of inventors. The results are presented in Table 9 Panel A.

Columns (1) and (2) show that a large exposure to scientific breakthroughs is associated with substantial increases in onboarding inventors and moderate decreases in offboarding inventors. Labs that are relatively less exposed to breakthroughs experience a higher outflow of human capital. According to the estimated coefficients for $Breakthrough \times Exposure$, given a breakthrough with an intensity equal to 1, an increase in technological exposure by one standard deviation (0.074) leads to 1.22% more new hires, that is, a 4.77% increase relative to the sample mean of the dependent variable; also leads to 0.16% decrease in inventor departure, 0.65% reduction relative to the sample mean. Results are consistent and stronger when considering the turnover of tech-class matched inventors.

Labs are more likely to take in human capital and retain incumbents after experiencing relevant breakthroughs. Furthermore, the lab is additionally better at bringing in talent if located in thick labor markets. Focusing on the coefficients for $Breakthrough \times Thickness \times Exposure$, an increase in market thickness by one standard deviation percent (1.744%) is associated with an additional increases by 0.29% in the inflow of talent and by 0.25% in the influx of tech-class matched talent, controlling for the intensity of breakthroughs. Interestingly, the outflow of human capital is more negative for exposed labs in thick markets, and thus they also are better at retaining talent. From the perspective of cross-sectional comparisons, a lab that is favorably affected by scientific breakthroughs tends to acquire human capital, and a lab least exposed to productivity shocks is associated with the outflow of human capital. Thus, my findings suggest that strong exposure to breakthroughs and access to thick local labor markets both help largely-exposed labs to "buy" assets, human capital with specialized skills, from labs that are least or not treated by the productivity shocks

Table 9 Panel A: [INSERT TABLE HERE]

4.3.2 Exposure to Breakthroughs and Productivity Gains

The ex-ante measure of exposure to breakthroughs is constructed to assess the potential of a lab to capture and utilize technological opportunities. I then turn to examine whether the ex-ante potential is realized ex-post, and whether the realization of innovation productivity gains is associated with the labor market channel established in the previous section.

Panel B of Table 9 reports the estimated effects of scientific breakthroughs, lab-level exposure to breakthroughs, and labor market thickness on the patent-based measures of innovation outputs. The estimated coefficients for $Breakthrough \times Exposure$ show that following breakthroughs, exposed labs enjoy significant and positive gains in producing patents. They generate more patents; the patents tend to be well-cited by subsequent work and are more important. These positive effects are amplified by the labor market thickness. According to the coefficient for $Breakthrough \times Thickness \times Exposure$ in Column 1, a one-standard-deviation (1.744%) increase in market thickness will add a 0.35% rise in the number of patents filed, on top of the exposure-to-breakthrough effects, 0.51%. Also, R&D labs exhibiting higher levels of ex-ante technological exposure to breakthroughs produce patents that attract significantly more citations ex-post and are more likely to be important inventions, confirming the thick market effects on patent quality.

Overall, my results confirm that the exposure measure indeed captures the innovation potential induced by scientific breakthroughs. More exposed labs, effectively, are subject to stronger productivity shocks. Labor market thickness substantially impacts corporate innovation by drawing human capital, especially the tech-class matched inventors, to exposed labs, which later show superior performance in producing more and better inventions. The results are consistent with the theory that the additional innovation gains in thick labor markets are realized through productivity-enhancing allocation of human capital to R&D labs that have a higher potential to uptake the technological opportunities.

Table 9 Panel B: [INSERT TABLE HERE]

4.4 Characteristics of New Hires and Inventor Teams

The previous section examined the link between labs' exposure to technological shocks and the direction of human capital allocation. It showed that exposure is positively associated with the inflow of human capital and the consequent innovation productivity. To shed light on the precise mechanisms through which the newly-hired inventors in thick labor markets lead to better performance, I investigate whether R&D labs and workers form better matches in thick labor markets from two aspects, relevance in technologies used and in knowledge background. Specifically, are labs in the thick labor market more likely to bring in inventors working in the lab's core technologies that experienced radical breakthroughs? Do newly-hired inventors introduce unique knowledge to labs' existing teams?

Existing work on labor markets have theorized the way that larger labor markets lead to better job search outcomes because they give workers and firms more choice in potential jobs or employees(Helsley and Strange (1990), Acemoglu (1997), Moretti (2011) among others). Research on idea-based growth models and theories of human capital accumulation have proposed a knowledge-producing process as new ideas are generated from novel combinations of existing varieties of ideas (Weitzman (1998)). One potential benefit of bringing in new inventors with distinct knowledge backgrounds to a team is expanding the knowledge base and integrating and combining those ideas. If a thick labor market can provide more candidates with many sorts of backgrounds, then R&D labs may find inventors with a diversified knowledge base that encourages more innovative outputs. Unlike other empirical studies on the worker-firm match that rely on indirect proxy for matching quality, there are major methodological advantages when studying inventors and research labs. I can precisely characterize the inventor-lab match by exploiting variation across detailed technology classes and analyzing the rich information in patent applications that provide trackable footprints of their knowledge base.

Variable Definition To quantify the match quality in terms of technologies a lab uses and its onboarding inventors use, I rely on two measures. First, I calculate the percentage of onboarding inventors who exactly match the technology class of the lab j in the given year t, in which case those inventors work in the same niche field as the lab, $Tech\text{-}Class\,Match\,Rate_{it}$. Since inventors and labs could have experience in both core and other periphery technologies, I calculate their overall technological proximity based on the method firstly used by Jaffe (1986). It is a cosine distance between two vectors that capture the location of the focal lab i and each newly-hired inventor h in the multidimensional technology space. An element in the vector represents the loading proxied by patent shares in each technology class. So for each newly-hired inventor, I have a vector of patent shares, denoted as V_h, and I have such a vector V_i for the lab. Technological proximity between inventor h and lab i in a given year t can be computed as:

$$Proximity_{it,ht} = \frac{(T_{it}T_{ht}^{'})}{(T_{it}T_{it}^{'})^{1/2}(T_{ht}T_{ht}^{'})^{1/2}}$$

Then I compare all newly-hired inventors' average proximity with the focal lab in a given year.

$$Technological\,Proximity_{it} = \frac{1}{H_{it}}\sum_{h=1}^{H_{it}} Proximity_{it,ht}$$

H_{it} is the total number of onboarding inventors in lab i and year t. The index ranges between zero and one. A higher value indicates the new-hires are, on average "closer" to the R&D lab in the technology space.

To investigate the likelihood that that newly-hired inventors will introduce new ideas and broaden the existing knowledge base following a scientific breakthrough, I explore the textual content in previous inventions and compare the similarity between labs and newly-hired inventors in their stock of knowledge. The knowledge stock of an R&D lab in the given year consists of its previously filed patents, $\{P_{it}\}$; similarly, the knowledge stock of each newly-hired inventor, $\{P_{ht}\}$. I take the text-based similarity score described in Section 1 for each patent pair $Similarity(p_{it}, p_{ht})$ and calculate the average across all pairs to get a measure of knowledge overlapping between an onboarding inventor h and the lab i, $Knowledge\,Overlapping_{it,ht}$. The average knowledge overlapping between newly-hired inventors and the focal lab in a given year is measured as,

$$Knowledge\,Overlapping_{it} = \frac{1}{H_{it}}\sum_{h=1}^{H_{it}} Knowledge\,Overlapping_{it,ht}$$

Results I estimate Equation 3.1 for $Tech\text{-}Class\,Match\,Rate_{it}$, $Technological\,Proximity_{it}$ and $Knowledge\,Overlapping_{it}$ that measure characteristics of new hires, conditional on the number of onboarding inventors is positive. Results are presented in Table 10. I find that following scientific breakthrough, R&D labs in thick labor markets can bring in more tech-matched inventors. According to the estimated coefficient for $Breakthrough\,x\,Thickness$ in Column (1), given a breakthrough with an intensity equal to 1, an increase in market thickness by one standard deviation percent (1.744%) leads to 1.98% more tech-matched new hires, that is, a 4% increase relative to the average matching rate(48.72%). Results are consistent with Column (2) on technological proximity. Considering the experience in any tech classes, the new-hires in the thick labor market are closer to labs in the technology space.

Column (3) answers whether newly-hired inventors are more likely to introduce unique knowledge to labs' existing teams. By construction, inventors that had filed patents before her joining the focal labs will inevitably receive a zero similarity score with the lab. Thus I control the composition of new hires by counting the number of fresh new inventors and experienced inventors. Although *Breakthroughs* are not necessarily associated with diversified hiring, labs in the thick market following breakthroughs do bring in people with more dissimilar knowledge bases relative to a comparable lab in the thin market.[21] Match with inventors with a closer technological focus but with a non-overlapping knowledge base. In a word, new hires in thick labor markets are more likely to match the specific tech class of the labs, closer to the technology space, and have a more diversified knowledge background.

Table 10: [INSERT TABLE HERE]

4.5 Section Summary

To sum up, Section 4 provides evidence consistent with the theory that thick labor markets encourage innovation by facilitating productivity-enhancing allocation of human capital. By showing the results on productivity gains by inventor type and by the use of non-compete clauses, I do not necessarily to downplay the role of knowledge diffusion. On the other hand, my results emphasize the underlying mechanism for potential externalities arising from knowledge spillovers. In the context of utilizing technological breakthroughs, the benefits from knowledge spillovers are eventually realized through a market-based channel, the mobility of skilled labor across firms.

Put differently, the creation of new ideas and technologies certainly creates significant externalities. Knowledge spills over, being used as inputs for sequential inventions, the benefits from which are better captured by R&D labs in thick markets in the setting of scientific breakthroughs. Thick labor markets facilitate the allocation of human capital to R&D labs that are more favorably affected by productivity shocks. When meeting the demand for talent, thick labor markets also help labs to bring in inventors working in the same tech niche and carrying diverse knowledge bases. In this regard, the mobility of workers acts as a vehicle for local spillovers.

The results also shed light on how the use of non-compete clauses can limit the scope for technology diffusion. The legal enforceability of non-compete agreements places constraints on how much research facilities can take advantage of technological advances that would otherwise emerge. The use of innovation inputs-human capital- not in its most productive mode could extensively sweep the thick market benefits.

[21] The results are consistent when I repeat the test on knowledge overlapping for a subsample of experienced new hires.

5 Discussion

5.1 Baseline Specification with Additional Controls

In section 3, I investigate the extent to which R& D labs' responses to technological shocks are dependent upon their pre-determined labor market conditions. I emphasize the importance of labor mobility by examining the enforceability of non-compete agreements in Section 4. In the main specification with LLM x year fixed effects, I reply on cross-sectional variation from similar labs in the same research field and commuting zones but experienced differential productivity shocks during the same time window to minimize selection concerns. In this section, I consider a variety of additional controls to narrow down the comparison groups further.

Labs in the early stage of their life cycle might have a different innovation rate from the labs in the later stage. According the life-cycle differences in productivity might vary across research fields. To address the potential bias arising from the age effect, I classify each lab into by 5-Year age cohorts. By including the $LLM \times Age\,cohort$ fixed effects, I compare labs in the same research field and at the same life cycle. Innovation rate might differ in lab size, and more importantly, the enforceability could have a differential influence on labs with different sizes. For example, non-competes disproportionately hurt small firms disproportionately because they tend to be more constrained and lack the scale to enforce the agreements, while large firms have more resources to train new workers and retain their talents (Kang and Fleming (2020)). Thus, I divide labs into size cohorts based on their employment and include the $LLM \times Size\,cohort$ fixed effects. The internal labor market is the alternative channel by which labs can utilize human capital resources. Labs that operate as the solo research facility of the firm can only rely on external labor markets. The dependence of single-market labs on the local labor market might generate selections. To alleviate the concerns, I include $LLM \times SingleMarket\,Lab$ fixed effects. Besides, access to finance remains an essential aspect of the innovation capacity. There has been ample evidence that venture capital has a substantial impact on innovation. VC-backed firms can leverage the ecosystem of innovation established by VC and present superior performance. What's more, venture capital investors tend to be technology-specific, and powerful venture capital investors with large stakes can shape the direction of technological development(Lerner and Nanda (2020)). Thus, to solve the selection issues that arise from the incidence of VC financing and the interplay with the research field, I identify labs that belong to VC-backed firms and compare similar labs in terms of their VC status in the same field by using $LLM \times VC$ fixed effects. Lastly, to further narrow down the comparison between labs similar along the dimensions described above, I use the fixed effects accommodating the interactions among all these factors.

The results are presented in Table 11. I first re-examine the effect of thick labor markets on patent outputs, including the number of total patents and the important patents a lab produces, and inventor turnover following scientific breakthroughs with the additional fixed effects. Then I study whether these effects survive with the enforced non-compete agreements. The results are consistent with baseline findings. Across all specifications, despite these narrower comparison groups, I continue to find the thick market effects on innovation productivity and inventor turnover after breakthroughs, which are only profound without high enforceability of non-competes. The estimated effects are similar in magnitude to the baseline results found in previous sections. Although it's hardly the case that labs randomly enter into a local market, these results assure that it is unlikely that the selection issue would crowd out the thick labor market effects.

Table 11: [INSERT TABLE HERE]

5.2 Geography of Scientific Breakthroughs and Distant Shocks

In section 2, it is argued that the arrival of innovations is random and breakthroughs that depart significantly from existing technology are unexpected by construction. The results in Table 3 valid the idea of technological shocks in that scientific breakthroughs lead to growth in corporate innovation, not the other way around. Yet, it might be a concern that the spatial distribution of scientific breakthroughs is uneven. For example, suppose the locations of universities and other public research institutes that create breakthrough innovations overlap with the sites of corporate innovations. In such a case, the productivity gains might be attributed to the direct impact of the local university on labs. Firms could get access to nearby universities for advice, research, and students(Adams (2002)), in which case the estimated thick market effects are biased.

First, to examine the extent to which the origins of scientific breakthroughs overlap with corporate innovation, I plot the geographic distribution of breakthroughs and corporate patents by commuting zones on the same map, shown in Figure 7. The size of the circles represents the shares of innovations in each type. Breakthroughs and corporate patents populate commonly in the same areas, such as, Boston, the Bay Area and Seattle; while in many other regions, breakthroughs and corporate patents distribute differently. For example, many places in the Mideast and Midwest witnesses a large share of scientific breakthroughs but fewer industrial innovations, while North-Eastern region in general has a more robust performance in developing technologies patented by firms in the private sector. The discrepancy alleviates the concerns that the immediate impact of local public research drives the effects found in previous sections.

To further filter out the effects of the universities and other public research institutes on local

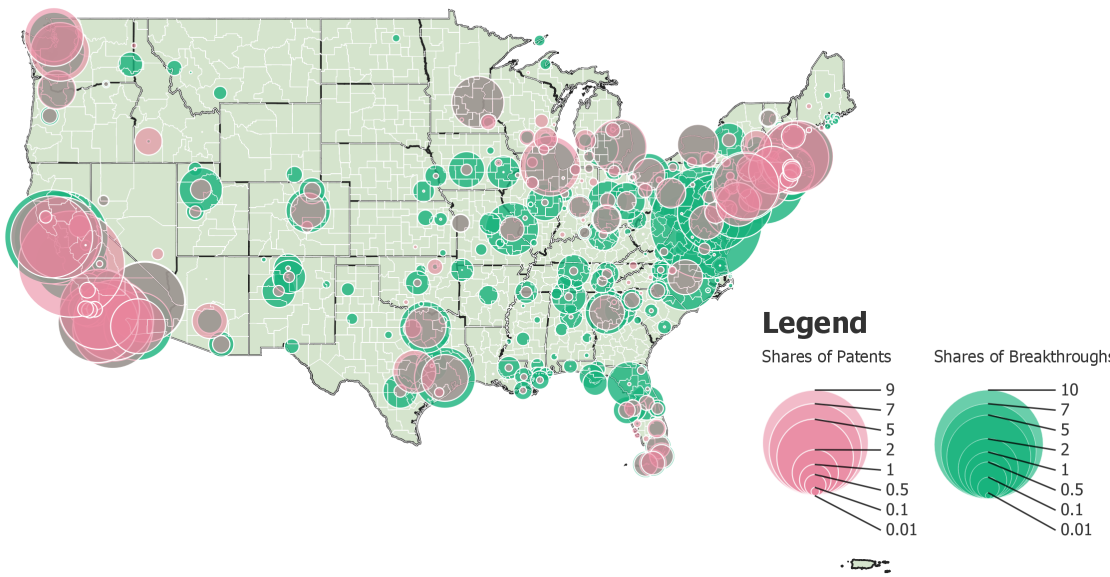

Figure 7: **Geographic Distribution of Scientific Breakthroughs and Corporate Patents.** The figure presents the spatial distribution of scientific breakthroughs and corporate patents from 1981 to 2010. Both are based on inventors' shares by commuting zones. The size of the circles represents the shares of innovation in each type. Innovation location is determined by the inventor's address listed on the patent application. When multiple inventors are associated with one application, each inventor's commuting zone receives a share of the patent.

innovation, I separate the breakthrough innovations based on their original locations. Specifically, I identify whether breakthroughs are generated by a within-state entity or out-of-state entity relative to focal labs. By focusing on the out-of-state breakthroughs and the interaction between local labor markets and distant shocks, the estimated effects are free from the bias due to co-location. The results are presented in Table 12. Controlling for in-state breakthroughs and its interaction with the labor market, the labs in thick local labor markets still disproportionately benefit from technological shocks originating from distant areas. Meanwhile, the productivity gains are more strongly reflected into patent quality, measured by the number of important patents.[22]. Labs also have higher (local) inventor turnover following distant shocks. The thick market effects are driven by labs that are not subject to high enforceability of noncompetes, consistent with the findings in Section 4

Table 12: [INSERT TABLE HERE]

5.3 First-Wave Scientific Breakthroughs and Historical Measure of Thickness

The baseline analysis exploits a cross-sectional comparison across comparable R&D labs that experienced differential productivity shocks during the same time window. It examines whether the

[22] Additional tests on patent citations support the same results.

responses to breakthroughs depend on the pre-determined labor market conditions evaluated by the start of breakthroughs. Yet, if the benefits from previous breakthroughs are cumulatively collected into recent labor market conditions, for example, by attracting talent with relevant expertise who are likely to stay in the locality even after the technology boom, then using the thickness measure evaluated at the beginning of later wave of breakthroughs to estimate thick market effects might result in biased estimates, although the direction of the bias is a priori unclear. It is possible that talent drawn by previous scientific breakthroughs stay in the same tech niche and thus have a favorably long-lasting effect on today's innovation by labs in the same tech class. On the other, it is also possible that the talent spill over to other tech niches that will serve as the comparison group in later waves so that the innovation "benchmark" in the local labor market becomes higher. To address this potential issue, I switch to using the historical measure of local market thickness and focusing on the first-wave scientific breakthroughs in each technology class.

I define a "technology year of emergence" as the first year when the annual count of breakthrough innovations attains 25% of its historical maximum, which is the peak year of breakthroughs in the technology class across 1981 to 2010. Since it takes two to three years on average for corporate labs to materialize the potential impacts of scientific breakthroughs, I base on the main Model 3.1 and modify the specification as below.

$$
\begin{aligned}
Y_{ikcf,t} =& \beta_1 Bkthr_{k,(t-3,t-1)} + \beta_2 Bkthr_{k,(t-3,t-1)} \times Thickness_{cf,t-10} \\
&+ Controls_{ikcf,t} + FEs + \epsilon_{ikcf,t}
\end{aligned}
\tag{5.1}
$$

Where t represents the focal year to assess labs' innovation outputs, and the measure of labor market thickness is based on spatial distribution of technology-specific inventors ten years ago. The three-year window to calculate $Bkthr_{k,(t-3,t-1)}$ starts from the "technology year of emergence." After a technology class is hit by the first-wave breakthrough shocks, it will be excluded from the sample afterward. Thus, the comparison is always made between labs in the technology that has not been affected by any breakthroughs and same-field labs that experienced the first unexpected technological shock. Table 13 reports regression results evaluating the differential effect of first-wave scientific breakthroughs depending on the historical labor market thickness on patenting activities and inventor turnover in corporate R&D labs generated from the first-shock sample instead of the full sample.

Table 13: [INSERT TABLE HERE]

The results show that the first-wave of breakthroughs has a strong impact on corporate innovation. Both the estimations of coefficients on breakthroughs and the interaction term are significantly positive and have sizable magnitude. On average, a one-standard-deviation increase in the breakthrough intensity would lead to labs producing 8.46% more patents and 6.28% more important patents. Given the same level of breakthroughs, a one-standard-deviation increase in historical labor market thickness leads to a 3.19% and 2.33% additional growth in the patent outputs, respectively. Consistent as the baseline, the productivity gains in thick markets are overwritten by the curtailing effects of noncompetes. The role of labor mobility is confirmed by checking the responses in labor turnover. The coefficients estimated from the "clean" shocks suggest a stronger effect of first-wave breakthroughs, indicating the thick market effects found in the main section are unlikely to be overstated.

5.4 Within Lab Analysis of Thick Market Effects and the Labor Mobility Channel

The baseline estimates in the previous analysis are based on cross-sectional comparisons between "affected" labs in the relevant technical domain that are simultaneously shocked by breakthroughs in a given year and similar labs that experienced no breakthroughs during the same time window. Another way to look into the question is to conduct a within-lab analysis utilizing the longitudinal structure of the data. With lab fixed effects, I exploit the time-series variation in which I compare innovative output within the same R&D lab that experienced differential breakthroughs shocks in different years and estimate the interaction of labor market thickness with breakthrough effects. While the identification of within-lab estimates relies on sufficient variation in the intensity of breakthroughs that a lab experience during its life cycle, the advantage of this method is that any unobserved heterogeneity in innovation productivity due to lab selection is absorbed by lab fixed effects. To account for unobservable location characteristics, research field-wide shocks, and economy-wide shocks, I include CZ fixed effects, research field fixed effects and year fixed effects respectively.[23]

Table 14 presents the within-lab results.[24] Panel 1 focuses on the effects on innovation outputs and lab size growth. Comparing the same lab in the years following strong scientific breakthroughs with the years without technological shocks, labs produce more patents, receive more citations and create more technological important inventions following breakthroughs. Moreover, the interaction term between $Breakthrough$ and local labor market $Thickness$ is statistically significant at the 1%

[23] Within-lab results remain robust when I include all pairwise fixed effects, $CZ \times Year\,FE$, $ResearchField \times Year\,FE$ and $CZ \times ResearchField\,FE$.

[24] Additional results can be found in Appendix Table 2.

level, indicating that the strength of reaction to breakthroughs strongly depends on the local labor market. On average, a one-standard-deviation increase in the breakthrough intensity would lead to labs producing 2.22% more patents and 3.52% more important patents. Given the same level of breakthroughs, a one-standard-deviation increase in labor market thickness leads to a 1.61% and 1.02% additional growth in the patent outputs, respectively. Besides, it shows that labs grow substantially more in both total employment and payroll per employment, indicating labs become more extensive and more human capital intensive, particularly in thick markets, after technological shocks. Panel 2 studies the mechanism of labor mobility from the perspective of labs. Specifically, focusing on the direction of human capital mobility within a lab, I investigate whether the inflow and outflow of talent depend on the breakthrough intensity and labor market conditions. More inventors are joining and successfully filing a patent with a lab after more significant breakthrough shocks, and the effects are magnified in thick labor markets. Meanwhile, the outflow of inventors is negatively related to the intensity of breakthroughs, and the relationship is more substantial in thick labor markets as well. The effects hold strongly for the flows of tech-class matched inventors.

Overall, the within-lab results show that thick market effects on innovation productivity hold in the selection-free within-lab analysis. Results on labor mobility indicate that thick labor markets help lab to streamline the inventor team in the technological downturns and acquire human capital when the demand for talent increases after breakthroughs create new innovation opportunities.

Table 14: [INSERT TABLE HERE]

6 Conclusion

By investigating how R&D labs benefit differently from unexpected scientific breakthroughs depending on labor market thickness, I show how labor mobility in thick labor markets facilitates the reallocation of human capital to more productive uses. I contribute to the growing literature on local agglomeration spillovers by distinguishing between the reallocation of human capital and potential spillovers of knowledge. While the spillovers of "knowledge in the air" cannot explain the thick market effects documented in this paper, labor mobility may foster spillovers of "knowledge embedded in the people." I find that labs tend to bring in new hires who have a distinct knowledge base from incumbents. I also find that productivity of incumbent inventors declines when NCs compress labor mobility, suggesting the mobility of talent also acts as a vehicle for productivity spillovers to incumbents following technological breakthroughs. Overall, the productivity-enhancing reallocation of human capital in thick labor markets speaks to the statement, "Invention creates spillovers whose value is not incorporated into market prices... Inventor mobility is one source of this spillover" (Bryan and Williams (2021)). Further research on reallocation of unskilled workers and skilled workers other than inventors would also be a useful supplement to this study.

Distinguishing between the reallocation of human capital and spillovers of "knowledge in the air" is important because the two mechanisms lead to different policy implications. They include but are not limited to the effects of non-compete agreements and other restrictive covenants. For example, the labor reallocation channel, which is more consistent with my results, suggests that the use of non-compete clauses should be more strictly regulated. In particular, when technology is booming, the costs of restraining labor mobility outweigh the benefits of protecting intellectual property and thus negate the advantages of innovation clusters. On the other hand, the cost to innovative firms in terms of seizing technological opportunities is lower if they obtain the most agglomeration benefits from spillovers of "knowledge in the air." In addition, how agglomeration of human capital promotes innovation speaks to the work-from-home debate. If "knowledge in the air" is the key innovation catalyst in a talent cluster, then remote work could be more counter-productive than expected because it largely prohibits knowledge diffusion through social interactions. Taken together, understanding these mechanisms is crucial for the design of innovation policies in promoting technology hubs, given policymakers' interest in creating the next Silicon Valley.

References

Acemoglu, Daron, 1997, Training and Innovation in an Imperfect Labour Market, *The Review of Economic Studies* 64, 445–464.

Adams, James D., 2002, Comparative localization of academic and industrial spillovers, *Journal of Economic Geography* 2, 253–278.

Agrawal, Ajay, Iain Cockburn, Alberto Galasso, and Alexander Oettl, 2014, Why are some regions more innovative than others? the role of small firms in the presence of large labs, *Journal of Urban Economics* 81, 149–165.

Ahmadpoor, Mohammad, and Benjamin F. Jones, 2017, The dual frontier: Patented inventions and prior scientific advance, *Science* 357, 583–587.

Akcigit, Ufuk, and Nathan Goldschlag, 2022, Measuring the characteristics and employment dynamics of u.s. inventors, Working papers, U.S. Census Bureau, Center for Economic Studies.

Almazan, Andres, Adolfo De Motta, and Sheridan Titman, 2007, Firm Location and the Creation and Utilization of Human Capital, *The Review of Economic Studies* 74, 1305–1327.

Atkin, David, M. Keith Chen, and Anton Popov, 2022, The returns to face-to-face interactions: Knowledge spillovers in silicon valley, Working Paper 30147, National Bureau of Economic Research.

Audretsch, David B., and Maryann P. Feldman, 1996, R&d spillovers and the geography of innovation and production, *The American Economic Review* 86, 630–640.

Autor, David H., and David Dorn, 2013, The growth of low-skill service jobs and the polarization of the us labor market, *American Economic Review* 103, 1553–97.

Babina, Tania, and Sabrina T Howell, 2018, Entrepreneurial spillovers from corporate r&d, *Working Paper* .

Babina, Tania, Paige Ouimet, and Rebecca Zarutskie, 2020, Ipos, human capital, and labor reallocation, *Available at SSRN 2692845* .

Bai, John (Jianqiu), Daniel Carvalho, and Gordon M. Phillips, 2018, The impact of bank credit on labor reallocation and aggregate industry productivity, *The Journal of Finance* 73, 2787–2836.

Belenzon, Sharon, and Mark Schankerman, 2013, Spreading the Word: Geography, Policy, and Knowledge Spillovers, *The Review of Economics and Statistics* 95, 884–903.

Bernstein, Shai, 2015, Does going public affect innovation?, *The Journal of Finance* 70, 1365–1403.

Bernstein, Shai, Timothy Mcquade, and Richard R. Townsend, 2021, Do household wealth shocks affect productivity? evidence from innovative workers during the great recession, *The Journal of Finance* 76, 57–111.

Bishara, Norman, 2011, Fifty ways to leave your employer: Relative enforcement of covenants not to compete, trends, and implications for employee mobility policy, *University of Pennsylvania Journal of Business Law* 13, 751–795.

Brav, Alon, Wei Jiang, Song Ma, and Xuan Tian, 2018, How does hedge fund activism reshape corporate innovation?, *Journal of Financial Economics* 130, 237–264.

Bryan, Kevin A., and Heidi L. Williams, 2021, Innovation: market failures and public policies, in *Handbook of Industrial Organization*, volume 5 of *Handbook of Industrial Organization*, 281–388 (Elsevier).

Buzard, Kristy, Gerald A. Carlino, Robert M. Hunt, Jake K. Carr, and Tony E. Smith, 2017, The agglomeration of american r&d labs, *Journal of Urban Economics* 101, 14–26.

Carlino, Gerald, and William R. Kerr, 2015, Chapter 6 - agglomeration and innovation, in Gilles Duranton, J. Vernon Henderson, and William C. Strange, eds., *Handbook of Regional and Urban Economics*, volume 5 of *Handbook of Regional and Urban Economics*, 349–404 (Elsevier).

Chen, Henry, Paul Gompers, Anna Kovner, and Josh Lerner, 2010, Buy local? the geography of venture capital, *Journal of Urban Economics* 67, 90–102.

Combes, Pierre-Philippe, and Laurent Gobillon, 2015, Chapter 5 - the empirics of agglomeration economies, in Gilles Duranton, J. Vernon Henderson, and William C. Strange, eds., *Handbook of Regional and Urban Economics*, volume 5 of *Handbook of Regional and Urban Economics*, 247–348 (Elsevier).

Dreisigmeyer, David, Nathan Goldschlag, Marina Krylova, Wei Ouyang, and Elisabeth Perlman, 2018, Building a better bridge: Improving patent assignee-firm links, Ces technical notes series, Center for Economic Studies, U.S. Census Bureau.

Duranton, Gilles, and Diego Puga, 2003, Micro-foundations of urban agglomeration economies, *Handbook of Regional and Urban Economics* 4.

Fallick, Bruce, Charles Fleischman, and James Rebitzer, 2006, Job-hopping in silicon valley: Some evidence concerning the microfoundations of a high-technology cluster, *The Review of Economics and Statistics* 88, 472–481.

Freedman, Matthew L., 2008, Job hopping, earnings dynamics, and industrial agglomeration in the software publishing industry, *Journal of Urban Economics* 64, 590–600.

Giroud, Xavier, and Holger M. Mueller, 2015, Capital and labor reallocation within firms, *The Journal of Finance* 70, 1767–1804.

Glaeser, Edward L, 1999, Learning in cities, *Journal of Urban Economics* 46, 254–277.

Golman, Russell, and Steven Klepper, 2016, Spinoffs and clustering, *The RAND Journal of Economics* 47, 341–365.

Graham, Stuart J.H., Cheryl Grim, Tariqul Islam, Alan C. Marco, and Javier Miranda, 2018, Business dynamics of innovating firms: Linking u.s. patents with administrative data on workers and firms, *Journal of Economics & Management Strategy* 27, 372–402.

Gross, Daniel P, and Bhaven N Sampat, 2020, America, jump-started: World war ii r&d and the takeoff of the u.s. innovation system, Working Paper 27375, National Bureau of Economic Research.

Hall, Bronwyn H, Adam B Jaffe, and Manuel Trajtenberg, 2001, The nber patent citation data file: Lessons, insights and methodological tools, Working Paper 8498, National Bureau of Economic Research.

Helsley, Robert W., and William C. Strange, 1990, Matching and agglomeration economies in a system of cities, *Regional Science and Urban Economics* 20, 189–212.

Hirshleifer, David, Angie Low, and Siew Hong Teoh, 2012, Are overconfident ceos better innovators?, *The Journal of Finance* 67, 1457–1498.

Hombert, Johan, and Adrien Matray, 2016, The Real Effects of Lending Relationships on Innovative Firms and Inventor Mobility, *The Review of Financial Studies* 30, 2413–2445.

Jaffe, Adam B., 1986, Technological opportunity and spillovers of r & d: Evidence from firms' patents, profits, and market value, *The American Economic Review* 76, 984–1001.

Jaffe, Adam B., 1989, Real effects of academic research, *The American Economic Review* 79, 957–970.

Jeffers, Jessica, 2019, The impact of restricting labor mobility on corporate investment and entrepreneurship, *Working Paper* .

Johnson, Matthew, Kurt Lavetti, and Michael Lipsitz, 2020, The labor market effects of legal restrictions on worker mobility, *Working Paper* .

Jovanovic, Boyan, and Peter L. Rousseau, 2002, The q-theory of mergers, *American Economic Review* 92, 198–204.

Jovanovic, Boyan, and Peter L. Rousseau, 2008, Mergers as reallocation, *The Review of Economics and Statistics* 90, 765–776.

Kaltenberg, Mary, Adam B Jaffe, and Margie Lachman, 2021, The age of invention: Matching inventor ages to patents based on web-scraped sources, Working Paper 28768, National Bureau of Economic Research.

Kang, Hyo, and Lee Fleming, 2020, Non-competes, business dynamism, and concentration: Evidence from a florida case study, *Journal of Economics & Management Strategy* 29, 663–685.

Kelly, Bryan, Dimitris Papanikolaou, Amit Seru, and Matt Taddy, 2021, Measuring technological innovation over the long run, *American Economic Review: Insights* 3, 303–20.

Kerr, William R., and Scott Duke Kominers, 2015, Agglomerative forces and cluster shapes, *The Review of Economics and Statistics* 97, 877–899.

Kerr, William R., and Frederic Robert-Nicoud, 2020, Tech clusters, *Journal of Economic Perspectives* 34, 50–76.

Kogan, Leonid, Dimitris Papanikolaou, Amit Seru, and Noah Stoffman, 2017, Technological Innovation, Resource Allocation, and Growth, *The Quarterly Journal of Economics* 132, 665–712.

Krugman, P., 1991a, *Geography and Trade*, Gaston Eyskens Lectures (MIT Press).

Krugman, Paul, 1991b, Increasing returns and economic geography, *Journal of Political Economy* 99, 483–499.

Lee, James., and Tom Nicholas, 2013, The origins and development of silicon valley, *Harvard Business School Case 813-098* .

Lerner, Josh, and Ramana Nanda, 2020, Venture capital's role in financing innovation: What we know and how much we still need to learn, *Journal of Economic Perspectives* 34, 237–61.

Lerner, Josh, and Amit Seru, 2021, The Use and Misuse of Patent Data: Issues for Finance and Beyond, *The Review of Financial Studies* 35, 2667–2704.

Lucas, Robert Jr., 1988, On the mechanics of economic development, *Journal of Monetary Economics* 22, 3–42.

Maksimovic, Vojislav, and Gordon Phillips, 2001, The market for corporate assets: Who engages in mergers and asset sales and are there efficiency gains?, *The Journal of Finance* 56, 2019–2065.

Maksimovic, Vojislav, and Gordon Phillips, 2002, Do conglomerate firms allocate resources inefficiently across industries? theory and evidence, *The Journal of Finance* 57, 721–767.

March, James G., 1991, Exploration and exploitation in organizational learning, *Organization Science* 2, 71–87.

Marshall, Alfred, 1890, *The Principles of Economics* (McMaster University Archive for the History of Economic Thought).

Marx, Matt, Deborah Strumsky, and Lee Fleming, 2009, Mobility, skills, and the michigan non-compete experiment, *Management Science* 55, 875–889.

Matray, Adrien, 2021, The local innovation spillovers of listed firms, *Journal of Financial Economics* 141, 395–412.

Melero, Eduardo, Neus Palomeras, and David Wehrheim, 2020, The effect of patent protection on inventor mobility, *Management Science* 66, 5485–5504.

Moretti, Enrico, 2011, Local Labor Markets, in O. Ashenfelter, and D. Card, eds., *Handbook of Labor Economics*, volume 4 of *Handbook of Labor Economics*, chapter 14, 1237–1313 (Elsevier).

Moretti, Enrico, 2021, The effect of high-tech clusters on the productivity of top inventors, *American Economic Review* 111, 3328–75.

Overman, Henry G., and Diego Puga, 2010, *Labor Pooling as a Source of Agglomeration: An Empirical Investigation*, 133–150 (University of Chicago Press).

Puri, Manju, and Rebecca Zarutskie, 2012, On the life cycle dynamics of venture-capital- and non-venture-capital-financed firms, *The Journal of Finance* 67, 2247–2293.

Roche, Maria P, Alexander Oettl, and Christian Catalini, 2022, (co-)working in close proximity: Knowledge spillovers and social interactions, Working Paper 30120, National Bureau of Economic Research.

Rosenthal, Stuart S., and William C. Strange, 2004, Chapter 49 - evidence on the nature and sources of agglomeration economies, in J. Vernon Henderson, and Jacques-François Thisse, eds., *Cities and Geography*, volume 4 of *Handbook of Regional and Urban Economics*, 2119–2171 (Elsevier).

Samila, Sampsa, and Olav Sorenson, 2011, Noncompete covenants: Incentives to innovate or impediments to growth, *Management Science* 57, 425–438.

Saxenian, AnnaLee, 1994, Regional advantage: Culture and competition in silicon valley and route 128. harvard university press, cambridge, ma., *Bulletin of Science, Technology & Society* .

Seru, Amit, 2014, Firm boundaries matter: Evidence from conglomerates and r&d activity, *Journal of Financial Economics* 111, 381–405.

Starr, Evan, 2019, Consider this: Training, wages, and the enforceability of covenants not to compete, *ILR Review* 72, 783–817.

Starr, Evan, Justin Frake, and Rajshree Agarwal, 2019, Mobility constraint externalities, *Organization Science* 30, 961–980.

Starr, Evan P., J.J. Prescott, and Norman D. Bishara, 2021, Noncompete agreements in the us labor force, *The Journal of Law and Economics* 64, 53–84.

Strange, William, Walid Hejazi, and Jianmin Tang, 2006, The uncertain city: Competitive instability, skills, innovation and the strategy of agglomeration, *Journal of Urban Economics* 59, 331–351.

Tate, Geoffrey, and Liu Yang, 2015, The Bright Side of Corporate Diversification: Evidence from Internal Labor Markets, *The Review of Financial Studies* 28, 2203–2249.

Tate, Geoffrey, and Liu Yang, 2016, The Human Factor in Acquisitions: Cross-Industry Labor Mobility and Corporate Diversification, *Working Paper* .

Trajtenberg, Manuel, Rebecca Henderson, and Adam B. Jaffe, 1997, University versus corporate patents: A window on the basicness of invention, *Economics of Innovation and New Technology* 5, 19–50.

von Hippel, Eric, 1994, "sticky information" and the locus of problem solving: Implications for innovation, *Management Science* 40, 429–439.

Weitzman, Martin L., 1998, Recombinant Growth, *The Quarterly Journal of Economics* 113, 331–360.

Yang, Liu, 2008, The real determinants of asset sales, *The Journal of Finance* 63, 2231–2262.

Zacchia, Paolo, 2019, Knowledge Spillovers through Networks of Scientists, *The Review of Economic Studies* 87, 1989–2018.

Table 1: **Local Labor Markets**

This table lists top ten local labor markets by *Thickness*, evaluated in year 2000. *Thickness* is the natural logarithm of total inventors in the research field x CZ in a given year. Only the main counties in the commuting zones are presented for the sake of saving space.

Top Ten Thick Labor Markets Across Research Fields, 2000

Main Counties in the Commuting Zones	*Thickness*	Main Counties in the Commuting Zones	*Thickness*
Research Field: Human Necessitates		**Research Field: Transporting (Performing Operations)**	
Los Angeles-Long Beach-Glendale, CA	8.03	Detroit-Livonia-Dearborn, MI	7.87
Cambridge-Newton-Framingham, MA	7.71	Los Angeles-Long Beach-Glendale, CA	7.58
New York-Wayne-White Plains, NY-NJ	7.61	Chicago-Naperville-Joliet, IL	7.41
Minneapolis-St. Paul-Bloomington, MN-WI	7.56	Minneapolis-St. Paul-Bloomington, MN-WI	7.12
Oakland-Fremont-Hayward, CA	7.51	Cambridge-Newton-Framingham, MA	6.97
Chicago-Naperville-Joliet, IL	7.34	New York-Wayne-White Plains, NY-NJ	6.84
San Jose-Sunnyvale-Santa Clara, CA	7.3	Bridgeport-Stamford-Norwalk, CT	6.81
New York-Wayne-White Plains, NY-NJ	7.16	San Jose-Sunnyvale-Santa Clara, CA	6.66
Philadelphia, PA	6.96	Buffalo-Cheektowaga-Tonawanda, NY	6.66
San Diego-Carlsbad-San Marcos, CA	6.94	Oakland-Fremont-Hayward, CA	6.66
Madison, WI	5.38	Saginaw-Saginaw Township North, MI	5.25
Fort Worth-Arlington, TX	5.38	Indianapolis, IN	5.25
West Palm Beach-Boca Raton-Boynton Beach, FL	5.37	Sacramento–Arden-Arcade–Roseville, CA	5.2
Edison, NJ	5.29	Tampa-St. Petersburg-Clearwater, FL	5.16
Kansas City, MO-KS	5.29	Albany-Schenectady-Troy, NY	5.16
Richmond, VA	5.17	Madison, WI	5.14
San Antonio, TX	5.08	Fort Worth-Arlington, TX	5.13
Santa Barbara-Santa Maria-Goleta, CA	5.03	Austin-Round Rock, TX	5.08
Canton-Massillon, OH	5.01	Lancaster, PA	5.06
Lancaster, PA	5	West Palm Beach-Boca Raton-Boynton Beach, FL	5.05
Research Field: Chemistry		**Research Field: Textiles (Paper)**	
New York-Wayne-White Plains, NY-NJ	7.93	Atlanta-Sandy Springs-Marietta, GA	4.74
Cambridge-Newton-Framingham, MA	7.71	Appleton, WI	4.47
Oakland-Fremont-Hayward, CA	7.68	New York-Wayne-White Plains, NY-NJ	4.11
Philadelphia, PA	7.61	Greenville, SC	4.09
Chicago-Naperville-Joliet, IL	7.27	Charlotte-Gastonia-Concord, NC-SC	4.06
San Diego-Carlsbad-San Marcos, CA	7.11	Philadelphia, PA	4.06
Houston-Baytown-Sugar Land, TX	7.07	Albany-Schenectady-Troy, NY	3.97
Los Angeles-Long Beach-Glendale, CA	7.04	Raleigh-Cary, NC	3.93
Bridgeport-Stamford-Norwalk, CT	7.01	Richmond, VA	3.89
San Jose-Sunnyvale-Santa Clara, CA	7.01	Cambridge-Newton-Framingham, MA	3.89
Edison, NJ	5.08	Pittsburgh, PA	2.56
Des Moines, IA	5.08	Allentown-Bethlehem-Easton, PA-NJ	2.56
Tulsa, OK	5.06	Lancaster, PA	2.56
Canton-Massillon, OH	4.95	Milwaukee-Waukesha-West Allis, WI	2.56
Providence-New Bedford-Fall River, RI-MA	4.91	Washington-Arlington-Alexandria, DC-VA-MD-WV	2.48
Lancaster, PA	4.87	Dallas-Plano-Irving, TX	2.48
Portland-Vancouver-Beaverton, OR-WA	4.87	Winston-Salem, NC	2.4
Kalamazoo-Portage, MI	4.83	Charleston-North Charleston, SC	2.4
Manchester-Nashua, NH	4.81	Athens-Clarke County, GA	2.4
Poughkeepsie-Newburgh-Middletown, NY	4.79	Canton-Massillon, OH	2.4

Table 1 (Continued)

Main Counties in the Commuting Zones	*Thickness*	Main Counties in the Commuting Zones	*Thickness*
Research Field: Constructions		**Research Field: Mechanical Engineering**	
Houston-Baytown-Sugar Land, TX	6.9	Detroit-Livonia-Dearborn, MI	7.28
Los Angeles-Long Beach-Glendale, CA	5.94	Los Angeles-Long Beach-Glendale, CA	6.89
Detroit-Livonia-Dearborn, MI	5.52	Chicago-Naperville-Joliet, IL	6.39
Chicago-Naperville-Joliet, IL	5.42	Bridgeport-Stamford-Norwalk, CT	6.19
Dallas-Plano-Irving, TX	5.33	Cambridge-Newton-Framingham, MA	6.06
Minneapolis-St. Paul-Bloomington, MN-WI	5.14	Minneapolis-St. Paul-Bloomington, MN-WI	5.99
Cambridge-Newton-Framingham, MA	4.84	Houston-Baytown-Sugar Land, TX	5.86
Denver-Aurora, CO	4.84	Cincinnati-Middletown, OH-KY-IN	5.63
Oakland-Fremont-Hayward, CA	4.82	New York-Wayne-White Plains, NY-NJ	5.61
Bridgeport-Stamford-Norwalk, CT	4.75	Buffalo-Cheektowaga-Tonawanda, NY	5.61
Manchester-Nashua, NH	3.66	Portland-Vancouver-Beaverton, OR-WA	4.52
Oklahoma City, OK	3.64	Raleigh-Cary, NC	4.47
Kansas City, MO-KS	3.58	Saginaw-Saginaw Township North, MI	4.42
Provo-Orem, UT	3.58	Tulsa, OK	4.42
Baltimore-Towson, MD	3.47	Austin-Round Rock, TX	4.39
Lancaster, PA	3.47	Fort Worth-Arlington, TX	4.39
San Antonio, TX	3.43	Salt Lake City, UT	4.39
Albany-Schenectady-Troy, NY	3.4	Kalamazoo-Portage, MI	4.38
Rockford, IL	3.4	Fort Wayne, IN	4.37
Tampa-St. Petersburg-Clearwater, FL	3.37	Toledo, OH	4.32
Research Field: Computers & Communications (Physics)		**Electricity**	
San Jose-Sunnyvale-Santa Clara, CA	8.93	San Jose-Sunnyvale-Santa Clara, CA	8.75
Oakland-Fremont-Hayward, CA	8.31	Los Angeles-Long Beach-Glendale, CA	8.04
Cambridge-Newton-Framingham, MA	8.17	Oakland-Fremont-Hayward, CA	7.97
Los Angeles-Long Beach-Glendale, CA	8.08	Cambridge-Newton-Framingham, MA	7.88
Seattle-Bellevue-Everett, WA	7.82	New York-Wayne-White Plains, NY-NJ	7.7
New York-Wayne-White Plains, NY-NJ	7.56	Chicago-Naperville-Joliet, IL	7.66
Austin-Round Rock, TX	7.53	Dallas-Plano-Irving, TX	7.55
New York-Wayne-White Plains, NY-NJ	7.48	San Diego-Carlsbad-San Marcos, CA	7.17
Buffalo-Cheektowaga-Tonawanda, NY	7.42	New York-Wayne-White Plains, NY-NJ	7.11
Minneapolis-St. Paul-Bloomington, MN-WI	7.38	Phoenix-Mesa-Scottsdale, AZ	7.06
Providence-New Bedford-Fall River, RI-MA	5.65	Allentown-Bethlehem-Easton, PA-NJ	5.53
Edison, NJ	5.59	York-Hanover, PA	5.51
Santa Barbara-Santa Maria-Goleta, CA	5.58	Palm Bay-Melbourne-Titusville, FL	5.49
Cincinnati-Middletown, OH-KY-IN	5.55	Providence-New Bedford-Fall River, RI-MA	5.48
Albuquerque, NM	5.47	Orlando, FL	5.45
Fort Worth-Arlington, TX	5.43	Colorado Springs, CO	5.45
Colorado Springs, CO	5.41	Fort Collins-Loveland, CO	5.4
Columbus, OH	5.35	Binghamton, NY	5.39
Orlando, FL	5.3	Albuquerque, NM	5.29
Indianapolis, IN	5.27	Santa Barbara-Santa Maria-Goleta, CA	5.24

Table 2: **Summary Statistics**

This table reports the estimated effects of scientific breakthroughs, lab level exposure to breakthroughs and the interplay with labor market thickness on the direction of human capital allocation in Panel A and patent-based innovation outputs in Panel B. The unit of observation is a lab-year. Panel C presents the distribution of R&D labs across fields. The unit of observation is a lab. All estimates are from the regression of quarterly mutual fund flows on prior-quarter activeness measure, fund returns, and controls. Standard errors are clustered at the LLM-year level. Stars denote standard statistical significance (***$p < 0.01$, **$p < 0.05$, *$p < 0.1$, respectively).

Panel A : Patent Measures

	Observations	Mean	Std Dev
Log(Patents)	710000	0.4019	0.7865
Log(Citations)	710000	0.3729	0.8421
Log(Core Patents)	710000	0.3142	0.6852
Log(Core Citations)	710000	0.2912	0.7368
Log(Noncore Patents)	710000	0.1789	0.5278
Log(Noncore Citations)	710000	0.1621	0.5568
Log(Top-Cited Patents)	710000	0.09844	0.3714
Log(Important Patents)	710000	0.07438	0.3467
Log(Exploratory Patents)	710000	0.327	0.7491
Log(Exploitative Patents)	710000	0.1045	0.3236

Panel B : Patent Measures Correlation Matrix

	Top-Cited	Important	Cites	Core Cites	Noncore Cites	Exploratory
Log(Important Patents)	0.6507					
Log(Citations)	0.8673	0.6391				
Log(Core Citations)	0.8423	0.6337	0.9406			
Log(Noncore Citations)	0.7583	0.6038	0.793	0.604		
Log(Exploratory Patents)	0.7269	0.6786	0.8683	0.8114	0.7649	
Log(Exploitative Patents)	0.2629	0.1317	0.4113	0.4146	0.1814	0.167

Panel C: Distribution of R&D Labs Across Research Fields

Research Field	Percent	N(Rounded)
Human Necessitates	17.19	
Transporting (Performing Operations)	18.66	
Chemistry	10.58	
Textiles (Paper)	1.027	
Constructions	4.567	
Mechanical Engineering	7.79	
Computers & Communications (Physics)	24.05	
Electricity	16.14	
Total	100	80000

Table 2 (Continued)

Panel D: Lab Characteristics

	Observations	Mean	Std Dev
Lab Size	710000	4.221	1.92
Firm Size	710000	6.501	3.168
Age	710000	21.21	9.111
Internal Labor Market	710000	23.15	38.65
Single-Market Lab	710000	0.4306	0.4952
Innovation Experience	710000	0.5351	0.9021
Exploratory Experience	710000	0.9659	1.319
Exploitative Experience	710000	0.5399	0.7934
$Log(Pay/Emp)_{t+1}$	710000	4.084	2.052
$Log(Emp)_{t+1}$	710000	3.779	1.037
$\mathbf{1}_{\{Star(TopCited)_{t,t+5}=1\}}$	710000	0.02974	0.1699
$\mathbf{1}_{\{Star(Important)_{t,t+5}=1\}}$	710000	0.0215	0.145
Exposure	710000	0.02307	0.07368

Panel E: Inventor-Related Measures

	Observations	Mean	Std Dev
Log(Patents by Incumbents)	710000	0.2878	0.6776
Log(Citations by Incumbents)	710000	0.2673	0.7216
Log(Patents by New-Hires)	710000	0.2104	0.5352
Log(Citations by New-Hires)	710000	0.1969	0.5797
Log(Patents by Recent New-Hires)	710000	0.0523	0.2456
Log(Citations by Recent New-Hires)	710000	0.04811	0.2682
Log(Turnover)	710000	0.4252	0.7714
Log(Local Turnover)	710000	0.1415	0.4223
Log(Recent Turnover)	710000	0.09401	0.3346
Log(Recent Local Turnover)	710000	0.06582	0.2771
Log(Remote Turnover)	710000	0.08536	0.3137
Log(Internal Turnover)	710000	0.0456	0.2241
Log(Onboarding Inventors)	710000	0.2557	0.6263
Log(Offboarding Inventors)	710000	0.2468	0.5761
Log(Onboarding Tech-Class Matched Inventors)	710000	0.1801	0.5174
Log(Offboarding Tech-Class Matched Inventors)	710000	0.1732	0.4701
Log(Onboarding Experienced Inventors)	710000	0.1083	0.3715
Log(Onboarding Inexperienced Inventors)	710000	0.1994	0.5483
Log(Onboarding Inexperienced Young Inventors)	710000	0.1994	0.5483
Log(Onboarding Local Inventors)	710000	0.07468	0.305
Log(Offboarding Local Inventors)	710000	0.08242	0.313
Tech-Class Match (%)	130000	48.72	42.68
Technological Proximity	130000	0.2354	0.3255
Knowledge Overlapping (%)	130000	6.895	12.13

Panel F: Local Labor Market and Breakthroughs

	Observations	Mean	Std Dev
Thickness	710000	6.234	1.744
Thickness_{t-10}	710000	5.928	1.698
$\mathbf{1}_{\{HighNCE=1\}}$	710000	0.2527	0.4345
HHI	710000	0.1881	0.2127
Breakthrough	710000	1.827	1.921
$\text{Breakthrough}_{OutState}$	710000	1.727	1.933
$\text{Breakthrough}_{InState}$	710000	0.4723	0.886

Table 3: **Main Effects of Scientific Breakthroughs on Corporate Innovation**

This table reports the main effects of scientific breakthroughs on the patent-based innovation outputs based on a Model 2.1 in Panel A and 3.1 in Panel B. The unit of observation is a lab-year. *Breakthrough* represents the intensity of breakthroughs measured by the natural logarithm of one plus the total scientific breakthroughs by technology class in year $t-j$. $Log(Patents)$ is constructed as the natural logarithm of one plus the sum of the patents generated by each lab-year. $Log(Citations)$ is constructed as the natural logarithm of one plus the sum of the adjusted citations received by patents filed by each lab-year. Similar definitions apply to core patents which are inventions in labs' core tech area, non-core patents as the rest, exploratory and exploitative patents. Fixed effects included in each regression are indicated in the column. Standard errors are clustered at the LLM-year level. Stars denote standard statistical significance (***$p < 0.01$, **$p < 0.05$, *$p < 0.1$, respectively).

Panel A	(1)	(3)	(2)	(4)
Dependant Var:	Log(Patents)	Log(Patents)	Log(Core Patents)	Log(Core Patents)
Breakthrough(t-4)		0.0042		0.0049
		(0.0037)		(0.0034)
Breakthrough(t-3)	0.0163***	0.0139***	0.0137***	0.0110***
	(0.0037)	(0.0041)	(0.0033)	(0.0037)
Breakthrough(t-2)	0.0080*	0.0069	0.0086**	0.0072*
	(0.0041)	(0.0043)	(0.0037)	(0.0039)
Breakthrough(t-1)	-0.0062	-0.0064	-0.004	-0.0045
	(0.0043)	(0.0043)	(0.0038)	(0.0038)
Breakthrough(t-0)	0.0051	0.0046	0.0038	0.0035
	(0.0042)	(0.0042)	(0.0039)	(0.0039)
Breakthrough(t+1)	-0.0022	-0.0025	-0.0011	-0.001
	(0.0041)	(0.0042)	(0.0038)	(0.0038)
Breakthrough(t+2)	0.0062	0.0055	0.0042	0.004
	(0.0041)	(0.0042)	(0.0037)	(0.0038)
Breakthrough(t+3)	0.0039	0.0021	0.0037	0.0029
	(0.0038)	(0.0042)	(0.0035)	(0.0039)
Breakthrough(t+4)		0.0034		0.0015
		(0.0040)		(0.0036)
Lab Size	0.1432***	0.1432***	0.1140***	0.1140***
	(0.0015)	(0.0015)	(0.0014)	(0.0014)
Firm Size	0.0315***	0.0315***	0.0227***	0.0227***
	(0.0033)	(0.0033)	(0.0029)	(0.0029)
Age	-0.0536***	-0.0535***	-0.0498***	-0.0497***
	(0.0017)	(0.0017)	(0.0015)	(0.0015)
Internal Labor Market	0.0340***	0.0340***	0.0057***	0.0057***
	(0.0019)	(0.0019)	(0.0018)	(0.0018)
Innovation Experience	0.4608***	0.4608***	0.3897***	0.3897***
	(0.0025)	(0.0025)	(0.0026)	(0.0026)
Industry FE	Yes	Yes	Yes	Yes
CZ x Research Field x Year FE	Yes	Yes	Yes	Yes
Single-Market Lab FE	Yes	Yes	Yes	Yes
R-squared	0.5051	0.5051	0.4594	0.4594
Observations	455000	455000	455000	455000

Table 3 (Continued)

Panel B	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependant Var:	Log(Patents)			Log(Citations)			Log(Patents)	
	All	Core	Noncore	All	Core	Noncore	Exploratory	Exploitative
Breakthrough(t-3, t-1)	0.0326***	0.0301***	0.0057***	0.0235***	0.0177***	0.0065***	0.0164***	0.0034***
	(0.0014)	(0.0013)	(0.0010)	(0.0015)	(0.0014)	(0.0011)	(0.0012)	(0.0007)
Lab Size	0.1315***	0.1056***	0.0702***	0.1151***	0.0906***	0.0628***	0.0885***	0.0175***
	(0.0011)	(0.0011)	(0.0008)	(0.0012)	(0.0011)	(0.0008)	(0.0010)	(0.0005)
Firm Size	0.0327***	0.0243***	0.0288***	0.0329***	0.0238***	0.0266***	0.0464***	-0.0122***
	(0.0026)	(0.0024)	(0.0021)	(0.0028)	(0.0025)	(0.0022)	(0.0024)	(0.0012)
Age	-0.0483***	-0.0441***	-0.0178***	-0.0597***	-0.0535***	-0.0232***	-0.0705***	-0.0265***
	(0.0011)	(0.0010)	(0.0008)	(0.0012)	(0.0011)	(0.0008)	(0.0010)	(0.0006)
Internal Labor Market	0.0390***	0.0100***	0.0473***	0.0251***	-0.0006	0.0398***	0.0107***	-0.0033***
	(0.0016)	(0.0015)	(0.0014)	(0.0017)	(0.0016)	(0.0015)	(0.0016)	(0.0006)
Innovation Experience	0.4475***	0.3787***	0.2814***	0.4930***	0.4160***	0.2887***		
	(0.0023)	(0.0023)	(0.0022)	(0.0026)	(0.0026)	(0.0025)		
Exploratory Experience							0.5282***	-0.0006
							(0.0030)	(0.0006)
Exploitative Experience							-0.0715***	0.1121***
							(0.0012)	(0.0009)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CZ x Research Field x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Single-Market Lab FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.5018	0.4554	0.4306	0.4831	0.4334	0.3855	0.5601	0.1849
Observations	710000	710000	710000	710000	710000	710000	710000	710000

Table 4: **Thick Labor Market Effects on Corporate Innovation Outputs**

This table reports the effects of scientific breakthroughs and the interaction effects of labor market thickness on the patent-based innovation outputs based on Model 3.1. The unit of observation is a lab-year. *Breakthrough* represents the intensity of breakthroughs measured by the natural logarithm of one plus the total scientific breakthroughs by technology class in year $t-3$ to $t-1$. *Thickness* is the natural logarithm of total inventors in the research field x CZ in year $t-3$. $Log(Patents)$ is constructed as the natural logarithm of one plus the sum of the patents generated by each lab-year. $Log(Citations)$ is constructed as the natural logarithm of one plus the sum of the adjusted citations received by patents filed by each lab-year. $Log(Top-Cited)$ is constructed as the natural logarithm of one plus the sum of the top patents generated by each lab-year. $Log(Important)$ is constructed as the natural logarithm of one plus the sum of the importance-weighted patents generated by each lab-year. Similar definitions apply to core patents which are inventions in labs' core tech area, non-core patents as the rest, exploratory and exploitative patents. $\mathbf{1}_{\{Star(TopCited)_{t,t+5}=1\}}$ and $\mathbf{1}_{\{Star(Important)_{t,t+5}=1\}}$ indicate a lab as an innovation star if it ends up in the top 1% in the cumulative patenting measures across all labs in the same field. In addition to the variables shown, I control for all lab characteristics used in Table 3, including Lab Size, Firm Size, Age, Internal Labor Market and Innovation Experience. Fixed effects included in each regression are indicated in the column. Standard errors are clustered at the LLM-year level. Stars denote standard statistical significance (***$p < 0.01$, **$p < 0.05$, *$p < 0.1$, respectively).

Panel A	(1)	(2)	(3)	(4)
Dependant Var:	Log(Patents)	Log(Citations)	Log(Top-Cited)	Log(Important)
Breakthrough x Thickness	0.0081***	0.0061***	0.0035***	0.0118***
	(0.0018)	(0.0018)	(0.0007)	(0.0010)
Breakthrough	0.0313***	0.0226***	0.0049***	0.0258***
	(0.0014)	(0.0014)	(0.0006)	(0.0009)
R-squared	0.5019	0.4831	0.394	0.3068

Panel B	(1)	(2)	(3)	(4)	(5)	(6)
Dependant Var:	Log(Patents) Core	Log(Citations) Core	Log(Patents) Noncore	Log(Citations) Noncore	Log(Patents) Exploratory	Log(Patents) Exploitative
Breakthrough x Thickness	0.0088***	0.0068***	0.0035***	0.0028***	0.0071***	-0.0029***
	(0.0015)	(0.0016)	(0.0012)	(0.0012)	(0.0013)	(0.0008)
Breakthrough	0.0287***	0.0167***	0.0052***	0.0060***	0.0153***	0.0038***
	(0.0012)	(0.0013)	(0.0009)	(0.0010)	(0.0012)	(0.0007)
R-squared	0.4552	0.4334	0.4306	0.3855	0.5601	0.1849

Panel C	(1)	(2)	(3)	(4)
Dependant Var:	$Log(Pay/Emp)_{t+1}$	$Log(Emp)_{t+1}$	$\mathbf{1}_{\{Star(TopCited)_{t,t+5}=1\}}$	$\mathbf{1}_{\{Star(Important)_{t,t+5}=1\}}$
Breakthrough x Thickness	0.0078***	0.0024	0.0025***	0.0052***
	(0.0023)	(0.0021)	(0.0003)	(0.0004)
Breakthrough	0.0353***	0.0099***	0.0020***	0.0073***
	(0.0019)	(0.0018)	(0.0003)	(0.0003)
R-squared	0.1512	0.8263	0.2276	0.178
Industry FE	Yes	Yes	Yes	Yes
CZ x Research Field x Year FE	Yes	Yes	Yes	Yes
Single-Market Lab FE	Yes	Yes	Yes	Yes
Observations	710000	710000	710000	710000

Table 5: **Contribution to Productivity Gains by Inventor Type**

This table reports the effects of scientific breakthroughs and the interaction effects of labor market thickness on the patent-based innovation outputs by inventor types based on a Model 3.1. The unit of observation is a lab-year. *Breakthrough* represents the intensity of breakthroughs measured by the natural logarithm of one plus the total scientific breakthroughs by technology class in year $t-3$ to $t-1$. *Thickness* is the natural logarithm of total inventors in the research field x CZ in year $t-3$. $Log(Patents)$ and $Log(Citations)$ are constructed by inventor types. In addition to the variables shown, I control for all lab characteristics used in Table 3, including Lab Size, Firm Size, Age, Internal Labor Market and Innovation Experience. Fixed effects included in each regression are indicated in the column. Standard errors are clustered at the LLM-year level. Stars denote standard statistical significance (***$p < 0.01$, **$p < 0.05$, *$p < 0.1$, respectively).

	(1)	(2)	(3)	(4)	(5)	(6)
Dependant Var:	Log(Patents) by Incumbents	Log(Citations) by Incumbents	Log(Patents) by New-Hires	Log(Citations) by New-Hires	Log(Patents) by Recent New-Hires	Log(Citations) by Recent New-Hires
Breakthrough x Thickness	0.0037**	0.0019	0.0121***	0.0109***	0.0076***	0.0069***
	(0.0015)	(0.0015)	(0.0011)	(0.0012)	(0.0006)	(0.0007)
Breakthrough	0.0168***	0.0094***	0.0213***	0.0180***	0.0076***	0.0069***
	(0.0012)	(0.0012)	(0.0009)	(0.0010)	(0.0006)	(0.0007)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
CZ x Research Field x Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Single-Market Lab FE	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.4865	0.4743	0.4124	0.3687	0.2167	0.1789
Observations	710000	710000	710000	710000	710000	710000
Mean(Dependant Var)	0.2878	0.2673	0.2104	0.1969	0.0523	0.04811

Table 6: **Innovation Outputs and Enforceability of Noncompetes**

This table reports the effects of scientific breakthroughs, labor market thickness and the interplay with Noncompetes on the patent-based innovation outputs based on Model 4.1. The unit of observation is a lab-year. $\mathbf{1}_{\{HighNCE=1\}}$ is an indicator of high enforceability of noncompetes in the upper quartile in terms of non-competes enforceability (NCE). *Breakthrough* represents the intensity of breakthroughs measured by the natural logarithm of one plus the total scientific breakthroughs by technology class in year $t-3$ to $t-1$. *Thickness* is the natural logarithm of total inventors in the research field x CZ in year $t-3$. $Log(Patents)$ is constructed as the natural logarithm of one plus the sum of the patents generated by each lab-year. $Log(Citations)$ is constructed as the natural logarithm of one plus the sum of the adjusted citations received by patents filed by each lab-year. In addition to the variables shown, I control for all lab characteristics used in Table 3, including Lab Size, Firm Size, Age, Internal Labor Market and Innovation Experience. Fixed effects included in each regression are indicated in the column. Standard errors are clustered at the LLM-year level. Stars denote standard statistical significance (***$p < 0.01$, **$p < 0.05$, *$p < 0.1$, respectively).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependant Var:	Log(Patents)	Log(Citations)	Log(Patents)	Log(Citations)	Log(Patents)	Log(Citations)	Log(Patents)	Log(Citations)
	All		by Incumbents		by New-Hires		by Recent New-Hires	
Breakthrough x Thickness x $\mathbf{1}_{\{HighNCE=1\}}$	-0.0162***	-0.0164***	-0.0114***	-0.0124***	-0.0146***	-0.0135***	-0.0081***	-0.0073***
	(0.0024)	(0.0025)	(0.0020)	(0.0021)	(0.0016)	(0.0017)	(0.0008)	(0.0009)
Breakthrough x Thickness	0.0122***	0.0102***	0.0065***	0.0049***	0.0158***	0.0142***	0.0096***	0.0086***
	(0.0019)	(0.0019)	(0.0016)	(0.0016)	(0.0012)	(0.0013)	(0.0007)	(0.0008)
Thickness x $\mathbf{1}_{\{HighNCE=1\}}$	-0.0099***	-0.0034	-0.0034*	0.0029	-0.0074***	-0.0044**	-0.0053***	-0.0031***
	(0.0023)	(0.0024)	(0.0020)	(0.0020)	(0.0017)	(0.0018)	(0.0009)	(0.0009)
Breakthrough x $\mathbf{1}_{\{HighNCE=1\}}$	-0.0019	0.0026	-0.0006	0.0028	-0.0019	0.0014	-0.0039***	-0.0029***
	(0.0021)	(0.0022)	(0.0018)	(0.0019)	(0.0015)	(0.0016)	(0.0007)	(0.0008)
Breakthrough	0.0315***	0.0217***	0.0168***	0.0086***	0.0216***	0.0174***	0.0076***	0.0069***
	(0.0014)	(0.0015)	(0.0012)	(0.0013)	(0.0010)	(0.0011)	(0.0005)	(0.0006)
$\mathbf{1}_{\{HighNCE=1\}}$	0.0183***	0.0134***	0.0152***	0.0110***	0.0148***	0.0106***	0.0099***	0.0073***
	(0.0034)	(0.0033)	(0.0030)	(0.0028)	(0.0023)	(0.0023)	(0.0014)	(0.0013)
CZ x Research Field x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Single-Market Lab FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.5019	0.4831	0.4866	0.4744	0.4126	0.3687	0.217	0.1791
Observations	710000	710000	710000	710000	710000	710000	710000	710000

Table 7: **Breakthroughs and Effective Thickness: An Example**

This table reports a numerical example to illustrate economic magnitude of the total effect on the quantity of patent produced, $Log(Patents)$, shown in each cell represents and calculated as the sum of all main effects and interaction effects based on coefficients estimated in Column (1) of Table 6. $\mathbf{1}_{\{HighNCE=1\}}$ is an indicator of high enforceability of noncompetes in the upper quartile in terms of non-competes enforceability (NCE). $Breakthrough$ represents the intensity of breakthroughs measured by the natural logarithm of one plus the total scientific breakthroughs by technology class in year $t-3$ to $t-1$. The type of Local Labor Market is identified by $Thickness$. $Thickness$ is the natural logarithm of total inventors in the research field x CZ in year $t-3$. As an example, a $Thick$ labor market is taken such that its $Thickness$ is 1.5 standard deviation above an average market, representing a top 5% local labor market in terms of $Thickness$; while an $Average$ LLM has an average size of inventor cluster. As the intensity increases, the labs in the thick market without restrictions on labor mobility response increasingly stronger to breakthroughs, while in the market with NCs, the increase in patenting is weaker. Following a median wave breakthroughs, an average market without NCs can promote labs' innovation as good as a top 5% thick market with NCs. R&D labs in the top 5% thick market could have enjoyed 60% (=1.2%/2%) more boost in patent productivity that would otherwise emerge without NCs.

	(1)	(2)	(3)	(4)	(5)
Type of Local Labor Market	Thick	Thick	Average	(2)-(3)	(1)-(2)
Non-competes Enforceability	Low	High	Low		
Breakthrough Intensity					
1	-3%	-1.2%	-1.9%	0.7%	-1.8%
2	-1.8%	-0.6%	-1.2%	0.6%	-1.2%
3	3.2%	2%	2%	0%	1.2%
4	5.7%	3.2%	3.6%	-0.3%	2.4%
5	8.2%	4.6%	5.2%	-0.7%	3.7%

Table 8: **Inventor Turnovers, Labor Market Thickness and Enforceability of Noncompetes**

This table reports the effects of scientific breakthroughs, labor market thickness and the interplay with Noncompetes on the inventor turnovers based on Model 3.1 in Panel A and Model 4.1 in Panel B. The unit of observation is a lab-year. $\mathbf{1}_{\{HighNCE=1\}}$ is an indicator of high enforceability of noncompetes in the upper quartile in terms of non-competes enforceability (NCE). $Breakthrough$ represents the intensity of breakthroughs measured by the natural logarithm of one plus the total scientific breakthroughs by technology class in year $t-3$ to $t-1$. $Thickness$ is the natural logarithm of total inventors in the research field x CZ in year $t-3$. $Log(Turnover)$ is constructed as the natural logarithm of one plus the sum of inventor moves in each lab-year. $RecentMoves$ is defined as moves within the recent three years. In addition to the variables shown, I control for all lab characteristics used in Table 3, including Lab Size, Firm Size, Age, Internal Labor Market and Innovation Experience. Fixed effects included in each regression are indicated in the column. Standard errors are clustered at the LLM-year level. Stars denote standard statistical significance (***$p < 0.01$, **$p < 0.05$, *$p < 0.1$, respectively).

	(1)	(2)	(3)	(4)
Dependant Var:	Log(Turnover)	Log(Local Turnover)	Log(Turnover)	Log(Local Turnover)
	All Moves		Recent Moves	
PanelA				
Breakthrough x Thickness	0.0163***	0.0163***	0.0114***	(0.0102***
	(0.0015)	(0.0012)	(0.0008)	(0.0008)
Breakthrough	0.0310***	0.0160***	0.0104***	0.0079***
	(0.0013)	(0.0008)	(0.0006)	(0.0006)
R-squared	0.4809	0.3376	0.3195	0.2404
PanelB				
Breakthrough x Thickness x $\mathbf{1}_{\{HighNCE=1\}}$	-0.0150***	-0.0116***	-0.0088***	-0.0068***
	(0.0023)	(0.0014)	(0.0011)	(0.0010)
Breakthrough x Thickness	0.0200***	0.0190***	0.0135***	0.0118***
	(0.0016)	(0.0013)	(0.0009)	(0.0008)
Thickness x $\mathbf{1}_{\{HighNCE=1\}}$	-0.0078***	-0.0079***	-0.0042***	-0.0036***
	(0.0023)	(0.0014)	(0.0011)	(0.0009)
Breakthrough x $\mathbf{1}_{\{HighNCE=1\}}$	-0.0012	-0.0092***	-0.0046***	-0.0048***
	(0.0020)	(0.0012)	(0.0010)	(0.0008)
Breakthrough	0.0310***	0.0180***	0.0114***	0.0090***
	(0.0013)	(0.0009)	(0.0007)	(0.0006)
$\mathbf{1}_{\{HighNCE=1\}}$	0.0166***	0.0149***	0.0109***	0.0106***
	(0.0032)	(0.0023)	(0.0017)	(0.0016)
R-squared	0.481	0.3378	0.3196	0.2407
CZ x Research Field x Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Single-Market Lab FE	Yes	Yes	Yes	Yes
Observations	710000	710000	710000	710000

Table 9: **The Direction of Human Capital Reallocation: Exposure to Breakthroughs**

This table reports the estimated effects of scientific breakthroughs, lab-level exposure to breakthroughs, and the interplay with labor market thickness on the direction of human capital allocation (Panel A) and on the patent-based innovation outputs (Panel B), based on a modified Model 4.1. The unit of observation is a lab-year. *Exposure* measures the lab-level average exposure to breakthroughs in the given year based on the similarity of textual description between patents of the lab and the breakthroughs. $Log(Onboarding)$ is constructed as the natural logarithm of one plus the sum of onboarding inventors in each lab-year. $Log(Offboarding)$ is constructed as the natural logarithm of one plus the sum of offboarding inventors in each lab-year. Tech-Class Matched indicates a subset of inventors whose main technology area is the same as the lab's. In addition to the variables shown, I control for all lab characteristics used in Table 3, including Lab Size, Firm Size, Age, Internal Labor Market and Innovation Experience. Fixed effects included in each regression are indicated in the column. Standard errors are clustered at the LLM-year level. Stars denote standard statistical significance (***$p < 0.01$, **$p < 0.05$, *$p < 0.1$, respectively).

PanelA	(1)	(2)	(3)	(4)
Dependant Var:	Log(Onboarding)	Log(Offboarding)	Log(Onboarding)	Log(Offboarding)
	All Inventors		Tech-Class Matched	
Breakthrough x Thickness x Exposure	0.0028***	-0.0013	0.0025***	-0.0025***
	(0.0010)	(0.0009)	(0.0009)	(0.0009)
Breakthrough x Exposure	0.0122***	-0.0016*	0.0131***	-0.0017**
	(0.0010)	(0.0009)	(0.0008)	(0.0007)
Breakthrough x Thickness	0.0059***	0.0049***	0.100***	0.0078***
	(0.0013)	(0.0011)	(0.0010)	(0.0010)
Thickness x Exposure	0.0175***	0.0143***	0.0202***	0.0174***
	(0.0013)	(0.0013)	(0.0012)	(0.0012)
Breakthrough	0.0150***	0.0008	0.0216***	0.0084***
	(0.0011)	(0.0010)	(0.0009)	(0.0008)
Exposure	0.0195***	0.0212***	0.0163***	0.0196***
	(0.0013)	(0.0013)	-0.0012	(0.0011)
R-squared	0.4196	0.3981	0.3515	0.3173

PanelB	(1)	(2)	(3)	(4)
Dependant Var:	Log(Patents)	Log(Citations)	Log(Top-Cited)	Log(Important)
Breakthrough x Thickness x Exposure	0.0035***	0.0048***	0.0025***	0.0073***
	(0.0012)	(0.0013)	(0.0007)	(0.0011)
Breakthrough x Exposure	0.0051***	0.0122***	0.0055***	0.0237***
	(0.0011)	(0.0012)	(0.0006)	(0.0008)
Breakthrough x Thickness	-0.0004	-0.0027	-0.0018**	0.0044***
	(0.0017)	(0.0018)	(0.0007)	(0.0008)
Thickness x Exposure	0.0166***	0.0171***	0.0123***	0.0098***
	(0.0017)	(0.0019)	(0.0010)	(0.0014)
Breakthrough	0.0146***	0.0084***	0.001	0.0115***
	(0.0013)	(0.0014)	(0.0006)	(0.0007)
Exposure	0.048***	0.0260***	0.0039***	0.0144***
	(0.0016)	(0.0017)	(0.0009)	(0.0010)
Industry FE	Yes	Yes	Yes	Yes
CZ x Research Field x Year FE	Yes	Yes	Yes	Yes
Single-Market Lab FE	Yes	Yes	Yes	Yes
R-squared	0.5057	0.4858	0.3961	0.3236
Observations	710000	710000	710000	710000

Table 10: **Characteristics of New Hires and Inventor Teams**

This table reports the effects of scientific breakthroughs and labor market thickness on the Characteristics of New Hires based on Model 3.1. The unit of observation is a lab-year. $\mathbf{1}_{\{HighNCE=1\}}$ is an indicator of high enforceability of noncompetes in the upper quartile in terms of non-competes enforceability (NCE). $Breakthrough$ represents the intensity of breakthroughs measured by the natural logarithm of one plus the total scientific breakthroughs by technology class in year $t-3$ to $t-1$. $Thickness$ is the natural logarithm of total inventors in the research field x CZ in year $t-3$. $Tech-ClassMatch$ is the percentage of onboarding inventors who exactly match the technology class of the lab-year. $TechnologicalProximity$ is the average cosine distance in technology vectors between newly-hired inventors with the focal lab in a given year. $KnowledgeOverlapping$ is the average similarity in knowledge base between newly-hired inventors and the focal lab in a given year. In addition to the variables shown, I control for all lab characteristics used in Table 3, including Lab Size, Firm Size, Age, Internal Labor Market and Innovation Experience. Fixed effects included in each regression are indicated in the column. Standard errors are clustered at the LLM-year level. Stars denote standard statistical significance (***$p < 0.01$, **$p < 0.05$, *$p < 0.1$, respectively).

	(1)	(2)	(3)
Dependant Var:	Tech-Class Match (Percent)	Technological Proximity	Knowledge Overlapping (Percent)
Breakthrough x Thickness	1.980***	0.0174***	-0.2064***
	(0.3074)	(0.0022)	(0.0694)
Breakthrough	4.523***	0.0308***	0.0035
	(0.2368)	-0.0017	(0.0571)
Lab Size	1.062***	0.0109***	0.2911***
	(0.1669)	(0.0012)	(0.0441)
Firm Size	-4.712***	0.0310***	-0.9762***
	(0.4038)	(0.0030)	(0.1024)
Age	-3.034***	-0.0278***	-0.4039***
	(0.2083)	(0.0017)	(0.0551)
Internal Labor Market	-3.299***	-0.0182***	-0.2477***
	(0.1627)	(0.0012)	(0.0408)
Innovation Experience	-0.2395***	0.0264***	1.334***
	(0.0863)	(0.0007)	(0.0269)
Inexperienced New-Hires			-3.497***
			(0.0397)
Experienced New-Hires			3.117***
			(0.0195)
Industry FE	Yes	Yes	Yes
CZ x Research Field x Year FE	Yes	Yes	Yes
Single-Market Lab FE	Yes	Yes	Yes
R-squared	0.196	0.1957	0.3466
Observations	130000	130000	130000

Table 11: **Baseline Specification with Additional Controls**

This table reports the effects of scientific breakthroughs, labor market thickness and the interplay with Noncompetes patent outputs based and inventor turnovers based on Model 3.1 in Panel A and Model 4.1 in Panel B with additional fixed effects. The unit of observation is a lab-year. *Breakthrough* represents the intensity of breakthroughs measured by the natural logarithm of one plus the total scientific breakthroughs by technology class in year $t-3$ to $t-1$. *Thickness* is the natural logarithm of total inventors in the research field x CZ in year $t-3$. $Log(Patents)$ or Pat is constructed as the natural logarithm of one plus the sum of the patents generated by each lab-year. $Log(Important)$ or $Impt$is constructed as the natural logarithm of one plus the sum of the importance-weighted patents generated by each lab-year. $Log(Turnover)$ or TO is constructed as the natural logarithm of one plus the sum of inventor moves in each lab-year. In addition to the variables shown, I control for all lab characteristics used in Table 3, including Lab Size, Firm Size, Age, Internal Labor Market and Innovation Experience. Fixed effects included in each regression are indicated in the column. Standard errors are clustered at the LLM-year level. Stars denote standard statistical significance (***$p<0.01$, **$p<0.05$, *$p<0.1$, respectively).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependant Var:	Pat	Impt	TO	Local TO	Pat	Impt	TO	Local TO
Panel A : LLM x Age Cohort FE								
Breakthrough x Thickness	0.0082***	0.0117***	0.0167***	0.0165***	0.0123***	0.0131***	0.0204***	0.0193***
	(0.0017)	(0.0010)	(0.0015)	(0.0011)	(0.0019)	(0.0011)	(0.0016)	(0.0013)
Breakthrough x Thickness x $\mathbf{1}_{\{HighNCE=1\}}$					-0.0164***	-0.0061***	-0.0147***	-0.0115***
					(0.0023)	(0.0013)	(0.0022)	(0.0014)
Panel B : LLM x Size Cohort FE								
Breakthrough x Thickness	0.0079***	0.0107***	0.0161***	0.0160***	0.0119***	0.0120***	0.0198***	0.0188***
	(0.0018)	(0.0010)	(0.0015)	(0.0012)	(0.0019)	(0.0010)	(0.0016)	(0.0013)
Breakthrough x Thickness x $\mathbf{1}_{\{HighNCE=1\}}$					-0.0162***	-0.0058***	-0.0149***	-0.0116***
					(0.0024)	(0.0013)	(0.0023)	(0.0015)
Panel C : LLM x Single-Market Lab FE								
Breakthrough x Thickness	0.0073***	0.0114***	0.0156***	0.0158***	0.0114***	0.0128***	0.0193***	0.0186***
	(0.0018)	(0.0010)	(0.0015)	(0.0011)	(0.0019)	(0.0011)	(0.0016)	(0.0013)
Breakthrough x Thickness x $\mathbf{1}_{\{HighNCE=1\}}$					-0.0160***	-0.0062***	-0.0146***	-0.0115***
					(0.0023)	(0.0013)	(0.0022)	(0.0014)
Panel D : LLM x VC FE								
Breakthrough x Thickness	0.0086***	0.0117***	0.0165***	0.0163***	0.0129***	0.0132***	0.0205***	0.0193***
	(0.0017)	(0.0010)	(0.0015)	(0.0011)	(0.0019)	(0.0010)	(0.0016)	(0.0013)
Breakthrough x Thickness x $\mathbf{1}_{\{HighNCE=1\}}$					-0.0168***	-0.0067***	-0.0161***	-0.0124***
					(0.0024)	(0.0013)	(0.0023)	(0.0014)
Panel E : LLM x Age Cohort x Size Cohort x Single-Market Lab x VC FE								
Breakthrough x Thickness	0.0063***	0.0104***	0.0146***	0.0153***	0.0101***	0.0116***	0.0182***	0.0179***
	(0.0017)	(0.0009)	(0.0015)	(0.0012)	(0.0019)	(0.0010)	(0.0016)	(0.0013)
Breakthrough x Thickness x $\mathbf{1}_{\{HighNCE=1\}}$					-0.0157***	-0.0052***	-0.0142***	-0.0112***
					(0.0023)	(0.0012)	(0.0022)	(0.0014)
CZ x Research Field x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Single-Market Lab FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	710000	710000	710000	710000	710000	710000	710000	710000

Table 12: **Geography of Scientific Breakthroughs and Distant Shocks**

This table reports the effects of scientific breakthroughs, labor market thickness and the interplay with Noncompetes patent outputs based and inventor turnovers based on Model 3.1 in Panel A and Model 4.1 in Panel B with additional fixed effects. The unit of observation is a lab-year. Breakthrough$_{OutState}$ represents the intensity of breakthroughs generated out-of-state measured by the natural logarithm of one plus the total scientific breakthroughs by technology class in year $t-3$ to $t-1$. Breakthrough$_{InState}$ represents the intensity of breakthroughs generated within-state measured by the natural logarithm of one plus the total scientific breakthroughs by technology class in year $t-3$ to $t-1$. $Thickness$ is the natural logarithm of total inventors in the research field x CZ in year $t-3$. $Log(Patents)$ or Pat is constructed as the natural logarithm of one plus the sum of the patents generated by each lab-year. $Log(Important)$ or $Impt$is constructed as the natural logarithm of one plus the sum of the importance-weighted patents generated by each lab-year. $Log(Turnover)$ or TO is constructed as the natural logarithm of one plus the sum of inventor moves in each lab-year. In addition to the variables shown, I control for all lab characteristics used in Table 3, including Lab Size, Firm Size, Age, Internal Labor Market and Innovation Experience. Fixed effects included in each regression are indicated in the column. Standard errors are clustered at the LLM-year level. Stars denote standard statistical significance (***$p<0.01$, **$p<0.05$, *$p<0.1$

Panel A	(1)	(2)	(3)	(4)
Dependant Var:	Log(Patents)	Log(Important Patents)	Log(Turnover)	Log(Local Turnover)
Breakthrough$_{OutState}$ x Thickness	0.0035*	0.0140***	0.0102***	0.0098***
	(0.0020)	(0.0015)	(0.0017)	(0.0014)
Breakthrough$_{OutState}$	0.0225***	0.0251***	0.0236***	0.0091***
	(0.0017)	(0.0010)	(0.0016)	(0.0011)
Breakthrough$_{InState}$ x Thickness	0.0012	-0.0036***	0.0037**	0.0046***
	(0.0022)	(0.0014)	(0.0017)	(0.0015)
Breakthrough$_{InState}$	0.0098***	0.0027**	0.0078***	0.0065***
	(0.0016)	(0.0011)	(0.0016)	(0.0010)
R-squared	0.5018	0.3069	0.4809	0.3375
Panel B				
Breakthrough$_{OutState}$ x Thickness x $\mathbf{1}_{\{HighNCE=1\}}$	-0.0154***	-0.0069***	-0.0142***	-0.0101***
	(0.0024)	(0.0013)	(0.0023)	(0.0014)
Breakthrough$_{OutState}$ x Thickness	0.0079***	0.0157***	0.0142***	0.0126***
	(0.0022)	(0.0016)	(0.0019)	(0.0015)
Thicknessx $\mathbf{1}_{\{HighNCE=1\}}$	-0.0094***	0.0041***	-0.0072***	-0.0077***
	(0.0023)	(0.0011)	(0.0023)	(0.0014)
Breakthrough$_{OutState}$ x Thickness	-0.0017	0.0014	-0.0011	-0.0085***
	(0.0021)	(0.0013)	(0.0020)	(0.0012)
Breakthrough$_{OutState}$	0.0228***	0.0247***	0.0237***	0.0113***
	(0.0018)	(0.0011)	(0.0017)	(0.0012)
Breakthrough$_{InState}$ x Thickness	0.0004	-0.0039***	0.0030*	0.0041***
	(0.0022)	(0.0014)	(0.0018)	(0.0016)
Breakthrough$_{InState}$	0.0099***	0.0028**	0.0079***	0.0061***
	(0.0016)	(0.0011)	(0.0016)	(0.0010)
$\mathbf{1}_{\{HighNCE=1\}}$	0.0181***	0.0021	0.0163***	0.0147***
	(0.0034)	(0.0017)	(0.0032)	(0.0023)
R-squared	0.5019	0.307	0.4809	0.3377
CZ x Research Field x Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Single-Market Lab FE	Yes	Yes	Yes	Yes
Observations	710000	710000	710000	710000

Table 13: **First-Wave Scientific Breakthroughs and Historical Measure of LLM Thickness**

This table reports the effects of scientific breakthroughs, labor market thickness and the interplay with Noncompetes patent outputs based and inventor turnovers based on Model 5.1 in Panel A and a similarly-modified Model 4.1 in Panel B with additional fixed effects. The unit of observation is a lab-year. Breakthrough represents the intensity of first-wave breakthroughs measured by the natural logarithm of one plus the total scientific breakthroughs by technology class in year $t-3$ to $t-1$. The first-wave is defined as first year when the annual count of breakthroughs innovations attain 25% of its historical maximum. *Thickness* is the natural logarithm of total inventors in the research field x CZ in year $t-10$. $Log(Patents)$ or Pat is constructed as the natural logarithm of one plus the sum of the patents generated by each lab-year. $Log(Important)$ or $Impt$is constructed as the natural logarithm of one plus the sum of the importance-weighted patents generated by each lab-year. $Log(Turnover)$ or TO is constructed as the natural logarithm of one plus the sum of inventor moves in each lab-year. In addition to the variables shown, I control for all lab characteristics used in Table 3, including Lab Size, Firm Size, Age, Internal Labor Market and Innovation Experience. Fixed effects included in each regression are indicated in the column. Standard errors are clustered at the LLM-year level. Stars denote standard statistical significance (***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

Dependant Var:	(1) log(Patents)	(2) log(Important Patents)	(3) log(Turnover)	(4) log(Local Turnover)
Panel A				
Breakthrough x Thickness$_{t-10}$	0.0319**	0.0233**	0.0469***	0.0192***
	(0.0131)	(0.0094)	(0.0125)	(0.0064)
Breakthrough	0.0846***	0.0628***	0.0805***	0.0275***
	(0.0130)	(0.0090)	(0.0118)	(0.0062)
R-squared	0.2311	0.2193	0.2376	0.1801
Panel B				
Breakthrough x Thickness$_{t-10}$ x $\mathbf{1}_{\{HighNCE=1\}}$	-0.0342**	-0.0265**	-0.0227*	-0.0206**
	(0.0139)	(0.0106)	(0.0136)	(0.0087)
Breakthrough x Thickness$_{t-10}$	0.0258**	0.0251***	0.0363***	0.0194***
	(0.0112)	(0.0087)	(0.0108)	(0.0065)
Thickness$_{t-10}$x $\mathbf{1}_{\{HighNCE=1\}}$	-0.0192	-0.005	-0.0181	-0.0061
	(0.0152)	(0.0089)	(0.0148)	(0.0082)
Breakthrough x $\mathbf{1}_{\{HighNCE=1\}}$	0.0171	0.016	0.0194*	-0.0118
	(0.0119)	(0.0097)	(0.0113)	(0.0073)
Breakthrough	0.0542***	0.0511***	0.0466***	0.0207***
	(0.0108)	(0.0080)	(0.0098)	(0.0061)
$\mathbf{1}_{\{HighNCE=1\}}$	0.0017	-0.0032	0.0016	0.0024
	(0.0172)	(0.0111)	(0.0166)	(0.0088)
R-squared	0.4541	0.3167	0.5084	0.3078
CZ x Research Field x Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Single-Market Lab FE	Yes	Yes	Yes	Yes
Observations	26500	26500	26500	26500

Table 14: **With-Lab Analysis**

This table reports the effects of scientific breakthroughs and the interaction effects of labor market thickness on the patent-based innovation outputs based on Model 3.1 with lab fixed effects. The unit of observation is a lab-year. *Breakthrough* represents the intensity of breakthroughs measured by the natural logarithm of one plus the total scientific breakthroughs by technology class in year $t-3$ to $t-1$. *Thickness* is the natural logarithm of total inventors in the research field x CZ in year $t-3$. $Log(Patents)$ is constructed as the natural logarithm of one plus the sum of the patents generated by each lab-year. $Log(Citations)$ is constructed as the natural logarithm of one plus the sum of the adjusted citations received by patents filed by each lab-year. Other variables are defined in Table 3. Similar definitions apply to core patents which are inventions in labs' core tech area, non-core patents as the rest, exploratory and exploitative patents. In addition to the variables shown, I control for lab characteristics used in Table 3, including Lab Size, Firm Size, Internal Labor Market and Innovation Experience. Fixed effects included in each regression are indicated in the column. Standard errors are clustered at the LLM-year level. Stars denote standard statistical significance (***$p < 0.01$, **$p < 0.05$, *$p < 0.1$, respectively).

Panel A	(1)	(2)	(3)	(4)	(5)	(6)
Dependant Var:	Log(Patents)	Log(Citations)	Log(Top-Cited Patents)	Log(Important Patents)	$Log(Pay/Emp)_{t+1}$	$Log(Emp)_{t+1}$
Breakthrough x Thickness	0.0116***	0.0147***	0.0037***	0.0102***	0.0325***	0.0105***
	(0.0015)	(0.0017)	(0.0008)	(0.0011)	(0.0038)	(0.0030)
Breakthrough	0.0222***	0.0339***	0.0124***	0.0352***	0.0285***	0.0083***
	(0.0019)	(0.0021)	(0.0010)	(0.0014)	(0.0034)	(0.0032)
R-squared	0.7258	0.6805	0.6481	0.6515	0.4655	0.8579

Panel B	(1)	(2)	(3)	(4)	(5)	(6)
Dependant Var:	Log(Onboarding)	Log(Offboarding)	Log(Onboarding)	Log(Offboarding)	Log(Onboarding)	Log(Offboarding)
	All Inventors		Tech-Class Matched		Local Matched	
Breakthrough x Thickness	0.0107***	-0.0058***	0.0098***	-0.0062***	0.0013*	-0.0034***
	(0.0012)	(0.0012)	(0.0011)	(0.0011)	(0.0008)	(0.0010)
Breakthrough	0.0206***	-0.0048***	0.0169***	-0.0085***	0.0025**	-0.0032***
	(0.0016)	(0.0016)	(0.0015)	(0.0014)	(0.0010)	(0.0010)
R-squared	0.641	0.5607	0.5976	0.4915	0.508	0.4737
Lab FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Research Field FE	Yes	Yes	Yes	Yes	Yes	Yes
CZ FE	Yes	Yes	Yes	Yes	Yes	Yes
Single-Market Lab FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	710000	710000	710000	710000	710000	710000

Appendix

A1 Figures

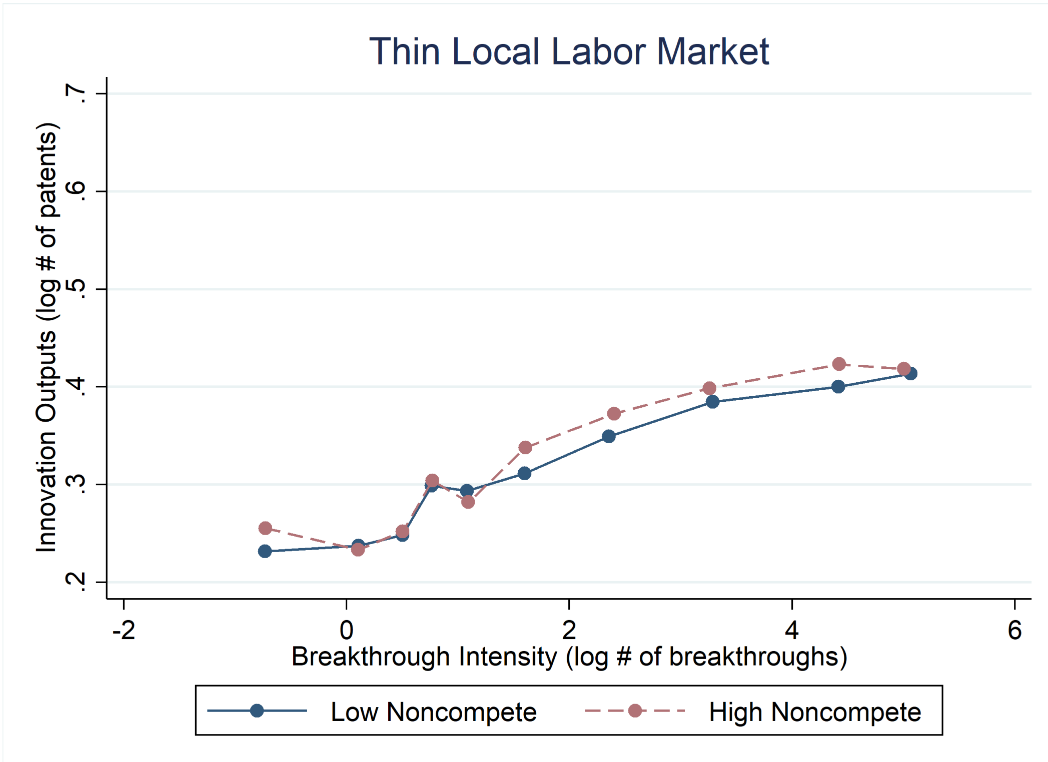

Figure A1: **Innovation of R&D Labs in Thin LLM by Enforceability of Noncompetes.** The figure shows the binned plots of innovation outputs (log number of patents) produced by R&D labs in a given year and the intensity of scientific breakthroughs measured by the log number of technology-specific breakthroughs in the past three years, conditioning only on application year effects. This plot corresponds to the regression in Table 4 Column 1. A same sample is used and variables in x and y-axis follow the same definitions. R&D labs are sorted into thick and thin local labor markets based on a median split of the labor market thickness.

A2 Tables

Table A1: **Labor Market Thickness and Enforceability of Noncompetes: Additional Results on Innovation Outputs**

This table reports the effects of scientific breakthroughs, labor market thickness and the interplay with Noncompetes on the patent-based innovation outputs based on Model 4.1. The unit of observation is a lab-year. $\mathbf{1}_{\{HighNCE=1\}}$ is an indicator of high enforceability of noncompetes in the upper quartile in terms of non-competes enforceability (NCE). *Breakthrough* represents the intensity of breakthroughs measured by the natural logarithm of one plus the total scientific breakthroughs by technology class in year $t-3$ to $t-1$. *Thickness* is the natural logarithm of total inventors in the research field x CZ in year $t-3$. In addition to the variables shown, I control for all lab characteristics used in Table 3, including Lab Size, Firm Size, Age, Internal Labor Market and Innovation Experience. Fixed effects included in each regression are indicated in the column. Standard errors are clustered at the LLM-year level. Stars denote standard statistical significance (***$p < 0.01$, **$p < 0.05$, *$p < 0.1$, respectively).

Panel A	(1)	(2)	(3)	(4)
Dependant Var:	Log(Top-Cited Pat)	Log(Important Pat)	Log(Exploratory Pat)	Log(Exploitative Pat)
Breakthrough x Thickness x $\mathbf{1}_{\{HighNCE=1\}}$	-0.0077***	-0.0062***	-0.0153***	-0.0006
	(0.0011)	(0.0013)	(0.0019)	(0.0012)
Breakthrough x Thickness	0.0053***	0.0132***	0.0107***	-0.0028***
	(0.0008)	(0.0011)	(0.0015)	(0.0008)
Thickness x $\mathbf{1}_{\{HighNCE=1\}}$	0.0023**	0.0040***	0.0002	0.0057***
	(0.0011)	(0.0011)	(0.0019)	(0.0012)
Breakthrough x $\mathbf{1}_{\{HighNCE=1\}}$	0.0028***	0.0016	0.0033*	0.0046***
	(0.0010)	(0.0013)	(0.0018)	(0.0010)
Breakthrough	0.0041***	0.0253***	0.0143***	0.007***
	(0.0007)	(0.0009)	(0.0012)	(0.0007)
$\mathbf{1}_{\{HighNCE=1\}}$	0.0063***	0.0023	0.057**	-0.0023
	(0.0014)	(0.0017)	(0.0026)	(0.0015)
CZ x Research Field x Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Single-Market Lab FE	Yes	Yes	Yes	Yes
R-squared	0..3941	0.3069	0.5601	0.185
Observations	710000	710000	710000	710000

Panel B	(5)	(6)	(7)	(8)
Dependant Var:	Log(Core Pat)	Log(Core Cite)	Log(Noncore Pat)	Log(Noncore Cite)
Breakthrough x Thickness x $\mathbf{1}_{\{HighNCE=1\}}$	-0.0096***	-0.0110***	-0.0161***	-0.0151***
	(0.0021)	(0.0023)	(0.0016)	(0.0017)
Breakthrough x Thickness	0.0111***	0.0093***	0.0077***	0.0067***
	(0.0016)	(0.0017)	(0.0013)	(0.0014)
Thickness x $\mathbf{1}_{\{HighNCE=1\}}$	0.002	0.0068***	-0.0164***	-0.0109***
	(0.0021)	(0.0021)	(0.0016)	(0.0017)
Breakthrough x $\mathbf{1}_{\{HighNCE=1\}}$	0.0001	0.0053**	-0.002	-0.0018
	(0.0019)	(0.0021)	(0.0014)	(0.0015)
Breakthrough	0.0286***	0.0153***	0.0054***	0.0062***
	(0.0013)	(0.0014)	(0.0010)	(0.0011)
$\mathbf{1}_{\{HighNCE=1\}}$	0.0105***	0.0070**	0.0228***	0.0191***
	(0.0030)	(0.0029)	(0.0026)	(0.0024)
CZ x Research Field x Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Single-Market Lab FE	Yes	Yes	Yes	Yes
R-squared	0.4552	0.4334	0.4309	0.3857
Observations	710000	710000	710000	710000

Table 2: **With-Lab Analysis: Additional Results**

This table reports the effects of scientific breakthroughs and the interaction effects of labor market thickness on the patent-based innovation outputs based on Model 3.1 with lab fixed effects. The unit of observation is a lab-year. *Breakthrough* represents the intensity of breakthroughs measured by the natural logarithm of one plus the total scientific breakthroughs by technology class in year $t-3$ to $t-1$. *Thickness* is the natural logarithm of total inventors in the research field x CZ in year $t-3$. $Log(Top-Cited)$ is constructed as the natural logarithm of one plus the sum of the top patents generated by each lab-year. $Log(Important)$ is constructed as the natural logarithm of one plus the sum of the importance-weighted patents generated by each lab-year. Similar definitions apply to core patents which are inventions in labs' core tech area, non-core patents as the rest, exploratory and exploitative patents. Other variables are defined in Table 3. In addition to the variables shown, I control for lab characteristics used in Table 3, including Lab Size, Firm Size, Internal Labor Market and Innovation Experience. Fixed effects included in each regression are indicated in the column. Standard errors are clustered at the LLM-year level. Stars denote standard statistical significance (***$p<0.01$, **$p<0.05$, *$p<0.1$, respectively).

Panel A	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependant Var:	Log(Patents) Core	Log(Citations) Core	Log(Patents) Noncore	Log(Citations) Noncore	Log(Patents) Exploratory	Log(Patents) Exploitative	$\mathbf{1}_{\{Star(TopCited)_{t,t+5}=1\}}$	$\mathbf{1}_{\{Star(Important)_{t,t+5}=1\}}$
Breakthrough x Thickness	0.0093***	0.0117***	0.0065***	0.0098***	0.0084***	-0.0001	0.0019***	0.0077***
	(0.0014)	(0.0015)	(0.0011)	(0.0012)	(0.0013)	(0.0008)	(0.0003)	(0.0005)
Breakthrough	0.0196***	0.0279***	0.0142***	0.0213***	0.0196***	0.0066***	-0.0018***	0.0031***
	(0.0018)	(0.0019)	(0.0013)	(0.0014)	(0.0017)	(0.0011)	(0.0004)	(0.0005)
Thickness	0.1613***	0.1376***	0.1093***	0.0908***	0.2198***	-0.0235***	0.0154***	-0.0060***
	(0.0072)	(0.0080)	(0.0056)	(0.0063)	(0.0077)	(0.0041)	(0.0017)	(0.0023)
R-squared	0.6924	0.6484	0.7089	0.6431	0.7456	0.4164	0.673	0.5317
Lab FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Research Field FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CZ FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Single-Market Lab FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations(Rounded)	710000	710000	710000	710000	710000	710000	710000	710000

Table 2 (Continued)

Panel B	(1)	(2)	(3)	(4)	(5)	(6)
Dependant Var:	Log(Patents) by Incumbents	Log(Citations)	Log(Patents) by New-Hires	Log(Citations)	Log(Patents) by Recent New-Hires	Log(Citations)
Breakthrough x Thickness	0.0073***	0.0102***	0.0099***	0.0128***	0.0030***	0.0061***
	(0.0013)	(0.0015)	(0.0011)	(0.0013)	(0.0007)	(0.0008)
Breakthrough	0.0178***	0.0287***	0.0176***	0.0227***	0.0048***	0.0080***
	(0.0017)	(0.0019)	(0.0014)	(0.0016)	(0.0008)	(0.0009)
Thickness	0.1498***	0.1212***	0.1151***	0.1055***	0.0741***	0.0651***
	(0.0065)	(0.0073)	(0.0064)	(0.0072)	(0.0044)	(0.0046)
R-squared	0.7218	0.6803	0.6478	0.5883	0.4755	0.4077
Lab FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Research Field FE	Yes	Yes	Yes	Yes	Yes	Yes
CZ FE	Yes	Yes	Yes	Yes	Yes	Yes
Single-Market Lab FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations(Rounded)	710000	710000	710000	710000	710000	710000

Table 3: **Variable Definitions**

This table provides variable definitions.

VARIABLE NAME	DEFINITION
Breakthrough	log (1+ number of scentific breakthroughs from year t-1 to t-3); standardized.
Breakthrough(t-j)	log (1+ number of scentific breakthroughs in year t-j respectively); standardized.
Thickness	log number of inventors in a specific research field in year t-3; standardized.
Thickness$_{t-10}$	log number of inventors in a specific research field in year t-10; standardized.
Lab Size	log employment of R&D labs; standardized.
Firm Size	log employment of firms that R&D labs belong to; standardized.
Age	age of firms that R&D labs belong to; standardized.
Internal Labor Market	the number of LLM where firms operate innovative activities; standardized.
Innovation Experience	log (1+ total number of top patents belonging to a R&D lab as of year t); standardized.
Exploratory Experience	log (1+ total number of exploratory patents belonging to a R&D lab as of year t); standardized.
Exploitative Experience	log (1+ total number of exploitative patents belonging to a R&D lab as of year t); standardized.
$\mathbf{1}_{\{HighNCE=1\}}$	binary, =1 if the location and industry has high enforceability of Noncompete agreements.
Exposure	lab level average explosure to the scientific breakthroughs; standardized.
Breakthrough$_{OutState}$	log (1+ number of scentific breakthroughs originated from other states from year t-1 to t-3); standardized.
Breakthrough$_{InState}$	log (1+ number of scentific breakthroughs originated from own states from year t-1 to t-3); standardized.
$\mathbf{1}_{\{Single-MarketLab=1\}}$	binary, =1 if lab operates in only one local labor market.
Log(Patents)	log (1+ number of patents filed by a R&D lab in year t)
Log(Citations)	log (1+ number of citation received by patents filed by a R&D lab in year t)
Log(Top-Cited Patents)	log (1+ number of top patents filed by a R&D lab in year t)
Log(Important Patents)	log (1+ number of important patents filed by a R&D lab in year t)
Log(Core Patents)	log (1+ number of core patents filed by a R&D lab in year t)
Log(Core Citations)	og (1+ number of citation received by core patents filed by a R&D lab in year t)
Log(Noncore Patents)	log (1+ number of non-core patents filed by a R&D lab in year t).
Log(Noncore Citations)	log (1+ number of citation received by non-core patents filed by a R&D lab in year t).
Log(Exploratory Patents)	log (1+ number of exploratory patents filed by a R&D lab in year t)
Log(Exploitative Patents)	continuous, log (1+ number of exploitative patents filed by a R&D lab in year t)
Log(Patents by Incumbents)	log (1+ number of patents contributed by incumbent inventors in year t)
Log(Citations by Incumbents)	log (1+ number of citation received by patents contributed by incumbent inventors in year t))
Log(Patents by New-Hires)	log (1+ number of patents contributed by newly-hired inventors in year t)
Log(Citations by New-Hires)	log (1+ number of citation received by patents contributed by newly-hired inventors in year t))
Log(Patents by Recent New-Hires)	log (1+ number of patents contributed by recently-newly-hired inventors in year t)
Log(Citations by Recent New-Hires)	log (1+ number of citation received by patents contributed by recently-newly-hired inventors in year t)
$Log(Emp)_{t+1}$	log annual payroll by employment of a lab in year t+1).
$Log(Pay/Emp)_{t+1}$	log annual payroll by employment of a lab in year t+1).
$\mathbf{1}_{\{Star(TopCited)_{t,t+5}=1\}}$	binary, =1 if a lab becomes an innovative star based on total number of top patents filed in the next 5 years.
$\mathbf{1}_{\{Star(Important)_{t,t+5}=1\}}$	binary, =1 if a lab becomes an innovative star based on total number of immportant patents filed in the next 5 years.

Table 3 (Continued)

VARIABLE NAME	DEFINITION
Log(Turnover)	log number of any inventor turnovers in a R&D lab in year t.
Log(Local Turnover)	log number of local inventor turnovers in a R&D lab in year t.
Log(Recent Turnover)	log number of recent job-hopping local inventor turnovers in a R&D lab in year t.
Log(Recent Local Turnover)	log number of recent job-hopping local inventor turnovers in a R&D lab in year t.
Log(Remote Turnover)	log number of remote inventor turnovers in a R&D lab in year t.
Log(Internal Turnover)	log number of internal inventor turnovers in a R&D lab in year t.
Log(Onboarding Inventors)	log number of onboarding inventors in a R&D lab in year t.
Log(Offboarding Inventors)	log number of offboarding inventors in a R&D lab in year t.
Log(Onboarding Tech-Class Matched Inventors)	log number of onboarding inventors in the same technology class as the R&D lab in year t.
Log(Offboarding Tech-Class Matched Inventors)	log number of offboarding inventors in the same technology class as the R&D lab in year t.
Log(Onboarding Experienced Inventors)	log number of onboarding experienced invenors in a R&D lab in year t.
Log(Onboarding Inexperienced Inventors)	log number of onboarding first-time invenors in a R&D lab in year t.
Log(Onboarding Inexperienced Young Inventors)	log number of onboarding first-time invenors aged under 30 in a R&D lab in year t.
Log(Onboarding Local Inventors)	log number of onboarding local inventors in year t.
Log(Offboarding Local Inventors)	log number of offboarding local inventors n year t.
Knowledge Overlapping (%)	a measure of knowledge overlapping between onboarding inventors and the R&D lab in year t.
Technological Proximity	a measure of proximity between onboarding inventors and the R&D lab in the technological space in year t.
Tech-Class Match (%)	percentage of onboarding inventors that match the technology class of the R&D lab in year t.