Local Labor Markets and Corporate Innovation

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Abstract

We construct a measure (*fLMA*) of the extent to which neighboring firms hire similar types of workers, based on the similarity between the labor profile of a firm and that of its locality. We show that a firm's innovation is positively related to *fLMA*. The enhanced labor mobility induced by higher *fLMA* is an important channel for this positive relation. This relation is stronger when firms have increased outside job opportunities for employees, increased knowledge spillovers via coworkership, and more employee stock options. Innovation is higher when intellectual property ownership is with employers, not employees. This effect increases in *fLMA*.

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We are grateful to Jarrad Harford (the editor) and an anonymous referee. We thank Anup Agrawal, Jack He, Lei Kong, Ron Masulis, Avri Ravid, Tony Saunders, Fabian Slonimczyk, and Cihan Uzmanoglu and conference and seminar participants at AFA 2021, CFEA 2019 at NYU, CICF 2021, FMA 2020, University of Alabama, Higher School of Economics ICEF, Kent State University, University of New Mexico, Suffolk University, and University of Washington Bothell for helpful comments and suggestions.

I. Introduction

Innovation is critical for business competitiveness and long-term economic growth, and its determinants have been studied extensively. In this literature, patents have often been used to measure a firm's innovation intensity and success.[1] Interestingly, patent activity exhibits important geographic variation. For instance, according to the U.S. Patent and Trademark Office (USPTO), the Worcester, Massachusetts, Metropolitan Statistical Area (MSA) produced 637 patents in 2015, whereas the Baton Rouge, Louisiana, MSA, which is similar in population size, generated only 82 patents that same year. This variation has attracted attention from researchers, some of whom attribute it to differences in local human capital. This interpretation is plausible, as human capital is a key input for innovation and labor markets are markedly local (Molloy, Smith, and Wozniak (2011)).

Chief among plausible explanations is *labor market agglomeration*, a concept from the seminal work of Marshall (1890). Labor market agglomeration (LMA) refers to the extent to which neighboring firms, albeit from different industries, hire similar types of workers, thereby creating a shared pool of skills. LMA can benefit local firm innovation in several ways that are non-mutually exclusive. First, enhanced employee mobility between firms exposed to LMA can promote innovation (Saxenian (1994)). Specifically, the presence of many firms hiring similar workers may enable employees to have more outside options in their job search, which provides a strong incentive to innovate (Fulghieri and Sevilir (2011)).[2] In addition, given a large pool of relevant workers in a locality, firms can more easily hire skilled workers who create synergies with incumbent employees (Fallick, Fleischman, and Rebitzer (2006)). These interfirm mobility

[1] See He and Tian (2018), (2020) for excellent reviews of the literature.
[2] Given many outside options, employees may find it attractive to invest in human capital, which they can sell to another employer at a competitive price. This dynamic may improve the quality of local human capital in the long term, likely leading to better innovation outcomes (Acemoglu (1997)).

mechanisms are particularly important for innovative firms because investments in innovation, in contrast to other types of corporate investment, often fail, and firms need to try a diverse mix of employee human capital until they find a successful one. In addition to knowledge transfer facilitated by employees moving among firms, geographic proximity among workers located closely to each other in an agglomerated zone *per se* may enhance knowledge sharing.

LMA can also protect employees from unemployment risk to some extent, because they are likely to see their skills in demand in the locality and believe another firm will hire them if laid off. Protection from involuntary dismissal can be a particularly important incentive for employees working on high-risk, long-gestation innovation projects (Manso (2011), Acharya, Baghai, and Subramanian (2014)). Furthermore, employers' intellectual property ownership against their employees (Suh (2023)) and employee stock options (John, Lee, Thorburn, and Xu (2021))—both of which are more likely to be prevalent in firms facing greater LMA—can incentivize employees to innovate.

However, LMA can also discourage firms from investing in innovation. With employees holding many external options in a pooled labor market, firms might struggle to retain key talent (Almazan, De Motta, and Titman (2007) and John et al. (2021)). The departure of key employees may disrupt ongoing innovation processes, and firms may incur significant costs to replace them due to labor market frictions (e.g., the hiring search and training costs). Moreover, departing employees may reveal trade secrets to their new employers, which can harm their former employers' profitability. In this regard, firms more exposed to labor market agglomeration could be less inclined to innovate.

Consistent with the benefits of labor market agglomeration, previous studies have documented a positive correlation between various measures of labor market agglomeration and innovation activity (for a comprehensive literature review, see, e.g., Carlino and Kerr (2015)). However, measures of agglomeration used in prior research are mainly regional characteristics (e.g., population density, population groups with high education) or intraindustry activity (e.g., spatial clustering of firms from the same industry) and thus are not suitable for studying firm-level exposure to interfirm/interindustry labor market pooling.[3] Moreover, the existing literature has yet to fully explore the various mechanisms through which LMA affects innovation.

In this paper, we provide, to the best of our knowledge, the first comprehensive study on the effects of labor market agglomeration on corporate innovation. One of our main contributions is that we create a novel measure of firm-specific exposure to labor market agglomeration and investigate plausible channels through which labor market agglomeration affects innovation.

We calculate firm-level exposure to labor market agglomeration and its impact on innovation for Compustat firms from 1997 to 2018. In essence, our measure captures the similarity between the skill profile of a firm's employees and that of all other workers in the same local labor market. We use Occupation Employment and Wage Statistics (OEWS) program data from the U.S. Bureau of Labor Statistics (BLS).[4] For each industry, the OEWS data provide a vector in which each element is the fraction of an industry's workers in 1 of about 800 occupations. Given that an occupation requires a certain set of skills, we consider these vectors as the skill profile of industry workers. We construct a firm's employee skill profile vector as the sales-weighted average of its segment-industry skill profile vectors. Likewise, for each MSA, the

[3] According to Rosenthal and Strange (2004, p. 2127), "With regard to the type of industrial activity, most studies have collapsed industrial activity into just two broad categories: activity within an establishment's industry (i.e., SIC code) and activity outside of the establishment's industry. This, of course, does not capture the possibility that some industries belonging to different industry categories are close cousins." One exception is Ellison, Glaeser, and Kerr (2010), who use the skill similarity of employment between industries to explain colocation choices by firms.
[4] Prior to Spring 2021, the OEWS program was called the Occupation Employment Statistics (OES) program (https://www.bls.gov/opub/hom/oews/history.htm#:~:text=In%20the%20spring%20of%202021,reflect%20the%20new%20program%20name).

OEWS data provide a skills profile vector in which each element is the fraction of all MSA workers in one of the occupations. We define local labor markets using U.S. commuting zones (CZs), which are a geographic unit to measure the economy in which people live and work. We aggregate MSA-level skill profile vectors at the CZ level by combining MSAs in the same CZ.[5] We identify the CZ where a firm is headquartered and the corresponding skill profile vector for all workers in that CZ. Our measure of firm-level exposure to labor market agglomeration, which we label *fLMA*, is defined as the cosine similarity between the skill profile vector of a firm and that of its CZ. Our measure is higher when more neighboring firms, many of whom might be from different industries, hire workers with skills relevant to a focal firm, thus leading to greater exposure to labor market agglomeration. Our measure reflects interfirm and interindustry employment activity, which is distinct from other measures of agglomeration based on regional variables or within-industry activity.[6]

Our baseline results, using multivariate regressions, show that firms with greater exposure to labor market agglomeration produce a higher number of patents. Additionally, their patents receive more citations (per patent), indicating higher impact. The results remain robust after controlling for firm-, industry-, and region-specific characteristics related to innovation, as well as high-dimensional fixed effects for industry, CZ, and year. Our measure is distinct from the clustering of firms within the same industry (i.e., intraindustry activity), which we control for in all regressions. In addition, we modify our *fLMA* to incorporate employee skill levels. Our

[5] We check the robustness of the results, which are reported in Table 10.
[6] Before relating our measure to firm innovation, we test whether and how it is associated with employee mobility. We perform a textual analysis of corporate annual reports and track inventor moves between firms. We find that *fLMA* is positively associated with the frequency of keywords related to employee mobility that appear in the risk factor section of a firm's annual report (see our Internet Appendix; Tables I.A.1–I.A.3). Thus, our measure of labor market agglomeration reflects management's perceptions of employee mobility. In addition, firms more exposed to LMA exhibit *de facto* greater levels of inventor-employee departures and new hires (Appendix C), a meaningful link between our measure and the mobility of high-skilled workers.

results hold for these modified *fLMA* measures and are driven by the pooling of high-skilled employees.

Our cross-sectional tests show that the positive effect of *fLMA* is stronger in R&D-intensive and high-tech industries. In addition, our *fLMA* calculation includes only existing job positions at local firms and excludes potential new ventures. We find that the effect of *fLMA* on innovation is stronger when it is more costly to start a venture and therefore less likely (Anton and Yao (1995)). This is the case when employment options at existing local firms are more relevant.

We also contribute by exploring the potential channels through which *fLMA* impacts innovation positively. Our findings strongly support the positive impact of *fLMA*, particularly through the enhanced labor mobility channel. This is primarily because increased outside opportunities incentivize local employees to innovate, as well as because knowledge spillovers between incumbent and newly joined employees promote innovation. Further, we find moderate support for the channel in which higher *fLMA* (and the increased retention pressure) leads firms to grant their employees more stock options (John et al. (2021)). This in turn encourages employees to take more risks and consequently drives more innovation. Additionally, we find evidence consistent with the channel in which *fLMA* affects the allocation of intellectual property (IP) rights between employees and employers.[7] We do not find evidence that *fLMA* reduces unemployment risk or transportation costs among vertically related firms, both of which could potentially facilitate innovation.

Lastly, although we are *not* able to establish a conclusive causal relationship between labor market agglomeration and innovation, we do provide some evidence suggestive of such a

[7] We thank the referee for pointing out these channels and encouraging us to validate them empirically.

relationship. We use an instrumental variable (IV) approach. Using a two-stage least squares (2SLS) regression, we extract the exogenous variation of *fLMA* driven by an IV and relate it to innovation. We discuss the rationale for our instruments and our results in more detail in Section III.F.

Our study contributes to the literature on the role of employee human capital in firms' innovation activities. An important area of study has been the optimal institutional, contractual and legal settings that incentivize innovation (e.g., Ederer and Manso (2011), Acharya et al. (2014)). In particular, Manso (2011) suggests that optimal incentive programs tolerate early failure and reward long-term success. Lerner and Wulf (2007), Chang, Fu, Low, and Zhang (2015), and Mao and Zhang (2018) suggest that firms may offer employees performance-based incentives to enhance innovation. Recent studies have focused on high-skilled employees, such as top executives and inventors, to show that employee human capital is critical to firm innovation (Chemmanur, Kong, Krishnan, and Yu (2019), Dimmock, Huang, and Weisbenner (2022)). Liu, Mao, and Tian (2023) highlight the importance of employees' human capital relative to the firms' organizational capital.

A growing number of studies that examine the characteristics of local labor markets and their effects on talented employees are closely related to our paper. For instance, Derrien, Kecskes, and Nguyen (2023) show that firms located in younger labor markets are more innovative. Fich, Nguyen, and Petmezas (2023) and Gao, Hsu, Li, and Zhang (2020) find that concerns related to employees' health and safety (e.g., terrorist attacks or workplace smoking) negatively affect firm innovation. We extend this literature by studying how the similarity in the skill profile of the firm and that of the local labor market impacts innovation.

Our paper also contributes to the literature that links agglomeration economies to corporate behavior. To the best of our knowledge, we are the first to comprehensively analyze the impact of labor market agglomeration on innovation by differentiating between various channels. Among the potential sources of agglomeration benefits proposed by Marshall (1890), Holmes (1999) studies the benefits of *input sharing* among downstream firms. Firms in proximity may outsource shared inputs and reduce production costs through economies of scale. Consistent with this idea, Holmes (1999) finds that firms in industrial clusters are less likely to be vertically integrated. Matray (2021) explores *knowledge spillover* among innovative local firms. Our study differs from these by focusing on *labor market pooling* as a source of agglomeration benefits. Notably, we create a firm-specific measure, *fLMA*, of exposure to labor market pooling. We validate our measure by performing textual analysis and tracking employee job changes. We document a positive impact of firm-specific exposure to labor market pooling on innovation and investigate various channels through which this effect occurs.

Our paper is closely related to the burgeoning literature on labor mobility and innovation. Many studies document that employee mobility, especially among high-skilled employees, positively affects innovation (e.g., Chemmanur et al. (2019), Liu et al. (2023)). Despite the well-documented positive relation between labor mobility and innovation, recent studies diverge on what causes this relation. For instance, Samila and Sorenson (2011), Kaiser, Kongsted, and Ronde (2015), and Matray (2021) find that the knowledge spillover by interfirm job movers drives the positive relation. However, Gu, Huang, Mao, and Tian (2022) find no evidence supporting knowledge spillover but rather evidence supporting outside opportunities that strongly incentivize employees to innovate.

Our study deviates from the above-mentioned studies by focusing on one precondition for labor mobility—labor market agglomeration—and finds that labor mobility is one of the key channels for the positive impacts of labor market agglomeration on innovation. Our further analysis supports outside opportunities associated with labor mobility as the main mechanism for the LMA impacts, along with knowledge transfer between local employees.

The remainder of the paper is organized as follows. Section II describes the data, sample, and variables. Section III presents the main empirical results, and Section IV concludes.

II. Data and Variables

A. Main Sample

We combine multiple databases to construct our main sample over the period 1997–2018.[8] We start with annual financial statements from Compustat and construct a panel of firm-year observations. We exclude firms in the utility (SIC 4900s), financial (SIC 6000s), and public (SIC 9000s) sectors. To construct a firm-level measure of labor market agglomeration, we obtain industry- and MSA-level occupational data from the OEWS program at BLS. We aggregate the MSA-level occupation data to the CZ level by merging MSAs in the same CZ, a process we will explain in more detail in Section II.B.3. Coverage of the MSA-level occupational data starts in 1997, while that of industry-level occupational data starts as early as 1988. We obtain information on patents, such as patent number, assignee, and the inventor, from USPTO PatentsView. We connect the patent data to our Compustat firms, using the crosswalk from the Global Corporate Patent Dataset (Bena, Ferreira, Matos, and Pires (2017)).[9] Following the

[8] Our dependent variables, patent-based variables, are measured in year *t*+1 (or over years *t*+1, *t*+2, and *t*+3), while our independent variables are measured in year *t*. That is, our main sample comprises Compustat firm-years from 1997 to 2018 and the corresponding patents data from 1998 to 2019 (to 2021 for the dependent variables measured over years *t*+1 to *t*+3).

[9] The crosswalk between patent number and GVKEY (Compustat firm identifier) is available at https://patents.darden.virginia.edu/.

literature, we set the number of patents and citations equal to zero for firm-years in which we find no patent information. We require CZs to have at least two firms for meaningful statistical comparisons.[10] Our final sample consists of 75,120 firm-years from 242 CZs. Below, we will construct our key variables. (Appendix A defines the variables.)

B. Measure of Firm-Specific Exposure to Labor Market Agglomeration

1. Occupational Data from the OEWS Program

Our main measure of firm-level exposure to labor market agglomeration (LMA) is the skill similarity between a firm's workforce and all other workers in the local labor market (i.e., CZ). To calculate skill similarity, we create a skill profile vector for a firm's employees and another vector for all employees by CZ. The OEWS occupational data provide MSA-level skill profile vectors that start from 1997. Firm-level skill profile vectors are not readily available.

We combine the industry-level skill profile vectors from the OEWS data and sales data from the Compustat Industry Segment (CIS) to construct a proxy for a firm's employee skill profile on the basis of industry segments (or what a firm reported as its product line). Until 1998, the OEWS program employed a taxonomy with 258 occupation titles. Since 1999, the OEWS program has used the Office of Management and Budget's (OMB) Standard Occupational Classification (SOC) taxonomy, which includes more than 800 detailed occupations.[11]

2. Firm-Level Employee Skill Profile

For each industry and each year, we obtain an industry-level employee skill profile vector from the OEWS data. Specifically, for industry i in year t, the OEWS data provide an employee skill profile, $H_{i,t} = (H_{i1}, \dots, H_{in})_t$, where element H_{ik} is the proportion of the total number of

[10] Our results are robust to alternative thresholds. Our Internet Appendix I.A.4 reestimates the main results with different thresholds for the minimum number of firms in a CZ, such as 1, 3, and 5.

[11] Each detailed occupation has a unique six-digit code, such as biochemist and biophysicist (19-1021), microbiologist (19-1022), or zoologist and wildlife biologist (19-1023).

workers in industry i assigned to occupation k. To construct a firm-level skill profile vector, we link industry-level skill profiles to industry segment data (CIS). For each industry segment, we identify a relevant industry-level skill profile based on the three-digit SIC code (four-digit NAICS codes start from the year 2002) of the segment. We define a firm's employee skill profile, $H_{a,t}$, as the segment's sales-weighted average for the associated industry skill profile ($H_{a,t} = \sum_{i=1}^{I} w_{i,t} H_{i,t}$), where a segment's weight, $w_{i,t}$, is sales to total firm sales, and I is the number of industry segments the firm reports. If a firm reports only a single segment, its employee skill profile is defined at the industry level.

3. CZ-Level Employee Skill Profile

For each MSA and each year, the OEWS data provide an MSA's employee skill profile vector. For MSA m in year t, we obtain the vector, $H_{m,t} = (H_{m1}, \dots, H_{mn})_t$, where element H_{mk} is the proportion of the total number of workers in MSA m assigned to occupation k. To identify the MSA relevant for a firm, we use the firm's ZIP code from Compustat and the crosswalk between the ZIP code and MSA code from the Office of Workers' Compensation Programs (OWCP).

Next, we aggregate the MSA-level occupation vectors to the CZ level as follows. We identify MSAs belonging to the same CZ using the U.S. Economic Research Service (ERS) data.[12] We define a CZ-level skill profile vector, $H_{c,t}$, as the weighted average of the MSA-level skill profile vectors within the CZ, in which the weights ($w_{m,t}$) are the MSA employees as a fraction of the total employees in the CZ: ($H_{c,t} = \sum_{m=1}^{M} w_{m,t} H_{m,t}$).

[12] *Source*: https://www.ers.usda.gov/data-products/commuting-zones-and-labor-market-areas/.

The OEWS occupation data provide the number of MSA workers for each occupation (six-digit SOC occupations). We calculate the total number of MSA employees by taking the sum of employees across all occupations.[13]

Consider, for example, the Cedar Rapids MSA and the Iowa City MSA, both of which belong to the same CZ. In 2015, the total number of employees in the Cedar Rapids MSA was 129,070, and that in the Iowa City MSA was 72,450. The former MSA had 1,750 software developers, while the latter MSA had 1,060. That is, the Cedar Rapids-Iowa City commuting zone had 2,810 software developers representing 1.4% (=(1,750+1,060)/(129,070+72,450)) of the total CZ workforce, which is one element in our CZ-level skill profile vector.

4. Skill Similarities between Firm and CZ

We calculate a firm's exposure to labor market agglomeration, $LMA_{a,t}$, for firm a headquartered in CZ c using the cosine similarity between the firm's employee skill profile vector, $H_{a,t}$, and the CZ-employee skill profile vector, $H_{c,t}$. More specifically, *fLMA* is defined as the scalar product of the firm's employee skill profile vector and the corresponding CZ-employee skill profile vector divided by the product of their lengths:

(1) $fLMA_{a,t} = \frac{H_{a,t}H'_{c,t}}{\sqrt{H_{a,t}H'_{a,t}}\sqrt{H_{c,t}H'_{c,t}}}$.

fLMA is bounded between 0 and 1. It increases with the extent to which a firm and its neighboring firms share common labor pools. High (low) *fLMA* indicates greater (less) exposure to labor market pooling in a locality. Our *fLMA* measure reflects interfirm/interindustry

[13] In some years, the BLS OEWS data directly record the total number of MSA employees ("All Occupations"). Our estimated sum is close to this reported number. For example, in the Cedar Rapids MSA, our summation shows that this MSA has 129,070 employees in 2015, while the BLS OEWS data reports 141,610 employees (i.e., an 8.9% gap). While some may find this gap nonnegligible, it does not affect our *fLMA* calculation because the cosine-similarity normalizes each vector (i.e., the dot product of two vectors is divided by the product of their lengths).

employment activity and includes neighboring firms that operate in industries different from the focal firm's industry. We further illustrate the calculation of *fLMA* using simple numerical examples in Appendix B. In Section III.C, we will adjust our *fLMA* measure to include high-skilled employees using (1) job descriptions and (2) patent technology classes.

C. Measures for Innovation Output

Our first measure of innovation output is the total number of patents a firm applies for (and is eventually granted). Patents are observable in the database only after they are granted, and a patent application generally takes a few years to be ultimately granted. As a result, our patent counts near the end of our sample period might suffer from truncation bias.[14] We follow Hall, Jaffe, and Trajtenberg (2001) and adjust for such truncation bias. $Patents_{t+1}$ ($Patents_{t+3}$) is defined as the total number of patent applications filed by a firm and ultimately granted in year t+1 (years t+1, t+2, and t+3) and is adjusted to address truncation bias. Because the patent distribution is right-skewed, we add one and then use the natural log transformation (i.e., $\ln(1+Patents_{t+1})$, $\ln(1+Patents_{t+3})$).

Patents differ from one another in terms of their economic and technological significance. Patent counts cannot account for this varying significance alone. Our second measure attempts to capture patent quality based on the number of non-self-forward citations a patent receives. Citation counts may suffer from truncation bias because recent patents have not had enough time to be cited. Again, we correct for such bias, following Hall et al. (2001). We define citations per patent, $Cites_{t+1}$ ($Cites_{t+3}$), as the ratio of the number of non-self-citations received in year t+1 (years t+1, t+2, and t+3) to the number of the corresponding patents. The numerator is adjusted

[14] In Panel A of Table 10, we exclude the last 5 years of our sample and continue to find supportive evidence.

to address possible truncation bias. Likewise, we use the natural log transformation in regressions (i.e., ln(1+$Cites_{t+1}$), ln(1+$Cites_{t+3}$)).

D. Inventor Moves

We also examine whether our measure of labor market agglomeration is related to employee mobility by tracking the job moves of inventors, who are one of firms' most valuable high-skilled workers. We follow Marx, Strumsky, and Fleming (2009) and identify inventor moves based on two successive patent applications by the same inventor. If an inventor has filed two successive patent applications that belong to two different assignee firms, we consider him/her as having moved to the latter firm and set the midpoint between the two patents' filing dates as the job change date. For a given firm and year, $Hires_{t+1}$ ($Departures_{t+1}$) is defined as the total number of inventors that have newly joined (have left) the firm in year *t*+1.

When the time gap between two consecutive patents is large, the midpoint could be distant from the actual time point of inventor moves, which may invalidate our annual analysis of inventor hires and departures. We alleviate this concern by using a longer time window of 3 years for inventor moves. $Hires_{t+3}$ ($Departures_{t+3}$) is defined as the total number of inventors who have newly joined (have left) the firm in years *t*+1, *t*+2, and *t*+3. In addition, we use the ExecuComp database on corporate executives, another key high-skilled employee, for whom we can more accurately identify the timing of departures. We will describe the details of our employee-moves analysis in Section II.F.

E. Control Variables

We control for an array of firm-, industry-, and region-specific characteristics that may influence innovation activities, in accordance with previous studies. We follow Almazan, De Motta, Titman, and Uysal (2010) and define *Industrial clustering* as the number of firms from the same three-digit SIC industry and headquartered in the same MSA as a focal firm, divided by the total number of firms in that three-digit SIC industry in year *t*. *Firm sale* is defined as the natural logarithm of one plus firm sales in the fiscal year *t*. A firm's productivity may vary along its life cycle, and we control for *Firm age*, which is defined as the natural logarithm of one plus the number of years that have passed since the firm's first appearance in Compustat. *M/B* is defined as total assets minus the book value of equity plus the market value of equity, all divided by total assets in year *t*. *ROA* is defined as the ratio of income before extraordinary items to total assets in year *t*. *PPE* is the natural logarithm of one plus the ratio of net property, plant, and equipment to the number of employees. *Net debt* is long-term debt plus debt in current liabilities minus cash and short-term investments, all scaled by the book value of assets. *Institutional ownership* is the proportion of a firm's stock owned by institutions in year *t*. We control for input for innovation and research and development (R&D) expenditures. *R&D/Sale* is defined as the ratio of R&D expenditures to firm sales. If R&D is missing, then we set it as zero. We also control for *HHI*, which is the Herfindahl index of the distribution of firm sales within the industry by three-digit SIC code. The relation between *HHI* and innovation may be nonlinear (Aghion, Bloom, Blundell, Griffith, and Howitt (2005)), so we control for a squared term of *HHI* (i.e., HHI^2). We control for a relative size of the local labor market, *Relative size of CZ*, which is the ratio of the number of employees by CZ to the number of firm employees (expressed in thousands). All variables are winsorized at the 1% and 99% tails, except for *fLMA*.

F. Descriptive Statistics

Table 1 presents summary statistics for our main sample. The mean (median) value of *fLMA* is 0.304 (0.299). The mean number of patents per firm-year is about 6.12, while the median is zero. Each year, firms receive approximately 5.89 citations per patent on average. In addition, the average firm in our sample loses one employee inventor and hires one new inventor each year. Our sample firms have a mean market-to-book ratio of 3.07 and a mean R&D-to-sales ratio of 0.62.

[Insert Table 1 approximately here]

We perform a textual analysis to examine whether and how a firm's exposure to labor market pooling is perceived by its management and reflected in its annual reports for shareholders. Specifically, we search the risk factors section (Item 1A) in a firm's 10-K filing for keywords that indicate employee mobility. Our keywords include "employees may depart", "turnover of qualified personnel", and "competition for talent".[15] Our Internet Appendix I.A.1 fully lists the keywords we have used. We obtain 10-Ks from the SEC EDGAR database for firms with Central Index Keys (CIKs). We define *#keywords for employee mobility* as the total number of times our keywords appear in the risk factors section of a firm's 10-K in a fiscal year. The mean value of *#keywords for employee mobility* is 0.98.

Our Internet Appendix Table I.A.2 reports the Pearson correlation coefficients between our key variables. *fLMA* is positively and significantly correlated with patent counts and citations per patent, which is consistent with our prediction. Turning to variables related to employee mobility, we see *fLMA* is positively correlated with inventor hires and departures, which implies higher interfirm employee mobility. For a more rigorous analysis, in columns 1 through 4 of our Appendix C, we estimate ordinary least squares (OLS) regressions and continue to find a positive relation between *fLMA* and inventor moves. In columns 5 and 6 of Appendix C, we consider the departure of CEO and executives. *CEO_left* is a dummy equal to one if a firm's

[15] For example, Tesla Motors states in the risk factors section of its 2017 10-K: "Key talent may leave Tesla due to various factors, such as a very competitive labor market for talented individuals with automotive or technology experience . . . ."

CEO leaves the firm during the year, and zero otherwise. *Exec left* is the number of a firm's executives who leave the firm during the year. We find both *CEO_left* and *Exec_left* are positively and significantly associated with *fLMA*.

We also find that the keywords related to employee mobility appear more frequently in the annual reports of firms more exposed to LMA, compared to those of firms with less exposure to LMA. Our Internet Appendix Table I.A.3 estimates OLS regressions and reports the positive effect of *fLMA* on the frequency of keywords used in firms' annual reports.

III. Results

This section presents our main findings. First, we test how LMA affects patent counts and citations per patent using OLS regressions with fixed effects. We estimate the following regression:

(2) $Innovation_{a,t+n} = \alpha + \beta fLMA_{a,t} + \gamma Z_{a,t} + FE + \varepsilon_{a,t}$.

$Innovation_{a,t+n}$ is a measure for innovation output, such as the number of patents and the number of citations per patent for firm a. $Z_{a,t}$ is a set of control variables at the firm, industry, and region levels. The dependent variable is measured in year *t*+1 or over years *t*+1 to *t*+3, while the independent variables including *fLMA* are measured in year *t*. Our regressions control for high-dimensional fixed effects (FE) based on three-digit SIC industry, CZ, and year (e.g., industry-by-year or CZ-by-year).[16] We cluster standard errors by CZ given that our focus is local labor market dynamics.

[16] Both *fLMA* and our dependent variables (i.e., innovation outcomes) are highly persistent, which weakens the power of a firm fixed effects estimator (Zhou (2001)). Regardless, we use firm fixed effects and present the estimation results in the Internet Appendix Table I.A.5.

Additionally, we investigate potential mechanisms by conducting cross-sectional tests in which the impact of labor market agglomeration varies across industry- and location-specific characteristics. Finally, we use instrumental variables to derive preliminary causal inferences.

[Insert Table 2 approximately here]

A. Patent Counts

In Table 2, we estimate equation (2) using the number of newly granted patent applications. In columns 1 and 2, the dependent variable is the natural logarithm of 1 plus the number of patents produced in year t+1; thus, the coefficient represents a semielasticity of innovation to *fLMA*. Column 1 controls for CZ-by-year and industry fixed effects, and column 2 controls for industry-by-year and CZ fixed effects. That is, time-varying CZ characteristics will be subsumed in column 1, while time-varying industry characteristics will be subsumed in column 2. In some cases, CZ spans multiple states, meaning that state-level control variables are not fully accounted for by CZ-by-year fixed effects.[17] Consistent with our prediction, we find that our firm-level LMA measure is significantly and positively related to the number of patents in both columns.

It may take many years for firms to produce innovative outcomes, so columns 3 and 4 examine a longer time window (patents produced over years +1, +2, and +3). We continue to find a positive relation between *fLMA* and the quantity of patents produced over 3 years in both columns. The results are also economically significant. A one-standard-deviation increase in *fLMA* leads to a 2.9% increase in the quantity of patents in column 1 and to a 3.6% increase in column 3. Overall, the results here lend support to our hypothesis; firms more exposed to labor market agglomeration produce a greater volume of patents.

[17] For example, the Chicago CZ includes parts of Illinois, Indiana, and Wisconsin.

B. Patent Citations

Table 3 examines the link between LMA and the quality of innovation. We use non-self-citations per patent to measure the quality of innovation in equation (2). In columns 1 and 2, our dependent variable, $\ln(1+Cites)_{t+1}$, is based on the number of non-self-citations received per patent in year t+1. Columns 3 and 4 use citations per patent over 3 years. Odd-numbered columns control for CZ-by-year and industry fixed effects, while even-numbered columns control for industry-by-year and CZ fixed effects.

[Insert Table 3 approximately here]

In all columns, we find a significantly positive relation between LMA and the number of citations. The relation is economically meaningful. A one-standard deviation-increase in *fLMA* leads to a 1.5% increase in citations in column 1 and a 1.7% increase in column 3.

As an alternative to citations per patent, we use the total number of non-self-citations as a dependent variable and continue to find the positive relation between *fLMA* and citations (reported in the Internet Appendix Table I.A.6). Therein, a one-standard-deviation increase in *fLMA* translates to a 4.3%–5.4% increase in non-self-citations.

Overall, the results here suggest that firms with higher exposure to labor market agglomeration generate innovation of higher quality, not just higher quantity. Two sets of fixed effects produce similar results, and therefore we only report the results based on CZ-by-year and industry fixed effects in the remaining tables to save space.[18]

C. Modified LMA Measures

[18] In our Internet Appendix I.A.7, we produce the main results using alternative sets of fixed effects (e.g., industry-by-CZ and year FEs, industry-by-CZ-by-year FEs). Overall, our results remain robust to these alternative fixed effects, although the results are at best marginally significant when using industry-by-CZ-by-year FEs.

fLMA measures the pooling of workers at all skill levels relevant to a firm. That is, *fLMA* does not distinguish between workers with high *versus* low skills. However, one may argue that the pooling of high-skilled workers should be more relevant for innovation than that of low-skilled workers. In this regard, we modify our measure using only high-skilled workers (reducing the size of the occupational vectors) and test whether our main results hold. We obtain data on the required skill level of each occupation from the U.S. Department of Labor's O*NET program. The O*NET program categorizes each occupation into five job zones based on education, experience, and training required for the occupation. The required skill level increases as one moves from job zones 1 to 5. Occupations in job zone 1, for instance, include baristas and sewing machine operators, while those in job zone 5 include neurologists and pharmacists. Occupations in job zones 4 and 5 typically require a 4-year college degree at a minimum, and we consider employees in these zones as "high-skilled" ones.

We adjust *fLMA* in the following ways. In equation (1), we eliminate low-skilled occupations in job zones 1, 2, and 3 from the two skill profile vectors $H_{a,t}$ and $H_{c,t}$ to define $T_{a,t}$ and $T_{c,t}$. In other words, we reduce the dimension of the skill profile vectors by removing the elements assigned to low-skilled occupations. $T_{a,t} = (T_{a1}, \dots, T_{al})_t$ is firm a's skill profile vector in which element T_{ak} is a firm's employees assigned to high-skilled occupation k as a fraction of the firm's total high-skilled employees. Similarly, $T_{c,t} = (T_{c1}, \dots, T_{cl})_t$ is a CZ c's skill profile vector in which element T_{ck} is a CZ's workers assigned to high-skilled occupation k as a fraction of the CZ's total high-skilled workers. Then, we define firm-level exposure to labor market agglomeration for "high-skilled employees" (*fLMA high skill*) as follows:

(3) $fLMA\ high\ skill_{a,c,t} = \frac{T_{a,t}T'_{c,t}}{\sqrt{T_{a,t}T'_{a,t}}\sqrt{T_{c,t}T'_{c,t}}}.$

Note that the O*NET program uses the SOC taxonomy to define occupations and that our skill profile vectors from the OEWS data start using this taxonomy from 1999. For this reason, we lose some observations in the analysis using *fLMA high skill* (i.e., observations in 1997 and 1998).

[Insert Table 4 approximately here]

Panel A of Table 4 reestimates the main results with *fLMA high skill*. We find a positive and significant relation between *fLMA high skill* and innovation activity in all columns. If anything, the coefficient seems larger than that of *fLMA* in the previous tables. A one-standard-deviation increase in *fLMA high skill* translates to a 6.8% increase in the number of patents over the next 3 years (column 2) and a 3.7% increase in citations per patent over the same period (column 4). These increases are greater overall than those associated with the baseline *fLMA*.

Alternatively, we reconstruct *fLMA* using the technology classes of firms' patents (i.e., inventor-employees' technological skills). For each firm, we prepare a vector of patent classes by using all the patents produced by the focal firm in the recent 3 years (years *t*-2, *t*-1, and *t*): $P_{a,t} = (P_{a1}, \dots, P_{an})_t$, where element P_{ak} is the ratio between the number of firm a's patents assigned to patent class k and the total number of patents the firm produces during the period. Likewise, we prepare a CZ-level vector of patent classes by using the patents produced by all the other firms (excluding the focal firm) in the same CZ over the 3-year-period: $P_{c,t} = (P_{c1}, \dots, P_{cn})_t$, where element P_{ck} is the ratio between the number of patents assigned to patent class k produced by all the other firms in the CZ and the total number of patents firms produced during the period. We define *fLMA patent class* as the cosine similarity between the focal firm's patent class vector ($P_{a,t}$) and the CZ-level patent class vector ($P_{c,t}$), which captures the degree to which neighboring firms employ similar inventor skills, compared to the focal firm.

Panel B of Table 4 reproduces the main results using *fLMA patent class*. Because the calculation of *fLMA patent class* requires a firm to have produced at least one patent within the 3 recent years, our sample size becomes smaller (26,934 obs.). Our main results continue to hold, and, if anything, the results seem more economically significant than those in Tables 2 and 3.

D. Cross-Sectional Tests: R&D Firms and Startup Costs

In Table 5, we perform cross-sectional tests. Panel A of Table 5 tests whether our results become stronger for R&D-intensive industries. For each three-digit SIC industry and year, we calculate the industry-level R&D expense and total assets by summing R&D expenses and total assets, respectively, across all industry member firms. We define *High R&D* as a dummy equal to one if the ratio of an industry's R&D expense to its total assets is above the median during the year, and zero otherwise. We predict that innovation should be more relevant for R&D-intensive industries and estimate the following equation:

(4) $$Innovation_{a,t+n} = \alpha + \beta_1 fLMA_{a,t} \times High\ R\&D_{a,t} + \beta_2 fLMA_{a,t} + \beta_3 High\ R\&D_{a,t} + \gamma\, Z_{a,t} + FE\ + \varepsilon_{a,t}.$$

We find that the positive impacts of LMA on innovation quantity and quality are mainly driven by R&D-intensive industries, consistent with our prediction. The magnitude of each coefficient seems much greater than those reported in Tables 2 and 3.

[Insert Table 5 approximately here]

Next, we will consider industries with high startups costs. *fLMA* is built on job positions at extant local employers and therefore may understate the true employment activity. For instance, workers may leave their current employers to start their own firms, which *fLMA* does not reflect. However, founding a startup may not be feasible if excessively high initial capital is needed (Anton and Yao (1995)) or if financing options are not readily available in the geographic location. In such cases, outside opportunities at existing neighboring firms could be more relevant for innovative workers. Therefore, we predict that the effect of *fLMA* on innovation output is stronger if employees are required to have a large amount of initial capital to start a new venture or if financing options are limited in their local area.

For each three-digit SIC industry and year, we calculate the industry-level PPE and employment by summing the firm-level net property, plant, and equipment (PPENT) and employees (EMP), respectively, across all industry member firms. We define *Capital intensive* as a dummy equal to one if the ratio between an industry's PPE and employment is above the median during the year, and zero otherwise. Panel B of Table 5 shows that our main results are stronger among capital-intensive industries (i.e., high-startup-cost industries), supporting our prediction.

In addition, startup costs for employees may be lower if there exist many early-stage financing opportunities in the locality. We use the SDC's Venture Xpert database on venture capital (VC) financing activities in the United States and define *High VC funding* as a dummy equal to one if the total value of venture capital investments made in a firm's CZ during the year is above the median, and zero otherwise. Consistent with our prediction, we find in Panel C that the positive impacts of LMA are overall weaker in localities with a high volume of VC financing.

E. Potential Mechanisms

There can be several, mutually nonexclusive channels through which higher *fLMA* leads to greater innovation output. This section presents our tests to validate mechanisms related to labor mobility, job security, intellectual property ownership, and transportation costs.

1. Labor Mobility

LMA may affect firm innovation through the enhanced labor mobility channel. Firms can benefit from employee mobility by recruiting desirable workers, leading to knowledge transfer between new and incumbent employees. In addition, employees' opportunities to move to other employers (i.e., outside options) may incentivize them to innovate, signaling their quality in local labor markets. Moreover, stock options granted to retain highly mobile employees may encourage their risk-taking, thus driving innovation. We test these possibilities nested within the labor mobility channel in the following paragraphs.

Employees who are more exposed to labor market agglomeration are likely to have more viable outside opportunities, a scenario incentivizing them to innovate. Employees signal their quality to other local employers through their performance, which can facilitate more or less attractive job offers or help them negotiate better pay and/or benefits with their current employers (Fulghieri and Sevilir 2011). Thus, the outside options reflected in *fLMA* and the corresponding incentives can create the positive relation between *fLMA* and innovation.

To test this channel, we follow Gu et al. (2022) and define *High mobility* based on industry-level realized inventor mobility: a dummy equal to one if the number of inventor-moves divided by the total number of inventors, both at the three-digit SIC industry level, is above the median during the year, and zero otherwise. As in Gu et al. (2022), our motivation for this variable is that employees' incentives to signal their quality should be more relevant in industries that exhibit a high incidence of pursuing outside options, i.e., industries with *de facto* high employee mobility. We estimate the following regression model:

(5) $Innovation_{a,t+n} = \alpha + \beta_1 fLMA_{a,t} \times High\ mobility_{a,t} + \beta_2 fLMA_{a,t} + \gamma\ Z_{a,t} + FE + \varepsilon_{a,t}.$

This test indicates whether *fLMA* affects firm-level innovation differently when employees have stronger incentives to signal their skills to other local firms. Panel A of Table 6 reports the estimation results. We continue to find a positive and significant coefficient on *fLMA* alone. Importantly, we find a significantly positive coefficient on the interaction term, *fLMA* × *High mobility.* The effects of *fLMA* are more pronounced when employees have stronger incentives to appeal to other employers, which supports the outside options channel.

[Insert Table 6 approximately here]

Next, we examine knowledge spillover spurred by employees moving between firms. Under high mobility, employees may move to new employers and (re)combine their knowledge with that of incumbent employees to collaborate on new inventions (i.e., knowledge spillover via coworkership or knowledge spillover by employees moving between firms). We test whether the positive effects of *fLMA* are stronger when knowledge transfer via employee mobility is more likely.

We follow Gu et al. (2022) and use patent citations to identify industries in which knowledge spillover via coworkership is more likely. Specifically, we define *Spillover via coworkership* as a dummy equal to one if within-industry citations divided by total citations, both at the three-digit SIC industry level, are above the median during the year, and zero otherwise. As in Gu et al. (2022), we posit that inventor-employees are more (less) likely to move between firms and collaborate with new coworkers if their technological knowledge and skills are related to a greater (lesser) extent.

Then, we add the interaction term, *fLMA* × *Spillover via coworkership*, to our main regression. Our setup allows us to determine whether *fLMA* affects innovation differently for firms/industries in which knowledge transfer as coworkers is more likely.

We present the estimation results in Panel B, Table 6. We find a significant and positive coefficient on *fLMA* × *Spillover via coworkership* in all regressions. The effects of *fLMA* are stronger when inventor-employees are more likely to collaborate as coworkers, which is consistent with the knowledge spillover channel. Alternatively, we use within-CZ citations, rather than within-industry citations, to test the knowledge spillover channel and find qualitatively similar results (reported in Table I.A.8 of the Internet Appendix).

Additionally, we consider stock options granted to mobile employees as another explanation for the positive effects of *fLMA*. John et al. (2021) suggest that firms facing more labor market agglomeration offer more stock options to retain employees. Relatedly, Chang et al. (2015) show that stock options encourage employee risk-taking, positively affecting firm innovation. Based on these studies, the positive relation between labor mobility reflected in *fLMA* and innovation could be driven by employee stock options.

Under the stock option channel, we expect the positive effects of *fLMA* to be stronger when more employee stock options are granted. To test this, we first calculate firm-level nonexecutive stock options as the difference between the total value of options granted to all firm employees and to its executives.[19] We then aggregate these values to the industry level and define *High nonexecutive options* based on the industry-level employee stock option grants: a dummy equal to one if the total value of nonexecutive stock options within a three-digit SIC industry divided by the industry's market capitalization during the year is above the median, and zero otherwise.

[19] Until 2005, we back out the option grants to all firm employees by dividing the value of option grants to a firm's executives by that as a percentage of the total employee option grants to all employees (PCTTOTOPT), both from ExecuComp. From 2006, we use the total value of option grants to all firm employees (OPTFVGR) from Compustat.

Panel C of Table 6 shows a positive coefficient for *fLMA* × *High nonexecutive options*, although it is at best marginally significant. Overall, we find moderate support for the employee stock options channel. In addition, we examine the interaction between executive stock options and *fLMA*. We do not find evidence that *fLMA* affects innovation through executive stock options (reported in Table I.A.8 of the Internet Appendix).

2. Unemployment Insurance

Next, we will consider the unemployment risk channel in which *fLMA* may (inversely) measure employee exposure to unemployment risk and motivate employees to innovate for the following reason. Typical innovation projects demand long-term efforts and involve an extremely high risk of failure. If employees are fired because of failed efforts to innovate, they will likely experience reductions in income as well as uncertainties about future employment. Labor market agglomeration may alleviate their unemployment risk, because employees will likely have many other local employers demanding their skills if they lose their jobs. The literature finds that protection against involuntary unemployment encourages employees to pursue long-term innovation projects (Acharya et al. (2014)). Our hypothesis is in line with the view that failure-tolerant employment and/or financing contracts are better-suited to innovation (Manso (2011), Tian and Wang (2014)).

To test this, we utilize the generosity of state-level unemployment insurance (UI) benefits, which vary across states and over time. Specifically, we quantify the generosity of UI benefits as the product of the maximum duration allowed and the maximum benefit amount, as in Agrawal and Matsa (2013). If *fLMA* reflects unemployment protection, its positive effects on innovation should be stronger (weaker) when state-level UI is weaker (stronger), making high *fLMA* more (less) desirable for employees.

We test whether the effects of *fLMA* are influenced by year-to-year changes in state-level UI. We define *UI up* (*UI down*) as a dummy equal to 1 if the UI benefits in a firm's headquarters state increase (decrease) by at least 5% compared to the previous year, and 0 otherwise. We interact *fLMA* with *UI up* and *UI down*, respectively, and include the interactions in the main regression.

[Insert Table 7 approximately here]

Panel A of Table 7 presents our estimation results. We find that the coefficients on *fLMA* interacted with *UI up* or *UI down* are insignificant across all columns, although the signs are consistent with our predictions. This evidence does not support the unemployment risk channel.

3. Allocation of Intellectual Property Rights from Employees to Employers

Another potential channel is that higher *fLMA* might reflect that employees have stronger bargaining power over their employers (i.e., weaker employer bargaining power) for intellectual property (IP) ownership. Employees at firms facing more labor market agglomeration (higher *fLMA*) may be able to leverage their outside options to negotiate for a higher ownership of the IP they create. Stronger employee IP rights, as reflected in higher *fLMA*, may incentivize employees to innovate more. However, these stronger employee IP rights (i.e., weaker employer IP rights) create holdup problems that would negatively affect employers' incentives to innovate (Suh (2023)). As a result, weak employer IP rights reflected in high *fLMA* might dampen the positive impact of *fLMA* on innovation, making the impact weaker than it could otherwise be.

To test the employee IP rights channel, we use the 2008 Federal Circuit ruling, which has strengthened firms' (employers') IP rights over their employees' IP rights in eight states (Suh (2023)).[20] We will briefly explain the background of the ruling: firms that hire employees to

[20] Prior to the ruling, employee-friendly states in terms of IP ownership included California, Delaware, Illinois, Kansas, Minnesota, North Carolina, Utah, and Washington.

invent typically become the owners of created IPs via pre-invention assignment agreements. During the 1970s and 1980s, employer IP ownership became weaker in the eight states that enacted legislation to challenge the abusive use of pre-invention assignment agreements by employers and to enhance employees' innovation incentives.

The 2008 Federal Circuit ruling overruled the state legislation in the eight states in the DDB Technologies case (*DDB Technologies LLC v. MLB Advanced Media, LLP*), thereby strengthening employers' IP rights over inventor-employees' rights. In essence, the ruling expands the scope of employers' claims on employees' inventions, and hence IPs created by employees belong to their employers upon their creation. Suh (2023) shows that the Federal Circuit ruling positively affects firm-level innovation by reducing potential holdup problems, which strengthens firms' incentives to innovate.

We follow Suh (2023) and use a difference-in-differences (DiD) approach to examine whether and how the Federal Circuit ruling's impact on firm innovation differs by *fLMA*. Specifically, we estimate the following equation over the period of 2002–2013:

(6) $$Innovation_{a,t+n} = \alpha + \beta_1 fLMA_{a,t} \times Treated \times Post_{a,t} + \beta_2 Treated \times Post_{a,t} + \beta_3 fLMA_{a,t} + \gamma\, Z_{a,t} + FE + \varepsilon_{a,t}.$$

Treated is a dummy equal to one if a firm is headquartered in one of the eight employee-friendly states in which employers' IP rights were strengthened over employees' rights, and zero otherwise. *Post* is a dummy equal to one for years from 2008 to 2013, and zero otherwise. We expect the effects of *fLMA* to be stronger among firms affected by the Federal Circuit ruling, as explained previously.

We use a fully saturated regression specification including all possible interaction terms. To conserve space, we only report the key variables of interest in Panel B of Table 7. We find that the positive impact of *fLMA* strengthens as employer IP rights become stronger. The results offer important insights into how the division of IP rights between firms and their employees can affect labor market agglomeration benefits.

4. Transportation Costs among Vertically Related Firms

One of the main benefits of (industrial) agglomeration is lower transportation costs due to the geographic proximity to vertically related firms. Our measure of labor market agglomeration is based on the distribution of employee human capital across firms and locations, so it differs from the clustering of vertically related firms. In addition, in all our regressions, we control for a traditional industrial agglomeration measure, which is based on similar three-digit SIC codes. Still, to some extent, *fLMA* may reflect a firm's distance to its vertically related partners, and thus the transportation cost channel may drive our results.

To test the transportation cost channel, we use the vertical relatedness scores from Frésard, Hoberg, and Phillips (2020) and quantify the degree to which a firm is vertical related to the other local firms. Specifically, for each pair of a focal firm and its local peer, we use the vertical relatedness score from Frésard et al. (2020). We define *Vertically related* as a dummy equal to one if the mean vertical relatedness score between the focal firm and each of the other firms in the same commuting zone is above the median, and zero otherwise. In Panel C of Table 7, we interact *fLMA* with *Vertically related* and present the results. We find that the coefficient of the interaction between *fLMA* and *Vertically related* is insignificant, while that of *fLMA* alone is significantly positive. This suggests that the transportation cost channel does not drive our results.

F. Instrumental Variable Approach

Our results thus far are subject to endogeneity concerns, although we do control for high-dimensional fixed effects and firm-, industry-, and locality-level characteristics in our regressions. For instance, if innovative firms attract innovative employees such that they choose to co-locate, then innovation may be causing agglomeration (i.e., reverse causality). Or unobservable variables may affect both labor market agglomeration and innovation. In this section, we present our tests to address endogeneity using an instrumental variable (IV) approach. Specifically, we extract the plausibly exogenous variation of *fLMA* driven by an instrument and relate it to firm-level innovation output. While the evidence presented in this section suggests a causal effect of *fLMA*, we acknowledge that our instrumental variables may not fully satisfy the required conditions for a good instrument.

1. Inevitable Disclosure Doctrine

First, we instrument *fLMA* using the Inevitable Disclosure Doctrine (IDD) adopted across several states in the United States in a staggered manner. Once adopted, IDD prevents firms' employees from moving to rival firms both in state and out of state. Prior research has shown that the adoption of IDD, which is largely exogenous to individual firms, has led to significantly decreased employee mobility, particularly among high-skilled employees (Klasa, Ortiz-Molina, Serfling, and Srinivasan (2018)). Such decreased labor mobility may lead, to a lesser extent, to labor market pooling in the locality. For instance, Samila and Sorenson (2011) and Jeffers (2024) find that local policies restricting employee mobility negatively affect employment growth and the entry of new firms, especially in sectors relying on high-skilled talents. Thus, if *fLMA* reflects employee mobility (between similar job positions) within the locality, we predict that IDD adoption will negatively affect *fLMA*.

We expect the use of IDD to plausibly satisfy the exclusion restriction, as it only prevents firms' employees from moving to rival firms, while keeping other economic conditions largely unchanged. Hence, in conjunction with its exogenous nature, we expect IDD to be uncorrelated with firm-level innovation, except through *fLMA* and the control variables. However, we cannot completely rule out the possibility that IDD does not satisfy the exclusion restriction. For example, in some occupations, employees' job opportunities may not be geographically constrained, and therefore less affected by local labor market agglomeration. In such cases, IDD may directly impact innovation, not necessarily through *fLMA*. In the first stage, we regress *fLMA* against IDD to isolate the exogenous variation of *fLMA* triggered by changes in labor mobility:

(7) $fLMA_{a,t} = \alpha + \beta IDD_{a,t} + \gamma\, Z_{a,t} + FE\ + \varepsilon_{a,t}.$

[Insert Table 8 approximately here]

As predicted, IDD is significantly and negatively related with *fLMA* (column 1 of Table 8). The *F*-statistic of 16.48 (*p*-value = 0.00) suggests that IDD is not a weak IV. In the second stage, we regress firm-level innovation against the fitted values of *fLMA*, and the estimates are reported in the remaining columns of Table 8:

(8) $Innovation_{a,t+n} = \alpha + \beta fLMA_{a,t}^{fitted} + \gamma\, Z_{a,t} + FE\ + \varepsilon_{a,t}.$

In all regressions, for both patent counts and citations per patent, we find a significant and positive coefficient on the predicted *fLMA*, which is consistent with our hypothesis. The magnitudes of the reported coefficients are larger than those reported in the baseline OLS estimation. For example, a one-standard-deviation increase in *fLMA* results in a 32.1% increase in the number of patents (column 2) and a 12.2% increase in the number of citations per patent (column 4). This may be due to the heterogenous sensitivity to an IDD event across the population of firms, as discussed in Jiang (2017). An IDD event yields 2SLS estimates centered on "compliers," that is, the firms in the affected states for which the event is intended and that, therefore, respond most strongly to it. As a result, these estimates can naturally be larger than those derived from the underlying OLS.

Overall, the results suggest a causal effect of *fLMA* on innovation. However, our findings here may not provide a complete identification. We caution that IDD may influence innovation through channels other than *fLMA*, thereby falling short of satisfying the exclusion restriction.

2. Peers' Patent Disclosure Speeds

Additionally, we employ an instrument that exogenously influences one information advantage of labor market agglomeration, thereby affecting inventor-employees' incentives to participate in knowledge clusters. One advantage of agglomeration is the possibility of knowledge spillover between local workers through professional or social networks, which is facilitated by geographic proximity, even without labor mobility. Local employees may interact face-to-face and share their knowledge with one another, by which they stay abreast of the most recent advances, industry developments, or competitors' innovation projects.

Specifically, we use the speed of patent publications (disclosures) by a firm's industry peers as our instrument. In patent publication, a firm is required to disclose the technical details of its patent under review at the USPTO. Once published, the details of a patent become immediately accessible online, regardless of geographic location. The speed of a firm's patent disclosure is important for other firms. Early patent publication allows rivals or related firms to stay informed about state-of-the-art innovations: they can timely initiate the development of follow-on innovation, or they can abandon existing R&D programs that appear too similar to published patents. In contrast, delayed publications can make disclosed information obsolete and thus less helpful for other firms.

The key force underlying our identification is that fast patent disclosures create automatic knowledge spillover to all other firms through the internet, regardless of the firm's geographic location or exposure to labor market agglomeration. Fast patent disclosures by rivals can significantly lower the information-gathering costs for the latest advancements in the focal firm's and their inventors' fields, thereby weakening the information advantage of labor market agglomeration.[21] Conversely, slow patent disclosures by rivals incentivize firms and inventors to work in/contribute to the formation of labor market agglomeration, so as to stay knowledgeable about the most recent innovations. In summary, when patent disclosures by rivals are slower (faster), employees may find the geographic proximity to a knowledge cluster (i.e., labor market agglomeration) to be a more (less) important work condition because of the associated information advantage.

Our use of *peers*' disclosure speeds, rather than the firm's *own* speed, alleviates the concern about endogenous choice of disclosure timing, although not completely. In addition, our estimation period includes an exogenous variation in the speed of peers' patent disclosures, triggered by the American Inventor's Protection Act (AIPA), which was enacted on November 29, 2000. The AIPA requires all patent-applicants to disclose the details of their patents upon granting of the patent or within 18 months after the application date, whichever is earlier. Pre-AIPA, patent disclosures were mandated upon the granting of a patent, which typically takes about 2–3 years after application. Consequently, post-AIPA, the patent publication has

[21] Relatedly, a recent study by Mao, Qin, Tian, and Zhang (2024) highlights that before the 2000s, a firm's geographic proximity to patent libraries facilitated access to the innovation of others and importantly affected corporate acquisitions.

accelerated for those firms that disclosed slowly prior to the AIPA (Hegde, Herkenhoff, and Zhu 2023; Kim and Valentine 2021).

Similar to Kim and Valentine (2021), we construct our instrument, *Publication Delay by Peers* (PDP) as the ratio between the average delay in patent publication by industry peers (*j*) and that by the focal firm (*i*) over the recent 10 years:

(9) $Publication\ Delay\ by\ Peers_i = \frac{\sum_{i \neq j} w_j \times the\ mean\ publication\ delay_j / n}{w_i \times the\ mean\ publication\ delay_i}.$

Specifically, the numerator is the ratio between the patent-weighted average of industry peer *j*'s mean publication delay and the number of peers (*n*) to account for differences in industry size. Publication delay for a patent is the number of days between application date and publication date, and for each (peer) firm, we calculate the mean publication delay. Weight (*w*) is based on the quartile rank of the number of patents the firm filed over the past 10 years (i.e., *w* = 1, 2, 3, or 4).[22] The denominator is the mean publication delay of the focal firm *i* over the recent 10 years multiplied by its quartile weight.

A *higher* level of PDP indicates a *slower* disclosure speed by peers; peers spend more days between patent application and publication, compared to the focal firm. As discussed above, we expect PDP to be positively related to *fLMA* because slower (faster) disclosures by peers means a greater (lesser) information advantage imbued by labor market agglomeration. Inventors may find it important to work in local labor market agglomeration in the case of slow peer disclosures, because geographic proximity to knowledge clusters helps them stay up-to-date with "bleeding edge" innovations before full disclosures become available online.

[Insert Table 9 approximately here]

[22] Our results are robust to equal weights (*w* = 1 for all firms) and are reported in our Internet Appendix Table I.A.9. In addition, Table I.A.9 report the coefficient estimates for all the independent variables for both patent-weighted and equal-weighted cases.

In the first-stage regression (column 1 of Table 9), we predict *fLMA* using the instrument, PDP. We find a significantly positive coefficient on *fLMA*, consistent with our prediction (the slower peers' disclosures, the greater the information advantage of LMA). The *F*-statistic of 13.54 supports the validity of the instrument at conventional levels. In the second stage reported in the remaining columns, we find that the fitted *fLMA* positively and significantly affects all innovation outcomes. A one-standard-deviation increase in *fLMA* leads to a 35.4% increase in patents (column 2) and a 30.5% increase in citations (column 4), Again, these estimates are much larger than the underlying OLS estimates, which can be attributed to the nature of "compliers" (Jiang (2017)).

Overall, the results provide some causal insights, suggesting that a firm's exposure to labor agglomeration positively affects innovation. However, we acknowledge that peers' relative disclosure speed may not be a good instrument, as it is partially influenced by the focal firm's own disclosure speed and could affect innovation through channels other than *fLMA*.

G. Robustness Tests

This section provides robustness tests that further corroborate the relation between *fLMA* and innovation. Table 10 presents the results. All the regressions shown in Table 10 include the control variables and high-dimensional fixed effects (CZ-by-year and industry FEs, except for Panel B in which we use the MSA-based *fLMA* and control for MSA-by-year and industry FEs).

[Insert Table 10 approximately here]

1. Addressing Potential Truncation Bias

To further address potential truncation bias, we exclude the last 5 years of our sample as suggested by Lerner and Seru (2022). Our main results, which are reported in Panel A, remain similar.

2. MSA-Based LMA

In Panel B, we use MSAs as a unit for local labor markets and recalculate our LMA measure (*fLMA_MSA*). Our results remain robust to defining local labor markets using MSAs.

3. Geographically Diversified Firms

Our LMA measure makes a tacit assumption that all the employees of a firm are located in its headquarters MSA. For firms that have employees across multiple geographic locations, our *fLMA* calculation may be problematic. To address this issue, we follow Agrawal and Matsa (2013) and exclude firms from wholesale (NAICS 42), retail (NAICS 44 and 45), and transportation (NAICS 48) sectors that are likely to hire employees in multiple geographic locations. Panel C reestimates the main results while excluding such sectors. Our results remain similar.

4. Industrial Clusters

fLMA, a measure of firm-specific exposure to labor market pooling, is constructed using interfirm/interindustry employment activity and therefore is different from industrial agglomeration (i.e., industrial clustering). Regardless, we further exclude industrial clusters (e.g., Silicon Valley and Route 128) from our sample and replicate the main results in Panel D. We follow Almazan et al. (2010) and classify a firm's CZ as an industrial cluster if (1) the CZ has at least 10 firms from the same three-digit SIC industry and (2) the CZ has at least 3% of the market value of that industry. We find that the effects of *fLMA* on innovation remain similar.

5. Dominant Local Employer

In a small local labor market where the focal firm's presence is relatively large, a firm's *fLMA* (i.e., the correlation between the firm's employee vector and the CZ employee vector) may be driven by the firm itself, and thus is not informative about labor market agglomeration. This is because the CZ-level skill profile vector in the *fLMA* calculation includes the focal firm's workforce. Given that the size of the firm's workforce is typically much smaller than that of the CZ (see *Relative size of CZ* in Table 1), the concern about dominant local employers may be negligible. However, we address the concern by eliminating dominant local firms from our sample. Panel E excludes the top decile of firm-years with the highest ratio of the number of firm employees to the number of employees by CZ. Our results are robust to the elimination of such firms.[23]

6. High-Tech Industries

Our earlier results show that the impact of *fLMA* is driven by R&D firms. Alternatively, we test whether *fLMA* has a stronger effect among high-tech industries (Eckbo, Makaew, and Thorburn 2018). The American Electronic Association classifies 47 four-digit SIC industries that belong to 6 two-digit SIC codes (28, 35, 36, 38, 48, and 73) as high-tech. *High-tech* is a dummy equal to one if a firm's four-digit SIC code is among the high-tech industries, and zero otherwise. Panel F indeed reports stronger results among high-tech industries.

7. Count Model

Cohn, Liu, and Wardlaw (2022) suggest that a Poisson model provides more consistent estimates than OLS regressions with the log transformation to address the right-skewness. In Panel H, we estimate a fixed effects Poisson model using raw patent counts (*Raw patents*) and raw citation counts (*Raw cites*) as dependent variables. Our results continue to hold.

IV. Concluding Remarks

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[23] Alternatively, in Table I.A.10 of our Internet Appendix, we address this issue by adjusting the CZ skill profile vectors: for each occupation in the CZ skill profile vector, we subtract the number of firm employees in the occupation from that of the employees by CZ. Using the adjusted CZ skill profile vectors, we recalculate *fLMA* as in equation (1) and label it *fLMA_2*. The mean and median of *fLMA_2* are 0.302 and 0.289, respectively, similar to those for *fLMA*. The results based on *fLMA_2* are similar to those based on *fLMA*.

Determinants of innovation has been an area of intense study. In this paper, we focus on a relatively underexplored explanation: the effect of labor market agglomeration on innovation intensity. We create a measure to quantify firm-specific exposure to labor market pooling, denoted as *fLMA*, and show it to positively affect a firm's innovative activity. We validate our measure by showing its positive relationship with interfirm inventor mobility. We also relate our measure to the frequency of employee-mobility keywords appearing in firms' 10-K filings. Consistent with our hypotheses, we show that firms with higher *fLMA* produce more patents and receive more patent citations.

Additionally, we investigate plausible mechanisms underlying the positive impact of *fLMA*. We find that this effect is associated with increased outside opportunities, knowledge spillovers via coworkership, and more employee stock options, all related to employee mobility. Moreover, our analysis shows that *fLMA* has higher impact when the IP rights are allocated to employers instead of employees.

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Table 1. Descriptive Statistics

This table reports descriptive statistics for the main variables. *fLMA* is firm-specific exposure to labor market agglomeration, which is the cosine similarity between a firm's skill profile vector and its CZ's (Commuting Zone's) skill profile vector. *fLMA high skill* is modified *fLMA* using only high-skilled employees (Job Zones 4 and 5). *fLMA patent class* is the cosine similarity between the patent class vector of a firm and that of all the other firms in the same CZ. *Patents*$_{t+1}$ (*Patents*$_{t+3}$) is the number of patents produced by a firm in year t+1 (years t+1, t+2, and t+3) that are ultimately granted and adjusted for truncation bias. *Cites*$_{t+1}$ (*Cites*$_{t+3}$) is the number of non-self forward citations per patent in year t+1 (years t+1, t+2, and t+3) adjusted for truncation bias. *Hires*$_{t+1}$ (*Departures*$_{t+1}$) is the number of inventors who have joined (left) a firm in year t+1. *Industrial clustering* is the number of other firms from the same three-digit SIC industry and headquartered in the same CZ as a firm, divided by the total number of firms in that industry. *Relative size of CZ* is the number of CZ employees divided by that of firm employees (in thousands). *Firm sale* is the natural logarithm of 1 plus sales. *Firm age* is the natural logarithm of 1 plus the number of years that have passed since a firm's first time appearance in Compustat. *M/B* is market value of assets divided by total assets. *ROA* is income before extraordinary items divided by total assets. *R&D/Sale* is the ratio of R&D expense to firm sales. *PPE* is the natural logarithm of 1 plus the ratio of net property, plant, and equipment to the number of firm employees. *Net debt* is long-term debt plus short-term debt minus cash and short-term investments, all scaled by total assets. *Institutional ownership* is the proportion of shares owned by institutions. *HHI* is the Herfindahl Index of concentration of firm sales within the 3-digit SIC industry. *State GDP growth* is the annual GDP growth rate of a firm's headquarters state. *State unemployment rate* is the unemployment rate of a firm's headquarters state. *#Key words for employee mobility* is the number of key words related to employee mobility that appear in the risk factors section of a firm's annual report. All variables are winsorized at the 1% and 99% tails, except *fLMA, fLMA high skill*, *fLMA patent class* and dummy variables.

	Mean	Std. Dev.	25th Pctl.	Median	75th Pctl.	Obs.
fLMA	0.304	0.117	0.237	0.299	0.383	75,120
fLMA high skill	0.433	0.138	0.345	0.426	0.518	65,277
fLMA patent class	0.146	0.200	0.013	0.069	0.194	26,934
Patents$_{t+1}$	6.124	25.013	0.000	0.000	1.000	75,120
Cites$_{t+1}$	5.889	16.991	0.000	0.000	2.000	75,120
Patents$_{t+3}$	10.664	99.072	0.000	0.000	1.000	75,120
Cites$_{t+3}$	9.157	22.820	0.000	0.000	7.333	75,120
Hires$_{t+1}$	1.072	4.454	0.000	0.000	0.000	75,120
Departures$_{t+1}$	1.020	4.171	0.000	0.000	0.000	75,120
Industrial clustering	0.091	0.163	0.004	0.021	0.089	75,120
Relative size of CZ (000s)	27.292	92.908	0.265	1.718	10.545	75,120
Firm sale	4.981	2.464	3.222	5.082	6.771	75,120
Firm age	1.251	0.239	1.080	1.271	1.430	75,120
M/B	3.068	5.401	1.152	1.622	2.705	75,120
ROA	-0.108	0.732	-0.053	0.088	0.152	75,120
R&D/sale	0.623	3.270	0.000	0.002	0.107	75,120
PPE	3.566	1.521	2.644	3.408	4.258	75,120
Net debt	0.086	0.588	-0.220	0.052	0.301	75,120
Institutional ownership	0.340	0.361	0.000	0.198	0.691	75,120
HHI	0.110	0.108	0.042	0.077	0.133	75,120
State GDP growth (%)	1.590	2.277	0.300	1.700	3.100	75,120
State unemployment (%)	5.808	1.890	4.600	5.400	6.600	75,120
#Key words for employee mobility	0.977	1.275	0.000	1.000	2.000	72,426

Table 2. Innovation (the Number of Patents) and fLMA

This table presents OLS regressions of innovation, measured by the number of patents, on *fLMA*. *fLMA* is firm-specific exposure to labor market agglomeration, which is the cosine similarity between a firm's skill profile vector and its CZ's (Commuting Zone's) skill profile vector. Columns 1 and 3 (2 and 4) control for CZ-by-year and industry (industry-by-year and CZ) fixed effects. $Patents_{t+1}$ ($Patents_{t+3}$) is the number of patents produced by a firm in year t+1 (years t+1, t+2, and t+3) that are ultimately granted and adjusted for truncation bias. The sample consists of all firm-years from 1997 to 2018 from Compustat. We require at least one patent per firm throughout the sample period. Industry fixed effects are based on a firm's primary 3-digit SIC industry code. Reported in parentheses are *t*-statistics based on standard errors clustered by CZ. ***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

	ln(1+$Patents_{t+1}$)	ln(1+$Patents_{t+1}$)	ln(1+$Patents_{t+3}$)	ln(1+ $Patents_{t+3}$)
	1	2	3	4
fLMA	0.246**	0.170**	0.308***	0.225***
	(3.72)	(2.26)	(3.92)	(3.02)
Industrial clustering	-0.050**	-0.034	-0.049*	-0.021
	(-2.15)	(-1.32)	(-1.70)	(-0.64)
Relative size of CZ	0.001***	0.001***	0.001***	0.001***
	(15.73)	(15.66)	(13.21)	(13.21)
Firm sale	0.244***	0.246***	0.306***	0.308***
	(45.41)	(45.76)	(49.99)	(50.19)
Firm age	0.203***	0.194***	0.340***	0.323***
	(12.92)	(12.13)	(17.67)	(16.34)
M/B	0.016***	0.017***	0.019***	0.020***
	(16.07)	(16.78)	(15.71)	(16.22)
ROA	-0.098***	-0.100***	-0.137***	-0.141***
	(-13.97)	(-14.43)	(-14.77)	(-15.55)
R&D/sale	0.022***	0.022***	0.032***	0.033***
	(17.71)	(17.79)	(19.34)	(19.86)
PPE	0.091***	0.094***	0.122***	0.126***
	(18.71)	(19.00)	(20.68)	(21.14)
Net debt	-0.152***	-0.157***	-0.222***	-0.228***
	(-22.30)	(-22.60)	(-24.06)	(-24.62)
Institutional ownership	0.054***	0.056***	0.143***	0.149***
	(3.55)	(3.60)	(7.67)	(7.86)
HHI	-0.030	–	-0.031	–
	(-0.16)		(-0.13)	
HHI^2	0.151	–	0.136	–
	(0.59)		(0.41)	
State GDP growth	-0.012	-0.005**	-0.014*	-0.005**
	(-1.57)	(-2.23)	(-1.76)	(-1.97)
State unemployment	0.023*	0.012**	0.030*	0.013**
	(1.68)	(2.42)	(1.93)	(2.21)
CZ × year FE	Yes	–	Yes	–
Industry FE	Yes	–	Yes	–
Industry × year FE	–	Yes	–	Yes
CZ FE	–	Yes	–	Yes
Adjusted R^2	0.41	0.41	0.46	0.46
Observations	75,120	75,120	75,120	75,120

Table 3. Innovation (Citations per Patent) and fLMA

This table presents OLS regressions of innovation, measured by the number of citations per patent, on *fLMA*. *fLMA* is firm-specific exposure to labor market agglomeration, which is the cosine similarity between a firm's skill profile vector and its CZ's (Commuting Zone's) skill profile vector. Columns 1 and 3 (2 and 4) control for CZ-by-year and industry (industry-by-year and CZ) fixed effects. $Cites_{t+1}$ ($Cites_{t+3}$) is the number of forward non-self-citations per patent in year t+1 (years t+1, t+2, and t+3) adjusted for truncation bias. The sample consists of all firm-years from 1997 to 2018 from Compustat. We require at least one patent per firm throughout the sample period. Industry fixed effects are based on a firm's primary 3-digit SIC industry code. Reported in parentheses are *t*-statistics based on standard errors clustered by CZ. ****p* < 0.01; ***p* < 0.05; **p* < 0.1.

	$\ln(1+Cites_{t+1})$	$\ln(1+Cites_{t+1})$	$\ln(1+Cites_{t+3})$	$\ln(1+Cites_{t+3})$
	1	2	3	4
fLMA	0.129**	0.142**	0.149**	0.111*
	(2.54)	(2.50)	(2.02)	(1.75)
Industrial clustering	-0.021	-0.066**	0.007	-0.037
	(-0.79)	(-2.28)	(0.21)	(-1.10)
Relative size of CZ	0.0001***	0.0001***	-0.0001	-0.0001
	(2.78)	(3.71)	(-1.43)	(-0.57)
Firm sale	0.149***	0.152***	0.147***	0.151***
	(43.76)	(44.52)	(42.84)	(42.84)
Firm age	0.007	-0.003	0.050**	0.035
	(0.33)	(-0.13)	(2.03)	(1.43)
M/B	0.018***	0.018***	0.018***	0.019***
	(12.68)	(12.69)	(11.66)	(11.35)
ROA	-0.057***	-0.058***	-0.067***	-0.071***
	(-6.22)	(-6.06)	(-6.44)	(-6.71)
R&D/sale	0.019***	0.020***	0.024***	0.025***
	(11.24)	(11.86)	(13.64)	(14.65)
PPE	0.088***	0.088***	0.096***	0.096***
	(19.25)	(18.49)	(19.21)	(18.85)
Net debt	-0.191***	-0.199***	-0.235***	-0.244***
	(-18.98)	(-19.46)	(-18.76)	(-19.21)
Institutional ownership	0.212***	0.196***	0.241***	0.222***
	(13.01)	(12.04)	(14.50)	(13.36)
HHI	0.994***	–	0.849***	–
	(4.62)		(3.64)	
HHI^2	-1.025***	–	-0.898***	–
	(-3.43)		(-2.74)	
State GDP growth	-0.016*	-0.010***	-0.008	-0.011***
	(-1.80)	(-3.15)	(-0.75)	(-3.27)
State unemployment	-0.027*	-0.006	-0.023	-0.009
	(-1.86)	(-0.97)	(-1.32)	(-1.29)
CZ × year FE	Yes	–	Yes	–
Industry FE	Yes	–	Yes	–
Industry × year FE	–	Yes	–	Yes
CZ FE	–	Yes	–	Yes
Adj. R^2	0.29	0.29	0.33	0.33
Obs.	75,120	75,120	75,120	75,120

Table 4. Modified Measures of Labor Market Agglomeration

This table presents OLS regressions of innovation on modified measures of *fLMA*. Panel A uses *fLMA high skill*, and Panel B uses *fLMA patent class*. *fLMA high skill* is modified *fLMA* using only high-skilled employees. *fLMA patent class* is the cosine similarity between the patent class vector of a firm and that of all the other firms in the same CZ (Commuting Zone). We reduce the dimension of the two skill composition vectors ($H_{a,t}$ and $H_{m,t}$) by eliminating low-skilled occupations in Job Zones 1-3 and then recalculate *fLMA* in equation (1). *fLMA patent class* is the cosine similarity between the patent class vector of a firm and that of all the other firms in the same CZ. The dependent variable in Columns 1 and 2 (3 and 4) is the number of patents (citations per patent). $Patents_{t+1}$ ($Patents_{t+3}$) is the number of patents produced by a firm in year t+1 (years t+1, t+2, and t+3) that are ultimately granted and adjusted for truncation bias. $Cites_{t+1}$ ($Cites_{t+3}$) is the number of non-self-citations received by a firm's patents in year t+1 (years t+1, t+2, and t+3) adjusted for truncation bias. The sample consists of all firm-years from 1997 to 2018 from Compustat. We require at least one patent per firm throughout the sample period. All regressions control for CZ-by-year and industry fixed effects. Industry fixed effects are based on a firm's primary 3-digit SIC industry code. Reported in parentheses are *t*-statistics based on standard errors clustered by CZ. ***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

Panel A. Agglomeration of only high skilled workers

	ln(1+$Patents_{t+1}$)	ln(1+$Patents_{t+3}$)	ln(1+$Cites_{t+1}$)	ln(1+$Cites_{t+3}$)
	1	2	3	4
fLMA high skill	0.356***	0.482***	0.206***	0.263***
	(7.58)	(8.09)	(4.48)	(5.02)
Controls	Yes	Yes	Yes	Yes
CZ × year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Adj. R^2	0.42	0.47	0.30	0.34
Obs.	65,277	65,277	65,277	65,277

Panel B. Agglomeration based on patent classes

	ln(1+$Patents_{t+1}$)	ln(1+$Patents_{t+3}$)	ln(1+$Cites_{t+1}$)	ln(1+$Cites_{t+3}$)
	1	2	3	4
fLMA patent class	1.762***	2.037***	0.796***	0.594***
	(23.76)	(24.56)	(11.06)	(9.34)
Controls	Yes	Yes	Yes	Yes
CZ × year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Adj. R^2	0.49	0.49	0.24	0.28
Obs.	26,934	26,934	26,934	26,934

Table 5. R&D Intensity and Startup Costs

This table presents OLS regressions for cross-sectional variation in the effect of *fLMA* on innovation. Panel A examines high R&D industries, and Panels B and C examine industries/geographic locations of high startup costs. *High R&D* is a dummy equal to one if the ratio between the 3-digit SIC industry-level R&D expense and the industry-level total assets is above the median during the years, and zero otherwise. *Capital intensive* is a dummy equal to one if net property, plant, and equipment divided by the number of employees, both at the industry-level, is above the median during the year, and zero otherwise. *High VC funding* is a dummy equal to one if the total venture capital investments made in a firm's CZ (Commuting Zone) during the year is above the median, and zero otherwise. The dependent variable in Columns 1 and 2 (3 and 4) is the number of patents (citations per patent). $Patents_{t+1}$ ($Patents_{t+3}$) is the number of patents produced by a firm in year t+1 (years t+1, t+2, and t+3) that are ultimately granted and adjusted for truncation bias. $Cites_{t+1}$ ($Cites_{t+3}$) is the number of non-self forward citations per patent in year t+1 (years t+1, t+2, and t+3) adjusted for truncation bias. *fLMA* is firm-specific exposure to labor market agglomeration. The sample consists of all firm-years from 1997 to 2018 from Compustat. All regressions control for CZ-by-year and industry fixed effects. Industry fixed effects are based on a firm's primary 3-digit SIC industry code. Reported in parentheses are *t*-statistics based on standard errors clustered by CZ. ***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

Panel A. High R&D industries

	ln(1+$Patents_{t+1}$)	ln(1+$Patents_{t+3}$)	ln(1+$Cites_{t+1}$)	ln(1+$Cites_{t+3}$)
	1	2	3	4
fLMA × High R&D	0.786***	0.856***	0.880***	0.832***
	(7.19)	(6.20)	(7.91)	(6.23)
fLMA	0.057	0.165*	0.068	0.043
	(1.28)	(1.76)	(1.23)	(0.61)
High R&D	0.353***	0.613***	0.330***	0.508***
	(10.54)	(14.51)	(9.38)	(11.79)
Controls, CZ × year and industry FE	Yes	Yes	Yes	Yes
Adj. R^2	0.44	0.50	0.32	0.36
Obs.	75,120	75,120	75,120	75,120

Panel B. Capital intensive industries

	1	2	3	4
fLMA × Capital intensive	0.188**	0.223*	0.047*	0.046
	(1.98)	1.86)	(1.75)	(1.43)
fLMA	0.174***	0.244***	0.167**	0.198*
	(5.13)	(5.26)	(2.20)	(1.88)
Capital intensive	0.359***	0.446***	0.235***	0.172***
	(9.50)	(10.42)	(6.11)	(4.27)
Controls, CZ × year and industry FE	Yes	Yes	Yes	Yes
Adj. R^2	0.42	0.47	0.30	0.33
Obs.	75,120	75,120	75,120	75,120

Panel C. High VC funding locations

	1	2	3	4
fLMA × High VC funding	-0.085*	-0.096**	-0.049*	-0.017
	(-1.92)	(-2.02)	(-1.79)	(-1.23)
fLMA	0.318***	0.488***	0.212***	0.238***
	(4.05)	(4.70)	(4.14)	(4.15)
Controls, CZ × year and industry FE	Yes	Yes	Yes	Yes
Adj. R^2	0.41	0.46	0.30	0.33
Obs.	75,120	75,120	75,120	75,120

Table 6. Channels Based on Labor Mobility, Knowledge Spillover, and Stock Options

This table investigates potential channels based on labor mobility, knowledge spillover, and stock options by estimating OLS regressions. In Panel A, *High labor mobility* is a dummy equal to 1 if the number of inventor-moves divided by the total number of inventors, both at the industry level, is above the median, and 0 otherwise. In Panel B, *Spillover via coworkership* is a dummy equal to 1 if within-industry citations divided by total citations at the industry-level is above the median, and 0 otherwise. In Panel C, *High nonexecutive options* is a dummy equal to 1 if the ratio between the total value of non-executive stock options within the industry and the industry's total market capitalization is above the median, and 0 otherwise. $Patents_{t+1}$ ($Patents_{t+3}$) is the number of patents produced by a firm in year t+1 (years t+1, t+2, and t+3). $Cites_{t+1}$ ($Cites_{t+3}$) is the number of non-self forward citations per patent in year t+1 (years t+1, t+2, and t+3). The sample consists of all firm-years from 1997 to 2018 from Compustat. Reported in parentheses are *t*-statistics based on standard errors clustered by CZ (Commuting Zone). All regressions include the control variables, CZ-by-year and industry fixed effects. ***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

Panel A. Realized labor mobility channel

	$\ln(1+Patents_{t+1})$	$\ln(1+Patents_{t+3})$	$\ln(1+Cites_{t+1})$	$\ln(1+Cites_{t+3})$
	1	2	3	4
fLMA × High mobility	0.857***	1.018***	0.729***	0.676***
	(4.34)	(3.94)	(4.64)	(3.51)
fLMA	0.145*	0.126*	0.219**	0.216
	(1.69)	(1.81)	(2.01)	(1.44)
Controls, CZ × year- and industry-FE	Yes	Yes	Yes	Yes
Adj. R^2	0.41	0.46	0.30	0.33
Obs.	75,120	75,120	75,120	75,120

Panel B. Knowledge spillover via coworkership channel

	1	2	3	4
fLMA × Spillover via coworkership	0.399*	0.573**	0.616***	0.591***
	(1.78)	(2.16)	(3.74)	(3.36)
fLMA	0.093*	0.101*	0.100**	0.108
	(1.85)	(1.72)	(1.96)	(1.56)
Controls, CZ × year- and industry-FE	Yes	Yes	Yes	Yes
Adj. R^2	0.41	0.46	0.30	0.33
Obs.	75,120	75,120	75,120	75,120

Panel C. Employee stock options channel

	1	2	3	4
fLMA × High nonexecutive options	0.135	0.151*	0.192*	0.209*
	(1.42)	(1.91)	(1.69)	(1.73)
fLMA	0.178**	0.254**	0.055	0.025
	(1.99)	(2.34)	(1.42)	(1.17)
Controls, CZ × year- and industry-FE	Yes	Yes	Yes	Yes
Adj. R^2	0.41	0.46	0.30	0.33
Obs.	75,120	75,120	75,120	75,120

Table 7. Channels Based on Job Security, IP Rights, and Transportation Costs

This table presents OLS regressions to examine the effects of *fLMA* on innovation through, the unemployment insurance (UI) channel (Panel A), the intellectual property (IP) ownership channel (Panel B), and transportation costs channel (Panel C). Panel B estimates a triple difference estimator around the 2008 Federal Circuit ruling which shifted the IP ownership from inventor-employees to employers. *UI up* (*UI down*) is a dummy equal to 1 if the UI benefits in a firm's headquarters state increase (decrease) by at least 5% compared to the previous year, and 0 otherwise. The UI benefits in a state are defined as the product of the maximum UI benefit amount and the maximum duration during the year. *Treated* is a dummy equal to 1 if a firm is headquartered in one of the 8 employee-friendly states regarding IP rights, and 0 otherwise. *Post* is dummy equal to 1 for years from 2008 to 2013, and 0 otherwise. *High vertical relatedness* is a dummy equal to 1 if the average pairwise vertical relatedness between a firm and the other firms in the same CZ (Commuting Zone) is above the median, and 0 otherwise. The sample consists of all firm-years from 1997 to 2018 from Compustat, except for Panel B in which we restrict the sample to the years 2002 through 2013. The dependent variable in Columns 1 and 2 (3 and 4) is the number of patents (citations per patent). $Patents_{t+1}$ ($Patents_{t+3}$) is the number of patents produced by a firm in year t+1 (years t+1, t+2, and t+3) that are ultimately granted and adjusted for truncation bias. $Cites_{t+1}$ ($Cites_{t+3}$) is the number of forward non-self-citations per patent in year t+1 (years t+1, t+2, and t+3) adjusted for truncation bias. *fLMA* is firm-specific exposure to labor market agglomeration. All regressions include control variables, and CZ-by-year and industry fixed effects. Reported in parentheses are *t*-statistics based on standard errors clustered by CZ. ***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

Panel A. Unemployment insurance

	Full sample			
	ln(1+$Patents_{t+1}$)	ln(1+$Patents_{t+3}$)	ln(1+$Cites_{t+1}$)	ln(1+$Cites_{t+3}$)
	1	2	3	4
fLMA × UI up	-0.117	-0.118	-0.143	-0.130
	(-1.15)	(-1.04)	(-1.36)	(-1.13)
fLMA × UI down	0.139	0.160	0.053	0.062
	(1.07)	(1.22)	(0.26)	(0.23)
fLMA	0.273***	0.368***	0.222**	0.215*
	(2.78)	(2.87)	(1.98)	(1.69)
Controls, CZ × year and industry FE	Yes	Yes	Yes	Yes
Adj. R^2	0.41	0.46	0.30	0.33
Obs.	75,120	75,120	75,120	75,120

Panel B. Intellectual property rights

	Years 2002-2013			
	1	2	3	4
fLMA × Treated × Post	0.399*	0.486**	0.269	0.394*
	(1.91)	(1.96)	(1.46)	(1.74)
Treated × Post	0.186	0.350	0.127	0.019
	(1.01)	(1.64)	(0.97)	(0.15)
fLMA	0.353***	0.416***	0.196**	0.169*
	(4.28)	(4.02)	(2.16)	(1.65)
Controls, CZ × year and industry FE	Yes	Yes	Yes	Yes
Adj. R^2	0.43	0.47	0.31	0.34
Obs.	41,514	41,514	41,514	41,514

Panel C. Transportation costs

	Full sample			
	1	2	3	4
fLMA × High vertical relatedness	0.039	0.101	0.195	-0.051
	(0.43)	(0.94)	(1.28)	(-0.49)
fLMA	0.278***	0.356***	0.146***	0.191***
	(3.13)	(3.19)	(4.17)	(2.81)
Controls, CZ × year and industry FE	Yes	Yes	Yes	Yes
Adj. R^2	0.41	0.46	0.30	0.33
Obs.	75,120	75,120	75,120	75,120

Table 8. Inevitable Disclosure Doctrine (IDD) as an Instrumental Variable

This table presents the 2SLS estimation results using IDD as an instrumental variable. Column 1 presents the first stage regression in which the dependent variable is *fLMA*. Columns 2-5 present the second stage regression in which we relate the predicted *fLMA* from the first stage to innovation output. The dependent variable in Columns 2 and 3 (4 and 5) is the number of patents (citations per patent). $Patents_{t+1}$ ($Patents_{t+3}$) is the number of patents produced by a firm in year t+1 (years t+1, t+2, and t+3) that are ultimately granted and adjusted for truncation bias. $Cites_{t+1}$ ($Cites_{t+3}$) is the number of non-self forward citations per patent in year t+1 (years t+1, t+2, and t+3) adjusted for truncation bias. *IDD* is a dummy equal to one if IDD has been adopted and not rejected in a firm's headquarters state by the beginning of the year, and zero otherwise. *fLMA* is firm-specific exposure to labor market agglomeration within its CZ (Commuting Zone). The sample consists of all firm-years from 1997 to 2018 from Compustat. We require at least one patent per firm throughout the sample period. All regressions control for CZ-by-year and industry fixed effects. Industry fixed effects are based on a firm's primary 3-digit SIC industry code. Reported in parentheses are *t*-statistics based on standard errors clustered by CZ. ***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

	fLMA	ln(1+$Patents_{t+1}$)	ln(1+$Patents_{t+3}$)	ln(1+$Cites_{t+1}$)	ln(1+$Cites_{t+3}$)
	1	2	3	4	5
IDD	-0.009***				
	(-2.82)				
$fLMA^{fitted}$		2.867***	3.716***	1.089*	1.107*
		(2.71)	(2.61)	(1.93)	(1.70)
Industrial clustering	0.048***	-0.753***	-0.931***	-0.216	0.215
	(10.33)	(-2.70)	(-2.58)	(-1.32)	(1.12)
Relative size of CZ	0.0002***	0.0001	0.0001	0.0001	0.0001
	(7.62)	(1.38)	(1.53)	(0.16)	(0.25)
Firm sale	0.004***	0.180***	0.225***	0.131***	0.166***
	(17.86)	(3.04)	(2.85)	(4.64)	(4.43)
Firm age	0.008***	0.079	0.185*	-0.027	0.087*
	(5.21)	(1.49)	(1.71)	(-0.76)	(1.71)
M/B	0.002***	0.020***	0.025***	0.019***	0.017***
	(3.04)	(6.51)	(6.15)	(8.92)	(6.71)
ROA	-0.001*	-0.081***	-0.115***	-0.053***	-0.072***
	(-1.77)	(-3.94)	(-4.68)	(-5.15)	(-6.13)
R&D/sale	0.001	0.020***	0.030***	0.018***	0.025***
	(1.45)	(8.85)	(9.76)	(10.57)	(12.79)
PPE	-0.001*	0.101***	0.134***	0.091***	0.093***
	(-1.94)	(9.27)	(9.08)	(16.90)	(15.99)
Net debt	-0.002***	-0.122***	-0.185***	-0.183***	-0.244***
	(-3.13)	(-4.91)	(-6.28)	(-12.98)	(-14.27)
Institutional ownership	-0.003**	0.091***	0.190***	0.222***	0.230***
	(-2.32)	(3.58)	(5.79)	(11.71)	(11.24)
HHI	-0.073***	1.053**	1.327*	1.293***	0.528
	(-3.66)	(1.97)	(1.92)	(3.81)	(1.41)
HHI^2	0.067**	-0.846	-1.115	-1.301***	-0.602
	(2.34)	(-1.34)	(-1.38)	(-3.34)	(-1.36)
State GDP growth	-0.003**	0.027	0.035	-0.006	-0.020
	(-2.28)	(1.04)	(1.03)	(-0.39)	(-1.36)
State unemployment	-0.014***	0.245**	0.309**	0.034	-0.089
	(-5.61)	(2.50)	(2.43)	(0.60)	(-1.46)
CZ × year and industry FE	Yes	Yes	Yes	Yes	Yes
F-statistic	16.48				
	(0.00)				
Adj. R^2	0.56				
Obs.	75,120	75,120	75,120	75,120	75,120

Table 9. Publication Delay by Peers (PDP) as an Instrumental Variable

This table presents the 2SLS tests for the knowledge spillover channel using publication delay by peers (PDP) as an instrumental variable. In Column 1, we report the first stage regression in which the dependent variable, *fLMA*, is regressed against *PDP*. *PDP* is the ratio between the weighted average of industry peers' publication delays and the focal firm's average publication delay, in which the weight is based on the quartile rank of patents a firm produces in the recent 10 years. Columns 2-5 present the second stage regression. $Patents_{t+1}$ ($Patents_{t+3}$) is the number of patents produced by a firm in year t+1 (years t+1, t+2, and t+3). $Cites_{t+1}$ ($Cites_{t+3}$) is the number of non-self forward citations per patent in year t+1 (years t+1, t+2, and t+3). *fLMA* is firm-specific exposure to labor market agglomeration. The sample consists of all firm-years from 1997 to 2018 from Compustat. Reported in parentheses are *t*-statistics based on standard errors clustered by CZ (Commuting Zone). Column 1 reports the *F*-statistic from the 1st stage regression and the corresponding *p*-value. ***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

	fLMA	ln(1+$Patents_{t+1}$)	ln(1+$Patents_{t+3}$)	ln(1+$Cites_{t+1}$)	ln(1+$Cites_{t+3}$)
	1	2	3	4	5
ln(1+*PDP*)	0.013**				
	(2.32)				
$fLMA^{fitted}$		3.164***	1.570***	2.720*	7.175**
		(2.86)	(1.97)	(1.91)	(2.12)
Industrial clustering	0.048***	-0.758*	-3.865**	-6.065**	-12.916**
	(10.34)	(-1.93)	(-2.02)	(-2.07)	(-2.17)
Relative size of CZ	0.0002***	0.0001	-0.001	-0.004*	-0.008**
	(7.70)	(1.33)	(-1.28)	(-1.75)	(-1.98)
Firm sale	0.004***	0.179***	-0.044	-0.406***	-1.04-***
	(17.73)	(3.05)	(-0.49)	(-2.99)	(-3.58)
Firm age	0.008***	0.078	-0.332	-1.057***	-2.226***
	(4.88)	(1.47)	(-1.56)	(-3.21)	(-3.18)
M/B	-0.0001***	0.020***	0.042**	0.053*	0.094**
	(-3.01)	(4.55)	(2.49)	(1.69)	(2.03)
ROA	-0.001*	-0.081***	-0.042	0.092	0.253
	(-1.73)	(-5.95)	(-0.71)	(0.99)	(1.27)
R&D/sale	0.0001	0.020***	0.022***	0.002	-0.012
	(1.25)	(10.80)	(2.83)	(0.16)	(-0.44)
PPE	-0.001**	0.101***	0.175***	0.173**	0.277*
	(-2.08)	(3.36)	(3.60)	(2.55)	(1.69)
Net debt	-0.002***	-0.122**	-0.061	0.065	0.312
	(-2.89)	(-2.53)	(-0.92)	(0.63)	(1.44)
Institutional ownership	-0.003**	0.092***	0.345***	0.531**	0.924*
	(-2.43)	(2.68)	(2.52)	(2.46)	(1.83)
HHI	-0.073***	1.060**	5.845***	10.300***	20.748***
	(-3.64)	(2.08)	(2.69)	(3.02)	(2.86)
HHI^2	0.067**	-0.853	-5.276*	-9.596**	-19.227**
	(2.33)	(-1.40)	(-1.90)	(-2.18)	(-2.05)
State GDP growth	-0.003**	0.027	0.199	0.321	0.714
	(-2.12)	(1.06)	(1.51)	(1.52)	(1.57)
State unemployment	-0.015***	0.247**	1.239*	1.888*	4.072*
	(-5.82)	(2.55)	(1.92)	(1.85)	(1.87)
CZ × year and industry FE	Yes	Yes	Yes	Yes	Yes
F-statistic	13.54				
	(0.00)				
Adj. R^2	0.56				
Obs.	75,120	75,120	75,120	75,120	75,120

Table 10. Robustness Tests

This table reports robustness tests. Panel A excludes firm-years in the last 5 years from our sample. Panel B presents the result using *fLMA_MSA* constructed based on Metropolitan Statistical Areas (MSAs) rather than Commuting Zones (CZs). Panel C excludes wholesale (NAICS 42), retail (NAICS 44-45), and transportation (NAICS 48) industries. Panel D excludes industrial clusters. A given CZ is classified as an industrial cluster if it has at least 10 firms of the same three-digit SIC and at least 3% of that industry's market value. Panel E excludes the bottom 10% of firms with respect to the ratio of the number of CZ employees to that of firm employees during the year. Panel F interacts *fLMA* with *High tech*, a dummy indicating that a firm operates in high-tech industries. In Panel G, we control for executive and nonexecutive stock options for the subsample of firms. *Executive options* is the natural logarithm of 1 plus the average value of stock option grants for each top executive of the firm. *Nonexecutive options* is the natural logarithm of 1 plus the value of stock option grants per 1,000 non-executive employees during the year. Panel H presents Poisson regressions in which dependent variables are the number of patents produced by a firm (*Raw patents*) or the number of non-self forward citations (*Raw cites*). All regressions except Panel B include the control variables, CZ-by-year and industry fixed effects. Regressions in Panel B include the control variables, MSA-by-year and industry fixed effects. Reported in parentheses are *t*-statistics based on standard errors clustered by CZ (by MSA in Panel B). ***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

Panel A. Exclude the last 5 years

	$\ln(1+Patents_{t+1})$	$\ln(1+Patents_{t+3})$	$\ln(1+Cites_{t+1})$	$\ln(1+Cites_{t+3})$
	1	2	3	4
fLMA	0.272**	0.320**	0.191	0.131*
	(2.03)	(1.98)	(1.64)	(1.89)
Adj. R^2	0.41	0.46	0.30	0.33
Obs.	65,339	65,339	65,339	65,339

Panel B. MSA-based fLMA

	$\ln(1+Patents_{t+1})$	$\ln(1+Patents_{t+3})$	$\ln(1+Cites_{t+1})$	$\ln(1+Cites_{t+3})$
	1	2	3	4
fLMA_MSA	0.423***	0.551***	0.324***	0.347**
	(3.44)	(3.26)	(3.22)	(2.49)
Adj. R^2	0.41	0.46	0.30	0.33
Obs.	75,120	75,120	75,120	75,120

Panel C. Exclude multi-location industries

	$\ln(1+Patents_{t+1})$	$\ln(1+Patents_{t+3})$	$\ln(1+Cites_{t+1})$	$\ln(1+Cites_{t+3})$
	1	2	3	4
fLMA	0.335**	0.438**	0.290**	0.286*
	(2.38)	(2.45)	(2.20)	(1.95)
Adj. R^2	0.42	0.47	0.29	0.32
Obs.	66,386	66,386	66,386	66,386

Panel D. Exclude industrial clusters

	$\ln(1+Patents_{t+1})$	$\ln(1+Patents_{t+3})$	$\ln(1+Cites_{t+1})$	$\ln(1+Cites_{t+3})$
	1	2	3	4
fLMA	0.156**	0.188**	0.057	0.066*
	(2.15)	(1.99)	(1.54)	(1.73)
Adj. R^2	0.38	0.43	0.28	0.31
Obs.	62,026	62,026	62,026	62,026

Panel E. Exclude local dominant employers

	$\ln(1+Patents_{t+1})$	$\ln(1+Patents_{t+3})$	$\ln(1+Cites_{t+1})$	$\ln(1+Cites_{t+3})$
	1	2	3	4
fLMA	0.224**	0.297**	0.175**	0.142*
	(2.44)	(2.51)	(1.96)	(1.93)
Adj. R^2	0.43	0.48	0.31	0.35
Obs.	67,484	67,484	67,484	67,484

Table 10. Continued

Panel F. High tech industries

	$\ln(1+Patents_{t+1})$	$\ln(1+Patents_{t+3})$	$\ln(1+Cites_{t+1})$	$\ln(1+Cites_{t+3})$
	1	2	3	4
fLMA × High tech	0.295**	0.280*	0.501**	0.332
	(2.10)	(1.75)	(2.21)	(1.51)
fLMA	0.212***	0.310***	0.067	0.100*
	(2.68)	(2.88)	(1.57)	(1.69)
Adj. R^2	0.41	0.46	0.30	0.33
Obs.	75,120	75,120	75,120	75,120

Panel G. Control for employee stock options

	$\ln(1+Patents_{t+1})$	$\ln(1+Patents_{t+3})$	$\ln(1+Cites_{t+1})$	$\ln(1+Cites_{t+3})$
	1	2	3	4
fLMA	0.393**	0.450**	0.233**	0.114**
	(2.36)	(2.21)	(2.03)	(2.45)
Executive options	0.014**	0.020***	0.014***	0.016***
	(2.37)	(2.70)	(3.20)	(3.12)
Nonexecutive options	0.066	0.098	0.016	0.092
	(0.63)	(0.83)	(0.27)	(1.46)
Adj. R^2	0.55	0.59	0.42	0.45
Obs.	24,197	24,197	24,197	24,197

Panel H. Poisson regression

	$Raw\ patents_{t+1}$	$Raw\ patents_{t+3}$	$Raw\ cites_{t+1}$	$Raw\ cites_{t+3}$
	1	2	3	4
fLMA	0.353**	0.266*	0.430**	0.160*
	(2.14)	(1.78)	(2.40)	(1.69)
Obs.	75,120	75,120	75,120	75,120

Appendix A. Variable Definitions

Labor Market Agglomeration (fLMA)

- The cosine similarity between a firm's employee skill profile vector and the associated commuting zone's (CZ's) employee skill profile vector. A firm's employee skill profile vector is constructed as the segment-sales weighted average of its industry segments' employee skill profile vectors, where the weights are segment sales to total firm sales. We obtain industry-level employee skill profile vectors from the OES program of the BLS. For each 3-digit SIC code for years 1997-2001 and 4-digit NAICS code from 2002, OES reports an industry employee skill profile vector where the elements are the number of industry workers assigned to an occupation divided by the total number of workers in the industry. We obtain the CZ's employee skill profile vectors from OEWS. The elements of the MSA employee skill profile vector are the number of CZ workers assigned to an occupation title divided by the total number of workers in the CZ.

fLMA high skill

- *fLMA* for high-skilled employees. We reduce the dimension of the two skill composition vectors ($H_{a,t}$ and $H_{c,t}$) by eliminating the occupations in Job Zones 1-3 in equation (1).

fLMA patent class

- Cosine similarity between the patent class vector of a firm and that of all the other firms in the same CZ. Each element of a firm's patent class vector is the number of patents filed by a firm (and ultimately granted) in years t-2, t-1, and t, divided by the total number of its patents during the same period. Likewise, each element of a CZ's patent class vector is the number of patents filed by all the other firms in the CZ (excluding the focal firm) in years t-2, t-1, and t, divided by the total number of their patents during the same period.

$Patents_{t+1}$ ($Patents_{t+3}$)

- Number of patent applications filed by a firm in year t+1 (years t+1, t+2, and t+3) that are ultimately granted and adjusted for truncation bias as in Hall, Jaffe, and Trajtenberg (2001).

$Cites_{t+1}$ ($Cites_{t+3}$)

- Number of non-self forward citations, adjusted for truncation bias, divided by the number of a firm's corresponding patents in year t+1 (years t+1, t+2, and t+3).

$Hires_{t+1}$ ($Hires_{t+3}$)

- Number of inventors who have joined a firm in year t+1 (years t+1, t+2, and t+3). We identify an inventor's move between firms based on his/her two consecutive patent applications and regard the mid-point between the two filing dates as the job change date.

$Departures_{t+1}$ ($Departures_{t+3}$)

- Number of inventors who have left a firm in year t+1 (years t+1, t+2, and t+3). We identify an inventor's move between firms based on his/her two consecutive patent applications and regard the mid-point between the two filing dates as the job change date.

#Key words for employee mobility

- Number of key words related to employee mobility that appear in the risk factors section (Item 1A) of a firm's annual report (10-K) in year t. See Appendix C for the full list of the key words.

CEO_left

- Dummy equal to 1 if a firm's CEO leaves the firm during the year, and 0 otherwise.

Exec_left

- Number of executives who leave the firm during the year.

Industrial clustering

- Number of firms that are from the same three-digit SIC industry and headquartered in the same CZ as a focal firm, divided by the total number of firms in the three-digit SIC industry in year t.

Relative size of CZ

- Number of the CZ's employees divided by that of a firm's employees (EMP) during the year (expressed in thousands). The number of CZ employees is the sum of employees across MSAs that belong to the

CZ where the focal firm is headquartered. The BLS OES reports the number of MSA employees for each occupation. We sum MSA employees across all occupations to get the total number of MSA employees.

Firm sale

- Natural logarithm of 1 plus firm sales (SALE) during the year.

Firm age

- Natural logarithm of 1 plus the number of years a firm has appeared in the Compustat database.

M/B

- Total assets (AT) minus the book value of equity (CEQ) plus the market value of equity (PRCC_F*CSHO), all divided by total assets (AT) during the year.

ROA

- Ratio of income before extraordinary items (IB) to total assets (AT) during the year.

R&D/Sale

- Ratio of R&D expenditures (XRD) to firm sales (SALE). If XRD is missing from Compustat, we treat it as zero.

PPE

- Natural logarithm of 1 plus the ratio of net property, plant, and equipment (PPENT) to the total number of firm employees (EMP) during the year.

Institutional ownership

- Proportion of stock owned by institutions. If stock owned by institutions is missing, we set it equal to zero (*Source*: Refinitiv/Thomson Reuter).

Net debt

- Ratio of long-term debt (DLTT) plus debt in current liabilities (DLC) minus cash and short-term investments (CHE) to the book value of assets (AT).

HHI

- Herfindahl Index of concentration of firm sales within the 3-digit SIC industry during the year.

High R&D

- Dummy equal to 1 if the total R&D expense of a 3-digit SIC industry is above the median during the year, and 0 otherwise.

Capital intensive

- Dummy equal to 1 if the ratio between the industry-level net property, plant, and equipment (PPENT) and the industry-level employees (EMP) is above the median during the year, and 0 otherwise.

High VC funding

- Dummy equal to 1 if the total amount of VC investments made in a firm's CZ during the year is above the median, and 0 otherwise (*Source*: SDC's Venture Xpert).

High tech

- Dummy equal to 1 if a firm is in one of the 47 4-digit SIC industries classified as high-tech by the American Electronic Association. The 2-digit SIC codes of the 47 industries consist of 28, 35, 36, 38, 48, and 73.

IDD

- Dummy equal to 1 if IDD has been adopted and not rejected in a firm's headquarters state by the beginning of the year, and 0 otherwise.

High mobility

- Dummy equal to 1 if the ratio between the number of inventor-moves and the total number of inventors, both at the 3-digit SIC industry level, is above the median during the year, and 0 otherwise.

Spillover via coworkership

- Dummy equal to 1 if the total within-industry citations divided by the total citations at the 3-digit SIC industry-level is above the median during the year, and 0 otherwise.

Executive options

- Natural logarithm of 1 plus the ratio between the value of options granted to the top executives and the number of the top executives reported in ExecuComp during the year.

Nonexecutive options

- Natural logarithm of 1 plus the value of stock option grants per 1,000 non-executive employees during the year. To find the value of stock option grants to non-executive employees, we first identify the total value of option grants to all firm employees during the year and then subtract the value of option grants to the firm's top executives reported in ExecuComp from it. Up until 2005, we calculate the value of option grants to all firm employees by dividing the value of options granted to the executives by the percentage of the total employee option grants (PCTTOTOPT), both numerator and denominator are from ExecuComp. From 2006, we use the total value of options granted to all employees (OPTFVGR) reported in Compustat.

High nonexecutive options

- Dummy equal to 1 if the ratio between the total value of non-executive stock options within a 3-digit SIC industry and the industry's total market capitalization during the year is above the median, and 0 otherwise.

Publication Delay by Peers (*PDP*)

- Ratio between the patent-weighted industry-peers' average publication delay and the patent-weighted focal firm's average publication delay, where the weight is based on the quartile rank of the number of patents the firm files in the recent 10 years ($w = 1, 2, 3,$ or 4). Publication delay of a patent is the number of days between application date and publication date (*Source*: PatentsView).

Unemployment insurance (*UI*)

- Natural logarithm of the product of the maximum benefit amount and the maximum duration of the state-level unemployment insurance.

UI up (*down*)

- Dummy equal to 1 if the UI benefits in a firm's headquarters state increase (decrease) by at least 5% compared to the previous year, and 0 otherwise.

High vertical relatedness

- Dummy equal to 1 if the average pairwise vertical-relatedness score between a firm and the other firms in the same CZ is above the median during the year, and 0 otherwise (*Source*: Fresard et al. 2020).

Spillover via coworkership CZ

- Dummy equal to 1 if the total within-CZ citations divided by the total citations at the CZ-level is above the median during the year, and 0 otherwise.

High executive options

- Dummy equal to 1 if the ratio between the total value of the top executive stock options within a 3-digit SIC industry and the industry's total market capitalization during the year is above the median, and 0 otherwise.

fLMA_2

- *fLMA* re-calculated by excluding a firm's workforce from the CZ's skill profile vector. For each occupation in the CZ skill profile vector, we subtract the number of firm employees in the occupation from that of the CZ employees. Using this adjusted CZ skill profile, we re-calculate *fLMA* in equation (1).

Appendix B. Numerical Examples of fLMA Computation

We use the following examples to illustrate the calculation of our firm-level labor market agglomeration (*fLMA*) measure. Firms A and B operate in the same industry but in different locations; the former in CZ 1 and the latter in CZ 2. The two firms have the *identical* labor force composition: 2 computer scientists, 1 teacher, and 1 dietary cook. The two CZs have the identical size of local labor market but different labor force compositions. Both locations have a total of 100 employees. CZ 1 has 2 computer scientists (2% of all local employees in CZ 1), 40 teachers (40%), 15 drivers (15%), and 43 dietary cooks (43%). In other words, Firm A is the only firm in CZ 1 that hires computer scientists. On the other hand, CZ 2 has 30 computer scientists (30% of all local employees in CZ 2), 20 teachers (20%), 15 drivers (15%), and 35 dietary cooks (35%).

Panel A. Firm A in CZ 1

	Firm A		CZ 1	
	No. employees	%	No. employees	%
Computer scientist	2	50%	2	2%
Teacher	1	25%	40	40%
Driver	0	0%	15	15%
Dietary cook	1	25%	43	43%
Total	4	100%	100	100%
fLMA	**0.59**			

Panel B. Firm B in CZ 2

	Firm B		CZ 2	
	No. employees	%	No. employees	%
Computer scientist	2	50%	30	30%
Teacher	1	25%	20	20%
Driver	0	0%	15	15%
Dietary cook	1	25%	35	35%
Total	4	100%	100	100 %
fLMA	**0.90**			

We calculate *fLMA* for each firm-CZ pair. *fLMA* for Firm A is 0.59, while that for Firm B is 0.90. Firm B, on average, is more exposed to labor market pooling. In particular, the pooling of local computer scientists drives a higher level of *fLMA* for Firm B.

Appendix C. Validation of fLMA Using Realized Employee Mobility

This table reports OLS regressions for employee moves. Columns 1-4 report inventor moves, and columns 5-6 report CEO and executives' departures. $Hires_{t+1}$ ($Departures_{t+1}$) is the number of inventors who have joined (left) a firm in year t+1. $Hires_{t+3}$ ($Departures_{t+3}$) is the number of inventors who have joined (left) a firm in years t+1, t+2, and t+3. *CEO_left* is a dummy equal to 1 if a firm's CEO leaves the firm during the year, and 0 otherwise. *Exec_left* is the number of executives who leave the firm during the year. *fLMA* is firm-specific exposure to labor market agglomeration. Industry fixed effects are based on 3-digit SIC industries. Reported in parentheses are *t*-statistics based on standard errors clustered by Commuting Zone (CZ). ***p < 0.01; **p < 0.05; *p < 0.1.

	ln(1+$Hires_{t+1}$)	ln(1+$Departure_{t+1}$)	ln(1+$Hires_{t+3}$)	ln(1+$Departures_{t+3}$)	CEO_left_{t+1}	ln(1+$Exec\_left_{t+1}$)
	1	2	3	4	5	6
fLMA	0.156***	0.153***	0.228***	0.218***	0.022*	0.097**
	(2.99)	(2.68)	(4.34)	(4.13)	(1.90)	(2.14)
Industrial clustering	-0.030*	-0.056***	-0.019	-0.043**	-0.001	-0.005
	(-1.93)	(-3.87)	(-0.88)	(-2.21)	(-0.03)	(-0.93)
Relative size of CZ	0.001***	0.001***	0.001***	0.001***	0.0001***	0.0001***
	(17.05)	(16.37)	(16.41)	(16.46)	(6.12)	(6.68)
Firm sale	0.145***	0.137***	0.191***	0.185***	0.018***	0.018***
	(34.99)	(37.55)	(35.97)	(37.27)	(17.56)	(14.59)
Firm age	0.068***	0.161***	0.078***	0.149***	0.066***	0.059***
	(6.72)	(15.75)	(5.42)	(9.66)	(11.94)	(17.05)
M/B	0.010***	0.006***	0.015***	0.011***	0.001	0.001
	(14.73)	(10.61)	(15.11)	(13.12)	(1.01)	(0.54)
ROA	-0.043***	-0.066***	-0.051***	-0.072***	-0.010***	-0.012***
	(-10.93)	(-15.21)	(-9.27)	(-12.91)	(-9.38)	(-12.48)
R&D/sale	0.010***	0.012***	0.014***	0.016***	0.001***	0.001***
	(12.99)	(13.62)	(13.61)	(14.12)	(6.97)	(10.34)
PPE	0.050***	0.044***	0.066***	0.061***	0.002**	0.001
	(14.78)	(14.85)	(14.62)	(14.64)	(2.53)	(1.64)
Net debt	-0.066***	-0.057***	-0.102***	-0.091***	-0.002	-0.005***
	(-17.11)	(-15.09)	(-17.86)	(-17.46)	(-1.14)	(-4.49)
Insti. ownership	-0.036***	-0.031***	-0.026*	-0.040***	0.035***	0.009***
	(-3.74)	(-3.35)	(-1.95)	(-2.96)	(10.36)	(2.72)
HHI	-0.143	-0.031	-0.015	0.096	-0.089**	0.003
	(-1.47)	(-0.32)	(-0.11)	(0.71)	(-2.00)	(0.10)
HHI2	0.275**	0.101	0.223	0.075	0.103	0.039
	(1.98)	(0.74)	(1.13)	(0.40)	(1.55)	(0.81)
State GDP growth	-0.008	-0.005	-0.007	-0.003	0.001	0.0001
	(-1.32)	(-0.94)	(-0.95)	(-0.49)	(0.49)	(0.34)
State unemp.	0.007	-0.010	0.013	-0.011	-0.008**	-0.007**
	(0.67)	(-1.07)	(0.97)	(-0.94)	(-2.14)	(-2.47)
CZ × year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.32	0.32	0.33	0.32	0.06	0.09
Obs.	75,120	75,120	75,120	75,120	75,120	75,120

Internet Appendix for "Local Labor Markets and Corporate Innovation"

I.A.1. List of Key Words for Employee Mobility

This table reports the full list of key phrases we have used in the textual analysis to define *#key words for employee mobility* in Table 1. We search the risk factor section (Item 1A) of a firm's annual report (10-K) for the following key phrases:

['employees may leave', 'workers may leave', 'personnel may leave', 'employees may depart', 'workers may depart', 'personnel may depart', 'key talent may leave', 'talent may leave', 'employee departure', 'worker departure', 'personnel departure', 'employee may leave', 'worker may leave', 'personnel may leave', 'key talent departure', 'talent departure', 'employees turnover', 'workers turnover', 'personnel turnover', 'key talent turnover', 'talent turnover', 'employee may depart', 'workers may depart', 'personnel may depart', 'key talent may depart', 'talent may depart', 'turnover of employee', 'turnover of key employee', 'turnover of our employee', 'turnover of current employee', 'turnover of qualified employee', 'turnover of skilled employee', 'turnover of personnel', 'turnover of key personnel', 'turnover of our personnel', 'turnover of current personnel', 'turnover of qualified personnel', 'turnover of skilled personnel', 'turnover of worker', 'turnover of key worker', 'turnover of our worker', 'turnover of current worker', 'turnover of qualified worker', 'turnover of skilled worker', 'turnover of key talent', 'turnover of talent', 'departure of employee', 'departure of key employee', 'departure of our employee', 'departure of current employee', 'departure of qualified employee', 'departure of skilled employee', 'departure of personnel', 'departure of key personnel', 'departure of our personnel', 'departure of current personnel', 'departure of qualified personnel', 'departure of skilled personnel', 'departure of worker', 'departure of key worker', 'departure of our worker', 'departure of current worker', 'departure of qualified worker', 'departure of skilled worker', 'departure of key talent', 'departure of talent', 'competition for employee', 'competition for worker', 'competition for personnel', 'competition for talent', 'competition for their talent', 'competition for skilled', 'competition for skills', 'competition for key personnel', 'competition for key employee', 'competition for key worker', 'competition for key talent', 'competition for talent', 'retain employee', 'retain key employee', 'retain our employee', 'retain current employee', 'retain qualified employee', 'retain skilled employee', 'retain personnel', 'retain key personnel', 'retain our personnel', 'retain current personnel', 'retain qualified personnel', 'retain skilled personnel', 'retain worker', 'retain key worker', 'retain our worker', 'retain current worker', 'retain qualified worker', 'retain skilled worker', 'retain key talent', 'retain talent', 'retaining employee', 'retaining key employee', 'retaining our employee', 'retaining current employee', 'retaining qualified employee', 'retaining skilled employee', 'retaining personnel', 'retaining key personnel', 'retaining our personnel', 'retaining current personnel', 'retaining qualified personnel', 'retaining skilled personnel', 'retaining worker', 'retaining key worker', 'retaining our worker', 'retaining current worker', 'retaining qualified worker', 'retaining skilled worker', 'retaining key talent', 'retaining talent', 'retention of employee', 'retention of key employee', 'retention of our employee', 'retention of current employee', 'retention of qualified employee', 'retention of skilled employee', 'retention of personnel', 'retention of key personnel', 'retention of our personnel', 'retention of current personnel', 'retention of qualified personnel', 'retention of skilled personnel', 'retention of worker', 'retention of key worker', 'retention of our worker', 'retention of current worker', 'retention of qualified worker', 'retention of skilled worker', 'retention of key talent', 'retention of talent', 'employee retention', 'worker retention', 'personnel retention', 'talent retention']

I.A.2. Correlation Matrix

This table presents the Pearson correlations between the main variables. *fLMA* is firm-specific exposure to labor market agglomeration, which is the cosine similarity between a firm's skill profile vector and its CZ skill profile vector. *fLMA high skill* is modified *fLMA* using only high-skilled employees (job zones 4 and 5). *fLMA patent class* is the cosine similarity between the patent class vector of a firm and that of all the other firms in the same CZ. $Patents_{t+1}$ ($Patents_{t+3}$) is the number of patents a firm produced in year t+1 (years t+1, t+2, and t+3) that are ultimately granted and is adjusted for truncation bias. $Cites_{t+1}$ ($Cites_{t+3}$) is the number of non-self-forward citations per patent in year t+1 (years t+1, t+2, and t+3) and is adjusted for truncation bias. $Hires_{t+1}$ ($Departures_{t+1}$) is the number of inventors who have joined (left) a firm in year t+1. *Industrial clustering* is the number of other firms from the same three-digit SIC industry and headquartered in the same CZ as a firm, divided by the total number of firms in that industry. *Relative size* of CZ is the number of employees by CZ divided by that of firm employees (in thousands). *Firm sale* is the natural logarithm of 1 plus sales. *Firm age* is the natural logarithm of 1 plus the number of years that have passed since a firm's first-time appearance in Compustat. *M/B* is the market value of assets divided by total assets. *ROA* is income before extraordinary items divided by total assets. *R&D/Sale* is the ratio of R&D expense to firm sales. *PPE* is the natural logarithm of 1 plus the ratio of net property, plant, and equipment to the number of firm employees. *Net debt* is long-term debt plus short-term debt minus cash and short-term investments, all scaled by total assets. *Institutional ownership* is the proportion of shares owned by institutions. *HHI* is the Herfindahl Index of concentration of firm sales within the three-digit SIC industry. *State GDP growth* is the annual GDP growth rate of a firm's headquarters state. *State unemployment* is the unemployment rate of a firm's headquarters state. #key words for employee mobility is the number of key words related to employee mobility that appears in the risk factors section of a firm's annual report. All variables are winsorized at the 1% and 99% tails, except for *fLMA*, *fLMA high skill*, *fLMA patent class*, and dummy variables. $^{\$}p < 0.01$; $^{\#}p < 0.05$; $^{*}p < 0.1$.

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
1	*fLMA*	1.00																						
2	*fLMA high skill*	0.48[$]	1.00																					
3	*fLMA patent class*	0.02[$]	0.11[$]	1.00																				
4	$Patents_{t+1}$	0.02[$]	0.10[$]	0.25[$]	1.00																			
5	$Cites_{t+1}$	0.00	0.11[$]	0.02[$]	0.16[$]	1.00																		
6	$Patents_{t+3}$	0.00	0.04[$]	0.14[$]	0.57[$]	0.05[$]	1.00																	
7	$Cites_{t+3}$	0.00	0.11[$]	0.00	0.11[$]	0.77[$]	0.03[$]	1.00																
8	$Hires_{t+1}$	0.01[$]	0.10[$]	0.23[$]	0.86[$]	0.19[$]	0.50[$]	0.14[$]	1.00															
9	$Departures_{t+1}$	0.02[$]	0.09[$]	0.21[$]	0.87[$]	0.19[$]	0.51[$]	0.13[$]	0.85[$]	1.00														
10	*Ind. clustering*	0.05[$]	0.15[$]	0.09[$]	0.06[$]	-0.01[$]	0.02[$]	-0.02[$]	0.06[$]	0.05[$]	1.00													
11	*Rel. size of CZ*	-0.03[$]	-0.04[$]	-0.06[$]	-0.07[$]	-0.07[$]	-0.03[$]	-0.06[$]	-0.07[$]	-0.07[$]	-0.04[$]	1.00												
12	*Firm sale*	0.11[$]	0.04[$]	0.18[$]	0.31[$]	0.02[$]	0.17[$]	-0.02[$]	0.28[$]	0.28[$]	0.21[$]	-0.43[$]	1.00											
13	*Firm age*	-0.02[$]	-0.02[$]	0.04[$]	0.17[$]	-0.05[$]	0.10[$]	-0.08[$]	0.14[$]	0.16[$]	0.09[$]	-0.15[$]	0.41[$]	1.00										
14	*M/B*	-0.06[$]	-0.03[$]	0.00	-0.03[$]	0.02[$]	-0.01[$]	0.03[$]	-0.02[$]	-0.03[$]	-0.05[$]	0.43[$]	-0.35[$]	-0.21[$]	1.00									
15	*ROA*	0.07[$]	0.05[$]	0.07[$]	0.07[$]	0.02[$]	0.04[$]	0.01	0.07[$]	0.07[$]	0.09[$]	-0.48[$]	0.49[$]	0.23[$]	-0.70[$]	1.00								
16	*R&D/sale*	-0.05[$]	-0.03[$]	-0.04[$]	-0.02[$]	0.03[$]	-0.01[$]	0.03[$]	-0.02[$]	-0.01[#]	-0.05[$]	0.13[$]	-0.31[$]	-0.11[$]	0.16[$]	-0.27[$]	1.00							
17	*PPE*	-0.06[$]	0.02[$]	0.09[$]	0.11[$]	0.01[*]	0.06[$]	-0.02[$]	0.10[$]	0.10[$]	0.10[$]	-0.10[$]	0.26[$]	0.10[$]	-0.22[$]	0.21[$]	-0.04[$]	1.00						
18	*Net debt*	0.00	-0.08[$]	-0.03[$]	-0.05[$]	-0.12[$]	-0.02[$]	-0.13[$]	-0.05[$]	-0.05[$]	-0.02[$]	0.20[$]	0.01[$]	0.03[$]	0.34[$]	-0.37[$]	-0.10[$]	0.04[$]	1.00					
19	*Inst. ownership*	0.01[$]	0.04[$]	0.10[$]	0.16[$]	0.04[$]	0.07[$]	0.02[$]	0.15[$]	0.14[$]	0.16[$]	-0.23[$]	0.56[$]	0.28[$]	-0.16[$]	0.26[$]	-0.09[$]	0.16[$]	-0.10[$]	1.00				
20	*HHI*	0.05[$]	0.01[$]	-0.07[$]	-0.03[$]	-0.04[$]	-0.03[$]	-0.05[$]	-0.04[$]	-0.04[$]	0.25[$]	-0.03[$]	0.14[$]	0.11[$]	-0.06[$]	0.08[$]	-0.10[$]	-0.01[$]	0.08[$]	0.05[$]	1.00			
21	*State GDP gr.*	0.06[$]	0.07[$]	-0.03[$]	-0.02[$]	0.08[$]	-0.01[#]	0.09[$]	-0.02[$]	-0.02[$]	-0.02[$]	-0.02[$]	-0.08[$]	-0.14[$]	0.02[$]	0.01[$]	0.00	-0.04[$]	-0.03[$]	-0.11[$]	-0.06[$]	1.00		
22	*State unemp.*	-0.09[$]	-0.02[$]	0.06[$]	0.08[$]	-0.05[$]	0.03[$]	-0.06[$]	0.07[$]	0.07[$]	0.06[$]	0.05[$]	0.05[$]	0.09[$]	0.02[$]	-0.02[$]	0.02[$]	0.01	-0.05[$]	0.12[$]	0.02[$]	-0.37[$]	1.00	
23	*#key words emp. mobility*	0.01[*]	0.01[*]	0.03[$]	-0.01[$]	0.01[*]	-0.01[$]	0.01[*]	-0.02[$]	-0.02[$]	0.01[$]	0.00	-0.02[$]	-0.09[$]	0.01[#]	-0.01[$]	0.01[*]	0.02[$]	-0.02[$]	0.01	-0.01[$]	-0.01[#]	0.02[$]	1.00

I.A.3. Validation of fLMA using textual analysis of 10-K statements

This table uses OLS to examine the frequency of key words for employee mobility in annual reports. *#key words for employee mobility* is the number of key words related to employee mobility that appears in the risk factors section of a firm's annual report. *fLMA* is firm-specific exposure to labor market agglomeration, which is the cosine similarity between a firm's skill profile vector and its CZ skill profile vector. *fLMA high skill* is modified *fLMA* using only high-skilled employees (job zones 4 and 5). *fLMA patent class* is the cosine similarity between the patent class vector of a firm and that of all the other firms in the same CZ. The sample consists of firm-years from 1997 to 2018 from Compustat. Industry fixed effects are based on a firm's primary three-digit SIC industry. Reported in parentheses are *t*-statistics based on standard errors clustered by CZ. ***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

	#key words for employee mobility			ln(1+*#key words for employee mobility*)		
	(1)	(2)	(3)	(4)	(5)	(6)
fLMA	0.160**			0.077**		
	(2.30)			(2.55)		
fLMA high skill		0.103**			0.112**	
		(2.14)			(2.35)	
fLMA patent class			0.149**			0.065***
			(2.53)			(2.65)
Industrial clustering	0.078***	0.044	-0.123**	0.045***	0.031**	-0.036
	(2.72)	(1.41)	(-2.44)	(3.63)	(2.23)	(-1.55)
Relative size of MSA	-0.0001***	-0.0001***	0.0001	-0.0001***	-0.0001***	0.0001
	(-3.65)	(-3.44)	(0.47)	(-3.73)	(-3.48)	(0.68)
Firm sale	-0.002	-0.003	0.002	-0.001	-0.002	0.002
	(-0.59)	(-0.69)	(0.30)	(-0.82)	(-1.00)	(0.55)
Firm age	-0.605***	-0.675***	-0.573***	-0.285***	-0.320***	-0.291***
	(-24.74)	(-26.59)	(-11.39)	(-26.07)	(-28.57)	(-12.88)
M/B	-0.002*	-0.003**	0.004	-0.002***	-0.002***	0.001
	(-1.81)	(-2.37)	(1.27)	(-2.71)	(-3.36)	(0.06)
ROA	-0.011	-0.012	-0.001	-0.008	-0.009	-0.009
	(-1.04)	(-1.04)	(-0.02)	(-1.58)	(-1.64)	(-0.64)
R&D/sale	-0.001	-0.001	-0.007***	-0.0001	-0.0001	-0.003***
	(-0.81)	(-0.83)	(-2.83)	(-0.34)	(-0.50)	(-3.05)
PPE	-0.013***	-0.014***	-0.020**	-0.003	-0.003	-0.005
	(-2.77)	(-2.85)	(-2.05)	(-1.51)	(-1.55)	(-1.09)
Net debt	-0.020*	-0.020*	-0.066**	-0.008*	-0.008*	-0.034***
	(-1.94)	(-1.79)	(-2.57)	(-1.65)	(-1.69)	(-2.99)
Inst. ownership	0.048***	0.060***	0.030	0.017**	0.024***	0.007
	(2.64)	(3.16)	(1.12)	(2.01)	(2.64)	(0.56)
HHI	-0.199	-0.071	-0.878**	-0.078	-0.017	-0.352**
	(-0.92)	(-0.29)	(-2.25)	(-0.81)	(-0.15)	(-2.05)
HHI^2	0.533*	0.394	0.747	0.198	0.129	0.293
	(1.67)	(1.12)	(1.30)	(1.36)	(0.79)	(1.15)
State GDP growth	-0.014**	-0.012	-0.005	-0.005*	-0.004	0.002
	(-2.11)	(-1.50)	(-0.52)	(-1.71)	(-1.15)	(0.35)
State unemployment	-0.038*	-0.059**	-0.064*	-0.013	-0.025**	-0.021
	(-1.86)	(-2.44)	(-1.93)	(-1.37)	(-2.28)	(-1.26)
CZ × year and ind. FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.27	0.28	0.29	0.30	0.30	0.30
Observations	72,426	62,931	25,956	72,426	62,931	25,956

I.A.4. Minimum Number of Firms per CZ

This table presents the effects of *fLMA* on innovation using OLS regressions while using different thresholds for the minimum number of firms per CZ required to be included in our sample. In Panel A (B) {C}, the minimum number of firms per CZ required is 1 (3) {5}. *fLMA* is firm-specific exposure to labor market agglomeration, which is the cosine similarity between a firm's skill profile vector and its CZ skill profile vector. $Patents_{t+1}$ ($Patents_{t+3}$) is the number of patents a firm produced in year t+1 (years t+1, t+2, and t+3) that are ultimately granted and is adjusted for truncation bias. $Cites_{t+1}$ ($Cites_{t+3}$) is the number of forward citations per patent in year t+1 (years t+1, t+2, and t+3) and is adjusted for truncation bias. The sample consists of all firm-years from 1997 to 2018 from Compustat. We require at least one patent per firm throughout the sample period. Industry fixed effects are based on a firm's primary three-digit SIC industry code. Reported in parentheses are t-statistics based on standard errors clustered by CZ. ***p < 0.01; **p < 0.05; *p < 0.1.

Panel A. Require at least 1 firm per CZ (i.e., no requirement)

	$\ln(1+Patents_{t+1})$	$\ln(1+Patents_{t+3})$	$\ln(1+Cites_{t+1})$	$\ln(1+Cites_{t+3})$
	(1)	(2)	(3)	(4)
fLMA	0.287***	0.378***	0.196***	0.176***
	(4.87)	(4.89)	(3.46)	(2.65)
Controls, CZ × year and ind. FE	Yes	Yes	Yes	Yes
Adj. R^2	0.41	0.46	0.29	0.33
Obs.	76,376	76,376	76,376	76,376

Panel B. Require at least 3 firms per CZ

	(1)	(2)	(3)	(4)
fLMA	0.288***	0.380***	0.197***	0.179***
	(4.89)	(4.92)	(3.47)	(2.69)
Controls, CZ × year and ind. FE	Yes	Yes	Yes	Yes
Adj. R^2	0.41	0.46	0.30	0.33
Obs.	73,802	73,802	73,802	73,802

Panel C. Require at least 5 firms per CZ

	(1)	(2)	(3)	(4)
fLMA	0.293***	0.384***	0.183***	0.171**
	(4.86)	(4.87)	(3.18)	(2.54)
Controls, CZ × year and ind. FE	Yes	Yes	Yes	Yes
Adj. R^2	0.41	0.46	0.30	0.33
Obs.	71,408	71,408	71,408	71,408

I.A.5. Firm fixed effects

This table re-estimate the main results using firm fixed effects. Panel A reports the baseline, Panel B uses *fLMA high skill*, and Panel C uses *fLMA patent class*. $Patents_{t+1}$ ($Patents_{t+3}$) is the number of patents produced by a firm in year t+1 (years t+1, t+2, and t+3) that are ultimately granted and adjusted for truncation bias. $Cites_{t+1}$ ($Cites_{t+3}$) is the number of non-self forward citations per patent in year t+1 (years t+1, t+2, and t+3) adjusted for truncation bias. *fLMA* is firm-specific exposure to labor market agglomeration, which is the cosine similarity between a firm's skill profile vector and its MSA's skill profile vector. *fLMA high skill* is modified *fLMA* using only high-skilled employees (Job Zones 4 and 5). *fLMA patent class* is the cosine similarity between the patent class vector of a firm and that of all the other firms in the same CZ. Reported in parentheses are *t*-statistics based on standard errors clustered by CZ. ***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

Panel A. Baseline fLMA

	$\ln(1+Patents_{t+1})$	$\ln(1+Patents_{t+3})$	$\ln(1+Citations_{t+1})$	$\ln(1+Citations_{t+3})$
	(1)	(2)	(3)	(4)
fLMA	0.115*	0.230***	0.141	0.115
	(1.76)	(3.70)	(1.33)	(1.09)
Industrial clustering	-0.013	-0.009	-0.015	0.014
	(-0.70)	(-0.45)	(-0.48)	(0.45)
Relative size of CZ	0.0001	-0.0001*	-0.001***	-0.0001***
	(0.16)	(-1.90)	(-3.48)	(-3.18)
Firm sale	0.080***	0.099***	0.037***	0.029***
	(14.60)	(16.67)	(5.23)	(4.17)
Firm age	0.072**	0.128***	0.156***	0.237***
	(2.47)	(4.69)	(3.13)	(4.46)
M/B	-0.003***	-0.005***	0.001	-0.001
	(-3.12)	(-5.04)	(0.07)	(-0.92)
ROA	-0.041***	-0.052***	-0.029***	-0.028***
	(-7.17)	(-7.96)	(-2.88)	(-2.81)
R&D/sale	0.006***	0.008***	0.004**	0.005***
	(6.79)	(7.89)	(2.22)	(3.08)
PPE	0.031***	0.043***	0.039***	0.048***
	(8.55)	(10.41)	(6.10)	(7.40)
Net debt	-0.016***	-0.013**	-0.034***	-0.025**
	(-3.32)	(-2.07)	(-3.37)	(-2.35)
Inst. ownership	0.091***	0.143***	0.057**	0.088***
	(5.82)	(8.19)	(2.47)	(3.65)
HHI	0.168	0.083	0.919***	0.466**
	(1.43)	(0.67)	(4.40)	(2.27)
HHI^2	-0.084	0.020	-0.934***	-0.428
	(-0.48)	(0.11)	(-3.12)	(-1.49)
State GDP growth	-0.002	-0.004	-0.014**	-0.006
	(-0.67)	(-1.10)	(-1.97)	(-1.04)
State unemployment	0.057***	0.063***	0.006	0.024
	(3.08)	(3.39)	(0.25)	(1.00)
Firm and CZ × year FE	Yes	Yes	Yes	Yes
Adj. R^2	0.86	0.91	0.61	0.72
Obs.	75,120	75,120	75,120	75,120

I.A.5. Continued

Panel B. fLMA for only high-skilled employees

	ln(1+*Patents*$_{t+1}$)	ln(1+*Patents*$_{t+3}$)	ln(1+*Citations*$_{t+1}$)	ln(1+*Citations*$_{t+3}$)
	(1)	(2)	(3)	(4)
fLMA high skill	0.058	0.050*	0.208	0.269
	(1.61)	(1.87)	(0.90)	(1.58)
Controls	Yes	Yes	Yes	Yes
Firm and CZ × year FE	Yes	Yes	Yes	Yes
Adj. R^2	0.87	0.92	0.61	0.73
Obs.	65,277	65,277	65,277	65,277

Panel C. fLMA based on patent classes

	ln(1+*Patents*$_{t+1}$)	ln(1+*Patents*$_{t+3}$)	ln(1+*Citations*$_{t+1}$)	ln(1+*Citations*$_{t+3}$)
	(1)	(2)	(3)	(4)
fLMA patent class	1.473***	1.667***	0.750***	0.333***
	(17.95)	(18.21)	(6.17)	(3.03)
Controls	Yes	Yes	Yes	Yes
Firm and CZ × year FE	Yes	Yes	Yes	Yes
Adj. R^2	0.83	0.89	0.50	0.68
Obs.	26,934	26,934	26,934	26,934

I.A.6. Total Citations

This table uses OLS with fixed effects to examine the effects of *fLMA* on total non-self citations. In columns 1 and 3 (2 and 4), regressions control for CZ-by-year and industry (industry-by-year and CZ) fixed effects. *fLMA* is firm-specific exposure to labor market agglomeration, which is the cosine similarity between a firm's skill profile vector and its CZ skill profile vector. *Total* $cites_{t+1}$ (*Total* $cites_{t+3}$) is the number of non-self forward citations in year t+1 (years t+1, t+2, and t+3) and is adjusted for truncation bias. The sample consists of firm-years from 1997 to 2018 from Compustat. Industry fixed effects are based on a firm's primary three-digit SIC industry code. Reported in parentheses are *t*-statistics based on standard errors clustered by CZ. ***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

	ln(1+*Total* $cites_{t+1}$)	ln(1+*Total* $cites_{t+1}$)	ln(1+*Total* $cites_{t+3}$)	ln(1+*Total* $cites_{t+3}$)
	(1)	(2)	(3)	(4)
fLMA	0.364***	0.366***	0.456***	0.404***
	(4.60)	(3.51)	(4.58)	(3.64)
Industrial clustering	-0.075*	-0.118***	-0.059	-0.088
	(-1.72)	(-2.61)	(-1.15)	(-1.62)
Relative size of CZ	0.001***	0.001***	0.001***	0.001***
	(12.09)	(12.83)	(8.00)	(8.61)
Firm sale	0.374***	0.380***	0.441***	0.446***
	(47.57)	(48.41)	(52.24)	(52.81)
Firm age	0.177***	0.160***	0.328***	0.298***
	(5.31)	(4.82)	(8.74)	(7.81)
M/B	0.033***	0.034***	0.038***	0.039***
	(16.25)	(16.93)	(17.00)	(17.34)
ROA	-0.142***	-0.144***	-0.193***	-0.199***
	(-10.39)	(-10.38)	(-11.78)	(-12.25)
R&D/sale	0.036***	0.038***	0.051***	0.054***
	(15.07)	(15.58)	(17.61)	(18.68)
PPE	0.168***	0.169***	0.214***	0.216***
	(20.31)	(19.92)	(22.73)	(22.65)
Net debt	-0.316***	-0.328***	-0.435***	-0.451***
	(-21.41)	(-21.72)	(-22.48)	(-22.96)
Inst. ownership	0.224***	0.205***	0.361***	0.343***
	(7.79)	(7.11)	(11.10)	(10.53)
Employee options	0.959***	–	0.913**	–
	(2.73)		(2.22)	
HHI	-0.838*	–	-0.830	–
	(-1.75)		(-1.47)	
HHI^2	-0.027*	-0.014***	-0.023	-0.016***
	(-1.81)	(-3.59)	(-1.57)	(-3.80)
State GDP growth	-0.019	0.002	-0.003	0.002
	(-0.82)	(0.20)	(-0.11)	(0.15)
State unemp.	0.364***	0.366***	0.456***	0.404***
	(4.60)	(3.51)	(4.58)	(3.64)
CZ × year FE	Yes	–	Yes	–
Industry FE	Yes	–	Yes	–
CZ FE	–	Yes	–	Yes
Industry × year FE	–	Yes	–	Yes
Adj. R^2	0.37	0.37	0.42	0.42
Obs.	75,120	75,120	75,120	75,120

I.A.7. Alternative Fixed Effects

This table uses OLS with alternative fixed effects to examine the effects of *fLMA* on innovation. In Panel A (B), regressions control for industry-by-CZ and year (industry-by-CZ-by-year) fixed effects *fLMA* is firm-specific exposure to labor market agglomeration, which is the cosine similarity between a firm's skill profile vector and its CZ skill profile vector. $Patents_{t+1}$ ($Patents_{t+3}$) is the number of patents a firm produced in year t+1 (years t+1, t+2, and t+3) that are ultimately granted and is adjusted for truncation bias. $Cites_{t+1}$ ($Cites_{t+3}$) is the number of forward citations per patent in year t+1 (years t+1, t+2, and t+3) and is adjusted for truncation bias. The sample consists of all firm-years from 1997 to 2018 from Compustat. We require at least one patent per firm throughout the sample period. Industry fixed effects are based on a firm's primary three-digit SIC industry code. Reported in parentheses are t-statistics based on standard errors clustered by CZ. ***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

Panel A. Industry-by-CZ and year fixed effects

	ln(1+$Patents_{t+1}$)	ln(1+$Patents_{t+3}$)	ln(1+$Cites_{t+1}$)	ln(1+$Cites_{t+3}$)
	(1)	(2)	(3)	(4)
fLMA	0.108*	0.190**	0.162	0.075
	(1.92)	(2.15)	(1.29)	(1.17)
Industrial clustering	0.050	0.084**	-0.038	-0.023
	(1.64)	(2.23)	(-1.15)	(-0.63)
Relative size of CZ	0.001***	0.001***	0.001***	-0.000
	(14.54)	(12.72)	(3.60)	(-0.80)
Firm sale	0.269***	0.330***	0.156***	0.146***
	(33.94)	(37.91)	(33.82)	(31.38)
Firm age	0.260***	0.408***	0.047	0.101***
	(12.67)	(16.51)	(1.54)	(3.03)
M/B	0.012***	0.014***	0.015***	0.015***
	(11.34)	(10.37)	(9.82)	(8.67)
ROA	-0.099***	-0.134***	-0.062***	-0.068***
	(-12.87)	(-13.65)	(-6.21)	(-6.22)
R&D/sale	0.024***	0.033***	0.017***	0.021***
	(18.14)	(19.37)	(10.31)	(12.29)
PPE	0.092***	0.124***	0.104***	0.116***
	(15.59)	(17.07)	(17.31)	(18.09)
Net debt	-0.117***	-0.165***	-0.152***	-0.177***
	(-17.46)	(-18.26)	(-14.19)	(-13.14)
Inst. ownership	0.100***	0.201***	0.208***	0.236***
	(5.96)	(10.11)	(11.05)	(12.47)
HHI	0.027	-0.031	0.807***	0.320*
	(0.19)	(-0.18)	(4.39)	(1.65)
HHI^2	0.112	0.213	-0.814***	-0.219
	(0.57)	(0.91)	(-3.06)	(-0.81)
State GDP growth	-0.007***	-0.009**	-0.012***	-0.014***
	(-2.91)	(-2.56)	(-3.44)	(-3.82)
State unemp.	0.022***	0.023***	-0.013*	-0.021***
	(3.84)	(3.60)	(-1.86)	(-2.86)
Industry × CZ and year FE	Yes	Yes	Yes	Yes
Adj. R^2	0.57	0.63	0.40	0.46
Obs.	75,120	75,120	75,120	75,120

I.A.7. Continued

Panel B. Industry-by-CZ-by-year fixed effects

	ln(1+$Patents_{t+1}$)	ln(1+$Patents_{t+3}$)	ln(1+$Cites_{t+1}$)	ln(1+$Cites_{t+3}$)
	(1)	(2)	(3)	(4)
fLMA	0.164	0.177	0.111	0.161
	(1.57)	(1.39)	(0.89)	(1.15)
Industrial clustering	0.347	0.597	1.239***	1.352***
	(1.08)	(1.59)	(3.26)	(3.29)
Relative size of CZ	0.001***	0.001***	0.0001***	0.0001
	(9.54)	(8.44)	(3.06)	(0.01)
Firm sale	0.295***	0.357***	0.168***	0.154***
	(23.32)	(25.55)	(21.95)	(20.00)
Firm age	0.280***	0.449***	-0.010	0.050
	(8.08)	(10.80)	(-0.20)	(0.86)
M/B	0.016***	0.019***	0.018***	0.020***
	(8.27)	(8.19)	(6.62)	(6.54)
ROA	-0.117***	-0.155***	-0.068***	-0.079***
	(-8.33)	(-8.61)	(-3.60)	(-3.80)
R&D/sale	0.027***	0.037***	0.021***	0.024***
	(12.00)	(12.68)	(7.58)	(8.93)
PPE	0.117***	0.159***	0.116***	0.131***
	(10.31)	(11.31)	(10.39)	(10.87)
Net debt	-0.156***	-0.224***	-0.202***	-0.245***
	(-11.22)	(-12.16)	(-10.01)	(-9.64)
Inst. ownership	0.080**	0.196***	0.246***	0.285***
	(2.57)	(5.25)	(7.05)	(7.99)
State GDP growth	-0.027	-0.037	-0.029	-0.019
	(-1.21)	(-1.45)	(-1.19)	(-0.67)
State unemp.	0.003	0.007	-0.012	0.017
	(0.07)	(0.16)	(-0.33)	(0.42)
Industry × CZ × year FE	Yes	Yes	Yes	Yes
Adj. R^2	0.33	0.40	0.17	0.23
Obs.	75,120	75,120	75,120	75,120

I.A.8. Channels based on labor mobility and incentives

This table investigates potential channels built on labor mobility by estimating OLS regressions. In Panel A, *Spillover via coworkership CZ* is a dummy equal to 1 if within-CZ citations divided by total citations at the CZ-level is above the median, and 0 otherwise. In Panel B, *High executive options* is a dummy equal to 1 if the ratio between the total value of executive stock options within the industry and the industry's total market capitalization is above the median, and 0 otherwise. $Patents_{t+1}$ ($Patents_{t+3}$) is the number of patents produced by a firm in year t+1 (years t+1, t+2, and t+3). $Cites_{t+1}$ ($Cites_{t+3}$) is the number of non-self forward citations per patent in year t+1 (years t+1, t+2, and t+3). The sample consists of all firm-years from 1997 to 2018 from Compustat. Reported in parentheses are *t*-statistics based on standard errors clustered by CZ. All regressions include the control variables, CZ-by-year and industry fixed effects. ***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

Panel A. Knowledge spillover via coworkership channel

	1	2	3	4
fLMA × *Spillover via coworkership CZ*	0.126	0.206	0.117	0.169
	(1.08)	(1.30)	(1.11)	(1.29)
fLMA	0.221***	0.271**	0.138**	0.091
	(2.64)	(2.50)	(2.15)	(1.63)
Controls, CZ × year- and industry-FE	Yes	Yes	Yes	Yes
Adj. R^2	0.41	0.46	0.30	0.33
Obs.	75,120	75,120	75,120	75,120

Panel B. Executive stock options channel

	1	2	3	4
fLMA × *High executive options*	0.061	0.018	0.196	0.133
	(0.50)	(0.10)	(1.09)	(0.99)
fLMA	0.320**	0.384**	0.313**	0.254*
	(2.48)	(2.34)	(2.29)	(1.73)
Controls, CZ × year- and industry-FE	Yes	Yes	Yes	Yes
Adj. R^2	0.41	0.46	0.30	0.33
Obs.	75,120	75,120	75,120	75,120

I.A.9. General Knowledge Spillover Channel

This table presents the 2SLS estimation results. *PDP_eqwtd* is the ratio between the (equal-weighted) average of industry peers' publication delays and the focal firm's average publication delay based on patents produced in the recent 10 years. Column 1 presents the first stage regression. Columns 2-5 present the second stage regression in which we relate the instrumented *fLMA* from the first stage to innovation output. The dependent variable in Columns 2 and 3 (4 and 5) is the number of patents (citations per patent). *fLMA* is firm-specific exposure to labor market agglomeration. $Patents_{t+1}$ ($Patents_{t+3}$) is the number of patents a firm produced in year t+1 (years t+1, t+2, and t+3) that are ultimately granted and is adjusted for truncation bias. $Cites_{t+1}$ ($Cites_{t+3}$) is the number of forward citations per patent in year t+1 (years t+1, t+2, and t+3) and is adjusted for truncation bias. The sample consists of firm-years from 1997 to 2018 from Compustat. Reported in parentheses are t-statistics based on standard errors clustered by CZ. Column 1 reports the F-statistic from the first-stage regression. ***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

	fLMA	ln(1+$Patents_{t+1}$)	ln(1+$Patents_{t+3}$)	ln(1+$Cites_{t+1}$)	ln(1+$Cites_{t+3}$)
	(1)	(2)	(3)	(4)	(5)
ln(1+*PDP_eqwtd*)	0.019**				
	(2.47)				
$fLMA^{fitted}$		3.199***	5.858***	5.236***	6.265**
		(2.84)	(3.18)	(2.86)	(2.35)
Industrial clustering	0.047***	-6.850***	-11.969***	-10.730***	-15.939***
	(10.34)	(-4.96)	(-4.95)	(-4.98)	(-4.95)
Relative size of CZ	0.0001***	-0.003***	-0.006***	-0.006***	-0.010***
	(7.71)	(-3.66)	(-4.07)	(-4.54)	(-4.67)
Firm sale	0.004***	-0.380***	-0.789***	-0.835***	-1.318***
	(17.19)	(-2.87)	(-3.39)	(-4.02)	(-4.24)
Firm age	0.008***	-0.995***	-1.759***	-1.879***	-2.759***
	(4.63)	(-2.94)	(-2.96)	(-3.52)	(-3.46)
M/B	-0.0001***	0.056***	0.089***	0.080***	0.111***
	(-3.10)	(3.62)	(3.30)	(3.30)	(3.09)
ROA	-0.001	0.070	0.159	0.208	0.328
	(-1.64)	(0.67)	(0.87)	(1.27)	(1.34)
R&D/sale	0.0001	0.003	-0.001	-0.011	-0.020
	(1.11)	(0.22)	(-0.04)	(-0.50)	(-0.62)
PPE	-0.001**	0.186***	0.289***	0.238***	0.319***
	(-2.24)	(3.54)	(3.15)	(2.89)	(2.62)
Net debt	-0.002***	0.136	0.282	0.262	0.441*
	(-2.64)	(1.23)	(1.46)	(1.52)	(1.71)
Institutional ownership	-0.003**	0.414**	0.773***	0.778***	1.083***
	(-2.57)	(2.48)	(2.64)	(2.95)	(2.76)
HHI	-0.073***	10.442***	18.322***	17.483***	25.402***
	(-3.64)	(2.88)	(2.89)	(3.06)	(2.99)
HHI^2	0.067**	-9.494**	-16.769**	-16.213**	-23.513**
	(2.33)	(-1.96)	(-1.97)	(-2.12)	(-2.07)
State GDP growth	-0.003**	0.367	0.652	0.582	0.883
	(-2.11)	(1.63)	(1.64)	(1.61)	(1.63)
State unemployment	-0.015***	2.177***	3.806***	3.366***	5.029***
	(-5.82)	(3.22)	(3.20)	(3.14)	(3.13)
CZ × year and ind. FE	Yes	Yes	Yes	Yes	Yes
F-statistic	16.11				
Adj. R^2	0.56				
Obs.	75,120	75,120	75,120	75,120	75,120

I.A.10. fLMA_2

fLMA_2 is defined as follows. We recalculate *fLMA* by excluding a firm's workforce from its CZ skill profile vector. For each occupation in the CZ skill profile vector, we subtract the number of firm employees in the occupation from that of the employees by CZ. Using the adjusted CZ skill profile vectors, we re-calculate *fLMA* in equation (1). $Patents_{t+1}$ ($Patents_{t+3}$) is the number of patents a firm produced in year *t*+1 (years *t*+1, *t*+2, and *t*+3) that are ultimately granted and is adjusted for truncation bias. $Cites_{t+1}$ ($Cites_{t+3}$) is the number of non-self-citations a firm receives for its patents in year *t*+1 (years *t*+1, *t*+2, and *t*+3) and is adjusted for truncation bias. The sample consists of all firm-years from 1997 to 2018 (Compustat). Reported in parentheses are *t*-statistics based on standard errors clustered by CZ. ***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

	$\ln(1+Patents_{t+1})$	$\ln(1+Patents_{t+3})$	$\ln(1+Cites_{t+1})$	$\ln(1+Cites_{t+3})$
	(1)	(2)	(3)	(4)
fLMA_2	0.249***	0.331***	0.159***	0.120*
	(4.40)	(4.28)	(2.80)	(1.81)
Industrial clustering	-0.049**	-0.047*	-0.019	0.009
	(-2.10)	(-1.63)	(-0.71)	(0.30)
Relative size of CZ	0.001***	0.001***	0.0001***	0.0001
	(15.74)	(13.23)	(2.80)	(1.40)
Firm sale	0.245***	0.306***	0.149***	0.148***
	(45.43)	(50.00)	(43.79)	(42.89)
Firm age	0.203***	0.341***	0.008	0.051**
	(12.94)	(17.70)	(0.35)	(2.05)
M/B	0.016***	0.019***	0.018***	0.018***
	(16.07)	(15.70)	(12.67)	(11.65)
ROA	-0.098***	-0.137***	-0.057***	-0.067***
	(-13.97)	(-14.78)	(-6.23)	(-6.44)
R&D/sale	0.022***	0.032***	0.019***	0.024***
	(17.71)	(19.33)	(11.24)	(13.63)
PPE	0.091***	0.122***	0.088***	0.096***
	(18.71)	(20.68)	(19.26)	(19.21)
Net debt	-0.152***	-0.223***	-0.191***	-0.235***
	(-22.31)	(-24.07)	(-18.99)	(-18.77)
Institutional ownership	0.054***	0.143***	0.212***	0.241***
	(3.55)	(7.66)	(13.01)	(14.49)
HHI	-0.032	-0.035	0.991***	0.845***
	(-0.17)	(-0.15)	(4.60)	(3.62)
HHI^2	0.153	0.139	-1.022***	-0.894***
	(0.60)	(0.42)	(-3.42)	(-2.73)
State GDP growth	-0.012	-0.014*	-0.016*	-0.008
	(-1.57)	(-1.77)	(-1.81)	(-0.77)
State unemployment	0.022*	0.029*	-0.028*	-0.023
	(1.65)	(1.88)	(-1.90)	(-1.39)
CZ × year and ind. FE	Yes	Yes	Yes	Yes
Adj. R^2	0.41	0.46	0.30	0.33
Obs.	75,120	75,120	75,120	75,120

I.A.11. Size of CZ and Firm

This table uses OLS to perform cross-sectional tests of *fLMA*'s effects on innovation. For cross-sectional tests, in Panel A (B) {C}, regressions include *fLMA* interacted with a dichotomous variable, *Large CZ* (*Large firm*) {*High CZ to firm*}. *Large CZ* is a dummy equal to one if the total number of employees in a firm's CZ is above the median during the year, and zero otherwise. *Large firm* is a dummy equal to one if the number of a firm's employees is above the median within the CZ during the year, and zero otherwise. *High CZ to firm* is a dummy equal to one if the ratio between the total number of CZ employees to that of firm employees is above the median during the year, and zero otherwise. *fLMA* is firm-specific exposure to labor market agglomeration, which is the cosine similarity between a firm's skill profile vector and its CZ skill profile vector. $Patents_{t+1}$ ($Patents_{t+3}$) is the number of patents a firm produced in year t+1 (years t+1, t+2, and t+3) that are ultimately granted and is adjusted for truncation bias. $Cites_{t+1}$ ($Cites_{t+3}$) is the number of forward citations per patent in year t+1 (years t+1, t+2, and t+3) and is adjusted for truncation bias. The sample consists of all firm-years from 1997 to 2018 from Compustat. Industry fixed effects are based on a firm's primary three-digit SIC industry code. Reported in parentheses are t-statistics based on standard errors clustered by CZ. ***p < 0.01; **p < 0.05; *p < 0.1.

Panel A. Large versus small CZ workforce

	ln(1+$Patents_{t+1}$)	ln(1+$Patents_{t+3}$)	ln(1+$Cites_{t+1}$)	ln(1+$Cites_{t+3}$)
	(1)	(2)	(3)	(4)
fLMA × *Large CZ*	0.001	-0.008	0.043	0.057
	(0.01)	(-0.09)	(0.56)	(0.67)
fLMA	0.284***	0.380***	0.179***	0.154**
	(3.76)	(3.91)	(2.59)	(1.99)
Large CZ	-0.080***	-0.071**	-0.024	0.020
	(-2.91)	(-2.10)	(-0.60)	(0.49)
Controls, CZ × year and ind. FE	Yes	Yes	Yes	Yes
Adj. R^2	0.41	0.46	0.30	0.33
Obs.	75,120	75,120	75,120	75,120

Panel B. Large versus small firm workforce

	ln(1+$Patents_{t+1}$)	ln(1+$Patents_{t+3}$)	ln(1+$Cites_{t+1}$)	ln(1+$Cites_{t+3}$)
	(1)	(2)	(3)	(4)
fLMA × *Large firm*	-0.261***	-0.314***	-0.140	-0.052
	(-4.23)	(-4.88)	(-1.53)	(-1.61)
fLMA	0.581***	0.753***	0.272***	0.206***
	(8.34)	(9.11)	(3.82)	(2.76)
Large firm	0.252***	0.341***	0.136***	0.073**
	(6.16)	(7.41)	(4.85)	(2.55)
Controls, CZ × year and ind. FE	Yes	Yes	Yes	Yes
Adj. R^2	0.41	0.46	0.30	0.33
Obs.	75,120	75,120	75,120	75,120

Panel C. Relative workforce size of CZ versus firm

	ln(1+$Patents_{t+1}$)	ln(1+$Patents_{t+3}$)	ln(1+$Cites_{t+1}$)	ln(1+$Cites_{t+3}$)
	(1)	(2)	(3)	(4)
fLMA × *High CZ to firm*	0.002***	0.003***	0.008*	0.009**
	(6.27)	(6.48)	(1.87)	(2.05)
fLMA	0.226***	0.295***	0.181***	0.153**
	(3.67)	(3.63)	(3.06)	(2.21)
High CZ to firm	0.0001	-0.0002	-0.0002	-0.001**
	(1.20)	(-0.54)	(-0.64)	(-2.32)
Controls, CZ × year and ind. FE	Yes	Yes	Yes	Yes
Adj. R^2	0.41	0.46	0.30	0.33
Obs.	75,120	75,120	75,120	75,120

I.A.12. Other Characteristics of Patents

This table presents OLS regressions to examine the effect of *fLMA* on the characteristics of patents; *Exploratory*, *Exploitative*, *Original*, and *General*. $Exploratory_{t+1}$ is the ratio of the number of exploratory patents to the total number of patents produced by a firm in year t+1. A patent is defined as exploratory if at least 60% of its citations are out of the firm's existing knowledge base. $Exploitative_{t+1}$ is the ratio of the number of exploitative patents to the total number of patents produced by a firm in year t+1. A patent is defined as exploitative if at least 60% of its citations are based on the firm's existing knowledge base. $Original_{t+1}$ is the average originality of a firm's patents in year t+1. The originality of a patents in year t+1, which is 1 minus the Herfindahl index of concentration of the *backward* citations across 3-digit technology classes. $Patent\ i's\ originality = 1 - \sum_{j=1}^{J}(\frac{N_{ji}}{N_i})^2$, where N_i denotes the total number of backward citations made by the patent i, and N_{ji} denotes the number of backward citations made by patent i to technology class j ($N_{ji} \geq 0,\ j = 1, \ldots, J$). $General_{t+1}$ is the average generality of a firm's patents in year t+1. The generality of a firm's patents in year t+1, which is defined as 1 minus the Herfindahl index of concentration of the *forward* citations across 3-digit technology classes. $Patent\ i's\ generality = 1 - \sum_{j=1}^{J}(\frac{N_{ij}}{N_i})^2$, where N_i denotes the total number of forward citations received by the patent i, and N_{ij} denotes the number of forward citations received by patent i from technology class j ($N_{ij} \geq 0,\ j = 1, \ldots, J$). We exclude self-citations from our calculations of *Original* and *General*. *fLMA* is firm-specific exposure to labor market agglomeration, which is the cosine similarity between a firm's skill profile vector and its CZ's skill profile vector. The sample consists of all firm-years from 1997 to 2018 from Compustat. We require at least one patent per firm throughout the sample period. Reported in parentheses are *t*-statistics based on standard errors clustered by CZ. ***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

	Exploratory	*Exploitative*	*Original*	*General*
	(1)	(2)	(3)	(4)
fLMA	0.060**	0.022	-0.010	-0.029
	(1.99)	(1.10)	(-0.28)	(-1.13)
Industrial clustering	0.018**	-0.013**	-0.002	-0.001
	(2.54)	(-2.39)	(-0.17)	(-0.01)
Relative size of CZ	0.0001	0.0001	0.0001	0.0001
	(1.62)	(1.46)	(1.13)	(0.73)
Firm sale	0.033***	0.018***	-0.002	-0.002***
	(17.51)	(11.73)	(-1.38)	(-2.81)
Firm age	0.011	0.027***	-0.043***	-0.008
	(1.02)	(5.44)	(-4.66)	(-0.86)
M/B	0.002***	0.003***	0.001	0.001***
	(4.37)	(7.40)	(1.61)	(3.12)
ROA	-0.020***	-0.006***	-0.006	-0.003
	(-6.76)	(-3.24)	(-1.11)	(-0.81)
R&D/sale	0.005***	0.003***	-0.001***	-0.001***
	(9.25)	(4.70)	(-2.67)	(-3.53)
PPE	0.013***	0.015***	0.002	0.003*
	(5.10)	(6.12)	(1.00)	(1.94)
Net debt	-0.028***	-0.035***	-0.008	-0.013***
	(-5.82)	(-9.74)	(-1.23)	(-3.43)
Inst. ownership	0.042***	0.035***	0.005	0.011***
	(4.56)	(4.55)	(0.96)	(2.76)
HHI	0.094	-0.019	-0.126*	0.040
	(1.31)	(-0.27)	(-1.65)	(0.50)
HHI^2	-0.128	0.055	0.191*	-0.053
	(-1.24)	(0.54)	(1.82)	(-0.49)
State GDP growth	0.0001	-0.005***	-0.001	-0.001
	(0.30)	(-4.11)	(-0.30)	(-0.74)
State unemp.	0.008	0.001	0.003	-0.008
	(0.98)	(0.19)	(0.33)	(-1.58)
CZ × year and industry FE	Yes	Yes	Yes	Yes
Adj. R^2	0.19	0.20	0.07	0.72
Obs.	75,120	75,120	22,373	21,446

Reference for Internet Appendix

Trajtenberg, M., R. Henderson, and A. B. Jaffe, 1997, University versus corporate patents: A window on the basicness of invention, *Economics of Innovation and New Technology* 5(1): 19-50.