Local Employment Opportunities and Corporate Innovation

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Abstract

Using detailed occupational data, we measure employees' outside opportunities in the local labor market and investigate its effects on innovation outcomes. We find that the volume and quality of innovation are greater when the firm's employees have more local employment options. Such employees produce more original and more broadly applicable innovations. Our results are driven by high-tech industries and are stronger among industries in which it is more costly to found a startup, and therefore the opportunities from the extant employers are more valuable. Further, we employ the U.S. state courts' adoption of inevitable disclosure doctrine as a quasi-natural experiment that limits employees' outside opportunities. We find that the adoption of the doctrine weakens the effect of local employment options on the aforementioned innovation outcomes. Overall, our findings support the notion that employees' outside options provide a strong incentive to innovate.

1. Introduction

Innovation is vital to building a firm's competitive edge and sustainable long-term growth. It requires as input employees' human capital, which is inalienable. However, the activities to produce innovation typically entail high uncertainty and long-term efforts exerted by employees. Accordingly, a number of studies in finance and economics have examined efficient incentives and monitoring mechanisms to motivate employees to innovate (e.g., Holmstrom (1989) and Manso (2011)).[1] In this paper, we shed light on a less explored incentive mechanism for innovation – employees' outside options in the local labor market.

We use detailed occupation-level data in the U.S. to construct a measure of local employment opportunities (LEO) for a firm's employees as in Lee, Thorburn, and Xu (2019). We find that employees' outside options in the local labor market importantly affect innovation outcomes. Firms produce a greater volume of innovation when their employees on average have greater outside options in the local area (i.e., high LEO). The innovations by such employees exhibit higher quality measured by forward citations. In addition, employees with greater local employment options create innovations that are more original and more widely applicable. These results are mainly driven by high-tech industries. We find stronger results among industries in which founding a startup is more costly (e.g., industries of high capital intensity and of irreversible assets), therefore employment options at the existing employers are more valuable. Overall, our findings are consistent with the argument that employees' outside options provide an important motivation to innovate.

In constructing our measure of outside employment options, we consider options within the *local* labor market. Labor markets are characterized by geographic segmentation (Molloy et al.

[1] For a thorough review of recent literature, we refer the interested reader to Ederer and Manso (2011).

(2011)). Each local labor market consists of a distinctive set of employee skills demanded by local employers. Some employees may face many local employers that desire their job-related skills (i.e., many outside options), while others possessing a different set of skills face less. For instance, software engineers working for a high-tech firm at Boston's Route 128 might have more local employment options than their counterparts working at Cheyenne in Wyoming.

Such local employment opportunities produce conflicting hypotheses regarding their effect on innovation outcomes. On the one hand, greater local employment opportunities provide a strong incentive for employees to innovate. Fulghieri and Sevilir (2011) show that the presence of many firms competing for employee human capital grants employees greater bargaining power against their employer. Such bargaining power may allow employees to extract greater rents from innovation success, which *ex ante* incentivizes them to make effort. In addition, given many outside options (i.e., thick local labor market), employees may find it attractive to invest in their human capital, which they can sell to another employer at the competitive price. This may enhance the quality of the match between employer and employee, which will likely lead to better innovation outcomes (Acemoglu (1997)).

On the other hand, employee outside options may discourage the employer's innovative investment. In a thick local labor market, it is more difficult for employers to retain employees (Almazan et al. (2007), Lee et al. (2019)). The departure of key employees may disrupt the ongoing innovation process. Given the labor market frictions (e.g., search and training costs), the firm incurs nontrivial costs to replace them. Moreover, the departing employees may disclose the former employer's trade secrets at their new employer, which can substantially damage the former employer's profitability (Fallick et al. (2006)). In this regard, local employment options can dis-incentivize employers' innovation effort.

We calculate LEO for all Compustat firms from 1997 to 2010 and test their effect on innovation. Briefly put, our LEO is the cosine similarity between the employee skill profile vector of the firm and that of the metropolitan statistical area (MSA) the firm belongs to. As in Lee et al. (2019), we employ the Occupation Employment Statistics (OES) data from the Bureau of Labor Statistics (BLS). For each year and for each three-digit SIC industry (four-digit NAICS industry from year 2002), OES provides an employee skill profile vector in which each element is the fraction of an industry's employees in one of about 800 occupations. For each year and for each MSA, OES also provides an employee skill profile vector in which each element is the fraction of all MSA employees in one of the occupations.

We construct the firm's employee skill profile vector as the segment sales-weighted average of its segments' OES industry employee skill profile vectors, where segment sales are obtained from the Compustat Industry Segment (CIS) database. Using the firm headquarters' zip code from Compustat and the crosswalk between zip codes and MSA codes from the Office of Workers' Compensation Programs (OWCP), we create pairs of the firm employee skill profile and the corresponding MSA employee profile. Our LEO is defined as the scalar product of the employee skill profile of the firm and that of its MSA, scaled by the product of their lengths. LEO is a continuous variable and bounded between 0 (the two employee skill profiles are orthogonal) and 1 (the two employee skill profiles are identical). LEO increases as the similarity between the firm's employee skills and other local firms' employee skills increases. It captures the average local employment opportunities faced by firm employees in a given fiscal year. We test the effect of LEO on the features of corporate innovation using (1) panel regressions with fixed effects and (2) quasi-natural experiments.

Our panel regression estimates show that LEO has positive effects on a firm's innovation output while controlling for various firm characteristics that can also affect innovation. High LEO firms create more patents, and their patents receive more forward citations. The results are robust to including various levels of fixed effects – year, industry, state, and firm. That is, within the same industry, a firm with high LEO is more innovative than that with low LEO.

Including state fixed effects further tightens our comparison; two firms operating in the same industry and located in the same state produce different innovation outputs depending on LEO.[2]

Our results are mainly driven by high-tech industries, where innovation plays a pivotal role for a firm's competitiveness. Additionally, we find that the effect of LEO on innovation output is stronger in industries, where founding a startup requires a large initial capital outlay (Anton and Yao (1995)) or involves irreversible investment (Kim and Kung (2016)). In such cases, job offers from the extant local firms (i.e., LEO) are more relevant outside options because founding their own startup is not feasible.

We consider other important features of innovation – *originality* and *generality*. We find that patents produced by high LEO firms are more *original* and *general.* The latter is consistent with Wasmer (2006); given growing outside opportunities, employees are more likely to invest in *general* human capital, which provides a greater bargaining power against the current employer.

Further, we attempt to identify the causal effect of LEO on innovation by using a quasi-natural experiment. We follow a recent study by Klasa et al. (2018) and use the state-level adoption of inevitable disclosure doctrine (IDD) as an exogenous shock that decreases employee mobility. We predict that after the adoption of IDD, outside options proxied by high LEO are no longer valid for some employees with trade secrets. Employees might still be able to move to another local firms, but their opportunities may be limited to those considered as non-rivals. Consistent with our prediction, we find that the adoption of IDD attenuates the effect of LEO on innovation.

[2] Both our LEO and dependent variables (i.e., innovation outcomes) are highly persistent, which weakens the power of a firm fixed effects estimator (Zhou (2001)). Nevertheless, we reproduce our main results with firm fixed effects in Appendix B. We find consistent results when controlling for firm fixed effects.

Our research contributes to the literature on innovation, particularly focusing on employee incentives. Holmstrom (1989) and Manso (2011) discuss the optimal incentive scheme to foster innovation, given its risky, time-consuming nature. In particular, Manso (2011) suggests that employee incentive programs should not punish early failure and should reward for long-term success to encourage innovation. Learner and Wulf (2007), Chang et al. (2015), and Mao and Zhang (2018) document the positive effect of stock options on innovation output. Acharya, Baghai, and Subramanian (2014) show that laws forbidding wrongful termination increase employees' incentives to innovate. Our paper differs from these studies and rather focuses on incentives provided by the local labor market structure. We quantify employees' outside options in the local labor market and show that their outside options strongly motivate innovation, which is consistent with Fulghieri and Sevilir (2011).

Our paper also adds to the literature studying the effect of employee mobility on corporate policies. Younge, Tong, and Fleming (2015) show that firms disfavor merging with another firm whose valuable employees may leave after the deal is completed. Klasa et al. (2018) document that firms maintain conservative financial policies when their employees can move to another employer with their trade secrets. Lee et al. (2019) show that employers provide a better work environment and more stock options to their employees if the employees have more local employment options. Jeffers (2018) reports the negative effect of employee mobility on firm investment and entrepreneurial activities. We focus on innovation – a key driver for long-term economic growth – and show that employees with more outside options produce better innovation output.

The remainder of the paper is organized as follows. Section 2 describes the data, sample, and variables. Section 3 presents the main empirical results. Section 4 concludes.

2. Data and variables

2.1. Main sample

We combine multiple databases to construct our main sample. We start with annual financial statements from Compustat and construct a panel of firm-year observations. We obtain industry employee skill profiles and MSA employee skill profiles from the OES program at the BLS. The coverage of the OES MSA-level occupation data starts in 1997, while that of OES industry-level occupation data starts from as early as 1988. We obtain the information on patents from two different sources. For years 1976-2006, we obtain the patents information from the National Bureau of Economic Research (NBER) Patent Citation database, which covers all U.S. patents granted by the U.S. Patent and Trademark Office. For years 2007-2010, we use the data on granted patents provided by Kogan, Papanikolaou, Seru, and Stoffman (2017).[3] We exclude firms in the utility (SIC 4900-4999) and financial (SIC 6000-6999) industries. The final sample consists of 26,128 firm-years for which we can calculate our LEO measure.[4]

2.2. Local employment opportunities (LEO)

2.2.1. Occupational data from OES

The OES program provides MSA-level occupational data from 1997. The United States Office of Management and Budget (OMB) defines MSA as "a core urban area containing a substantial population nucleus, together with adjacent communities having a high degree of economic and social integration with that core". Each MSA contains a single core of 50,000 or more population.

[3] The patents data by Kogan et al. (2017) is available at https://iu.box.com/patents.

[4] Our dependent variables, patent 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 is comprised of Compustat firm-years from 1997 to 2009 and corresponding patents data from 1998 to 2010.

Firm-level occupation data are not readily available. Therefore, we combine the industry-level occupational data from OES and the segment sales data from the Compustat Industry Segment (CIS) to construct a proxy for a firm's employee skill profile on the basis of each segment's industry membership. Industries in the OES data are defined based on three-digit Standard Industrial Classification (SIC) code before 2002, and by four-digit North American Industry Classification System (NAICS) code since 2002.

2.2.2. Firm-level employee skill profile

For each year and for each industry, we obtain an industry-level employee skill profile vector from OES. Specifically, for industry i in year t, OES provides 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 workers in industry i assigned to occupation k. We use these industry employee skill profiles and a firm's industry membership to construct a firm's employee skill profile. The industry employee skill profile of a segment is matched based on three-digit SIC codes (four-digit NAICS codes from year 2002). When a firm has multiple segments covered by the CIS database, we compute the firm's employee skill profile, $H_{a,t}$, as $H_{a,t} = \sum_{i=1}^{I} w_{i,t} H_{i,t}$ (i.e., segment sales weighted-average of the associated industry employee skill profiles), where a segment's weight, $w_{i,t}$, is segment sales to total segment sales, and I is the number of industry segments within the firm.

2.2.3. MSA-level employee skill profile

For each year and for each MSA, OES provides 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 a firm's MSA, we use a firm's zip code from Compustat and the crosswalk between zip code and MSA code from the Office of Workers' Compensation Programs (OWCP).

2.2.4. LEO between for a pair of firm and MSA

We calculate local employment opportunities, $LEO_{a,m,t}$, for firm a whose headquarters is located in MSA m using cosine similarity between the firm's employee skill profile vector, $H_{a,t}$, and the MSA employee skill profile vector, $H_{m,t}$. More specifically, our LEO is defined as the scalar product of the firm's employee skill profile vector and the corresponding MSA's employee skill profile vector divided by the product of their lengths:

$$LEO_{a,m,t} = \frac{H_{a,t}H'_{m,t}}{\sqrt{H_{a,t}H'_{a,t}}\sqrt{H_{m,t}H'_{m,t}}}$$

LEO is bounded between zero and one. It is close to unity when a firm and its neighbor firms in the MSA have similar employee skill profiles and is close to zero when the two employee skill profiles are dissimilar. The positions at neighbor firms that require similar skills represent within-occupation mobility to employees. High (low) LEO indicates greater (less) local employment opportunities faced by the firm's average employees (i.e., thick (thin) local labor market).

2.3. Measures for innovation output

Our first measure of innovation output is the total number of patents applied for (and eventually granted) by a firm in a given year. Since the patent distribution is right-skewed, we use the natural logarithm. Specifically, we define *Log patents (t+1)* as the natural logarithm of one plus the total number of patents filed in year t+1. Likewise, *Log patents (t+1 to t+3)* is defined as the natural logarithm of one plus the total number of patents filed over years t+1, t+2, and t+3.

Patents differ from one another in terms of its economic and technological significance. Patent counts ignore such varying significance. Our second measure attempts to capture each patent's quality by using the total forward citations it receives. *Log citations (t+1)* is defined as the natural logarithm of one plus the total citations a given patent receives in year t+1. Similarly, *Log citations (t+1 to t+3)* is the natural logarithm of one plus the total citations a given patent receives over years t+1, t+2, and t+3. Since our sample period ends in 2010, our raw citation counts do not include citations received after 2010, therefore they may suffer from truncation bias. Our regression models include year fixed effects to account for such bias (Hirshleifer, Low, and Teoh (2012)).

2.4. Control variables

We control for an array of firm characteristics that may influence innovation activities documented in previous studies. *Log sales* is defined as the natural logarithm of firm sales in the fiscal year t. *MB* 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. *Log PPE* is the ratio of net property, plant, and equipment to the number of employees. We also control for industry concentration, *HHI* which is the three-digit SIC Herfindahl index. All variables are winsorized at the 1% and 99% tails, except for LEO.

3. Results

This section presents our main results. We first test how LEO affects patents and their citations using ordinary least squares (OLS) regressions. We also explore whether the effect of LEO on innovation varies along firm-/industry-characteristics related to outside options. Finally, we use a quasi-natural experiment (i.e., IDD) to make causal inference.

3.1.Descriptive statistics

Table 1 Panel A reports the summary statistics of our main variables. On average, firms in our sample has LEO of 0.316. The distribution of innovation variables (e.g., patent counts and citations) are similar to those reported elsewhere (see, for example, Mao and Zhang (2018)). Panel B reports Pearson correlation coefficients between variables. It is noteworthy that the correlation between LEO and all innovation output variables are positive and significant.

3.2.LEO and innovation quantity and quality

In Table 2, we regress patent applications filed by firms against LEO, other control variables, and fixed effects. In Panel A, our dependent variable, *Log patents (t+1)* is measured in year t+1, while independent variables are measured in year t. In all regressions, standard errors are clustered by firm. In column 1, we present our estimates with year fixed effects. Consistent with our prediction, we find a significant and positive coefficient on LEO. Industries differ from one another with respect to research and development intensity, therefore our result in column 1 might merely capture such heterogeneity across industries. To this end, in column 2, we include industry fixed effects based on two-digit SIC codes, by which we make within-industry comparisons. We continue to find a significantly positive effect of LEO on patents; firms with high LEO produce more patents than do their same industry peers with low LEO (at another location). In column 3, we include higher dimensional fixed effects – industry-by-year – to control for industry trends. Our result remains robust. If anything, the magnitude of coefficient becomes larger, and t-statistics becomes greater. Across the columns, we find that LEO has an economically meaningful impact on patent counts. A one standard deviation increase in LEO increases the number of patents by 6.43% in column 1 and by 9.53% in column 3.

Further, we control for state fixed effects to tighten our comparison. By so doing, we compare a firm to another firm which is operating in the same industry, headquartered in the same state, but in a different MSA. Column 4 reports our estimation. The coefficient on LEO remains statistically significant and positive, although its magnitude is smaller. Additionally, we include firm fixed effects and report the results in Appendix B.

In Panel B, our dependent variable is patent counts over years t+1 through t+3; *Log patents (t+1 to t+3)*. The results are similar to those reported in Panel A. A one standard deviation increase in LEO increases the number of patents by 7.44% in column 1 and by 12.17% in column 3. Overall, the results here lend support to our hypothesis. Firm employees with more outside options (i.e., high LEO) tend to produce more patents.

In Table 3, we consider citations received by the firm's patents to measure the quality of its innovation. In Panel A, our dependent variable, *Log citations (t+1)* is measured in year t+1, while independent variables are, again, measured in year t. We find that patents by high LEO employees receive more forward citations. Likewise, the results are robust to including industry and state fixed effects. The effects of LEO on citations are economically significant. A one standard deviation increase in LEO leads to a 10%-13% increase in citations across the regressions. In Panel B, we use *Log citations (t+1 to t+3)* measured over years t+1 through t+3 as a dependent variable. We continue to find the significantly positive effects of LEO on patent citations. A one standard deviation increase in LEO increases citations by 12%-16% across the regression models. The result, overall, suggests that not only LEO motivates employees to create a greater volume of patents, but also it motivates them to create the ones of better quality.

3.3.High-tech industries

In Table 4, we test if our results are stronger for high-tech industries. Innovation is necessary for firms in high-tech industries because it allows them to gain competitive advantages in their product markets. We obtain the list of high-tech industries from Eckbo et al. (2018) and define the *High tech* dummy. Our result here shows that the effect of LEO on innovation is mainly driven by high-tech industries.

3.4.Startup costs

Moving to another neighboring firm is not the only outside option for innovators. They may leave the current employer to start their own startup firm. Accordingly, our LEO may understate innovators' true outside options because it only includes the employment at the extant local employers. However, founding a startup may not be feasible for some employees, especially when the initial capital required for a startup is excessively high (Anton and Yao (1995)). In such case, the outside options from the existing neighboring firms should be more relevant for employee mobility. Therefore, we predict that the effect of LEO on innovation output is stronger when startups require a large amount of initial outlay.

In Table 5, we use two variables to identify whether employees face high startup costs or not. First, in Panel A, we sort firms by capital intensity and test whether LEO has a greater influence when innovators operate in capital intensive businesses. We define *capital intensive* as a dummy equal to one if the firm's ratio of net property, plant, and equipment (PPENT) to the number of employees (EMP) is above the median, and zero otherwise. We re-estimate the OLS regressions and find that the effect of LEO is *de facto* stronger for firms with high capital intensity, consistent with our prediction. In Panel B, we use the irreversibility of assets to identify industries of high startup costs. We use the asset specificity from Kim and Kung (2016) and define *Irreversible* as a dummy equal to one if the industry's asset specificity is above the median, and zero otherwise. We find that the effect of LEO on innovation is stronger when founding a startup involves more irreversible investments.

3.5.Originality and generality

In Table 6, we consider other features of innovation. We classify a new patent as *original* if it cites other patents from many different technology classes. Specifically, for a patent i, let N_i denote the number of citations made by the patent i, and let N_{ji} denote the number of citations made by patent i in technology class j ($N_{ji} \geq 0,\ j = 1, \ldots, J$). We define *Originality* as:

$$Originality = 1 - \sum_{j=1}^{J} \left(\frac{N_{ji}}{N_i}\right)^2$$

We classify a patent as *general* if it is cited by other patents from many different technology class. Specifically, for a patent i, N_i denotes the number of citations received by patent i, and N_{ij} is the number of citations received by patent i from patents in class j ($N_{ij} \geq 0,\ j = 1, \dots, J$). *Generality* is defined as:

$$Generality = 1 - \sum_{j=1}^{J} (\frac{N_{ij}}{N_i})^2$$

We find that LEO is positively and significantly related with both *Originality* and *Generality*. The latter finding is consistent with Wasmer (2006) that employees prefer to develop general skills to gain more bargaining power against the current employer when they face good outside opportunities.

3.6.Inevitable disclosure doctrine

We have shown a strong positive relation between employees' outside options (i.e., high LEO) and innovation outcomes. The results so far, however, do not allow us to rule out other possible explanations. To draw causal inferences between LEO and innovation, we use the inevitable disclosure doctrine rulings across U.S. states as a quasi-natural experiment. The adoption of IDD prevents employees from moving to a rival firm with trade secrets. After the passage of IDD, job positions at local rivals, which still appears as high LEO, no longer represent valid outside options. Employees might still be able to move to another local firm, but their opportunities may be limited to non-rival firms. Thus, post-IDD, the effect of LEO on innovation output should become weaker because employees may not be able to fully exercise their outside options included in LEO. We obtain the years of IDD adoptions/rejections from Klasa et al. (2018) and use the difference-in-differences approach to evaluate whether the effect of LEO on innovation changes around the IDD adoption/rejection. Table 7 Panel A presents our estimation results. Consistent with our prediction, we find that the effect of LEO on innovation becomes weaker following the IDD adoption. The coefficient on the interaction term between LEO and IDD is significantly negative. It is possible that unobservable variables correlated with a state's decision to adopt/reject IDD may be also related to a firm's innovation activity. To address this concern, in Panel B, we include state fixed effects. Our results remain robust. In addition, we re-produce our difference-in-differences results including firm fixed effects in Appendix B Panel B. The results continue to support our hypothesis.

3.7.Robustness test

Our calculation of LEO assumes that the firm's employment takes place only in its headquarters' MSA. In this regard, for firms with employees across multiple locations (MSAs), our LEO may not be a good proxy for local employment options. In Table 8, we exclude wholesale (NAICS 42), retail (NAICS 44-45), and transportation (NAICS 48), which tend to have employees at multiple geographic locations across the country, and re-estimate the regressions. The results remain quantitatively and qualitatively similar.

4. Concluding remarks

The literature has paid much attention to monitoring and incentive mechanisms to promote innovation. In this research, we focus on a rather unexplored mechanism – outside employment opportunities. We find that employees with better outside options in the local labor market create more patents, and such patents tend to be more impactful. Local employment options are also positively related to originality and generality of innovation. Our results are corroborated by exogenous shocks to employee mobility; the IDD adoptions. The effects of LEO on innovation seem to be causal. Overall, our findings suggest that employees' outside options strongly incentivize employees to innovate.

Appendix A. Variable definitions

Log patents (t+1)

- The natural logarithm of one plus the total number of patents filed in year t+1.

Log patents (t+1 to t+3)

- The natural logarithm of one plus the total number patents filed over years t+1, t+2, and t+3.

Log citations (t+1)

- The natural logarithm of one plus the total number of citations received in year t+1.

Log citations (t+1 to t+3)

- The natural logarithm of one plus the total number citations received over years t+1, t+2, and t+3.

Originality

- One minus the Herfindahl index (HHI) of the citations made by the patent across technology classes. For a patent i, N_i denotes the number of citations made by the patent i, and N_{ji} is the number of citations made by patent i in technology class j ($N_{ji} \geq 0,\ j = 1, \ldots, J$).

  $Originality = 1 - \sum_{j=1}^{J} (\frac{N_{ji}}{N_i})^2$

Generality

- One minus the Herfindahl index (HHI) of the citations received by the patent across technology classes. For a patent i, N_i denotes the number of citations received by patent i, and N_{ij} is the number of citations received by patent i from patents in technology class j ($N_{ij} \geq 0,\ j = 1, \ldots, J$).

  $Generality = 1 - \sum_{j=1}^{J} (\frac{N_{ij}}{N_i})^2$

Log sales

- The natural logarithm of firm sales (SALE) in the fiscal year t.

MB

- 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) in year t.

ROA

The ratio of income before extraordinary items (IB) to total assets (AT) in year t.

Log PPE

- The ratio of net property, plant, and equipment (PPENT) to the total number of firm employees (EMP) in year t.

HHI

- The three-digit SIC Herfindahl index based on firm sales (SALE) in year t.

High tech

- Dummy equal to one if a firm's industry belongs to one of the high-tech industries provided by Eckbo et al. (2018).

Capital-intensive

- Dummy equal to one if the ratio of net property, plant, and equipment (PPENT) to the number of employees (EMP) is above the median in year t, and zero otherwise.

Irreversible

- Dummy equal to one if the asset specificity provided by Kim and Kung (2016) is above the median in year t, and zero otherwise.

Appendix B. Firm fixed effects

This table examines the effect of local employment options (LEO) on innovation using firm fixed effects. We use OLS regressions of innovation output on LEO, control variables, and fixed effects. Panel A presents baseline regressions. In Panel B, we employ the IDD adoptions. *Log patents (t+1)* is defined as the natural logarithm of one plus the total number of patents filed in year t+1. *Log patents (t+1 to t+3)* is defined as the natural logarithm of one plus the total number of patents filed over years t+1, t+2, and t+3. *Log citations (t+1)* is the natural logarithm of one plus the total citations a given patent receives in year t+1. *Log citations (t+1 to t+3)* is the natural logarithm of one plus the total citations a given patent receives over years t+1, t+2, and t+3. All variables are winsorized at the 1 and 99 percentiles of their distributions, except for LEO. Standard errors are clustered by firm. An intercept is included and unreported.

Panel A. Baseline regressions

	Log patents (t+1)		*Log patents (t+1 to t+3)*		*Log citations (t+1)*		*Log citations (t+1 to t+3)*	
	[1]		[2]		[3]		[4]	
	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
LEO	**0.111**	***2.28***	**0.089**	***1.79***	**0.468**	***3.30***	**0.596**	***3.24***
Log sales	0.061	*9.01*	0.060	*6.39*	0.052	*4.68*	0.035	*2.31*
MB	-0.003	*-1.69*	0.005	*2.00*	0.011	*3.54*	0.014	*3.64*
ROA	-0.058	*-4.68*	-0.027	*-1.68*	-0.017	*-0.82*	0.005	*0.19*
Log PPE	0.051	*5.81*	0.057	*4.68*	0.058	*4.01*	0.052	*2.65*
HHI	-0.012	*-0.15*	-0.012	*-0.11*	0.317	*2.44*	0.237	*1.40*
Year F.E.	Yes		Yes		Yes		Yes	
Firm F.E.	Yes		Yes		Yes		Yes	
R-squared	0.77		0.83		0.67		0.72	
No. observations	26,128		21,079		26,128		21,079	

Appendix B. Continued

Panel B. IDD

	Log patents (t+1)		*Log patents (t+1 to t+3)*		*Log citations (t+1)*		*Log citations (t+1 to t+3)*	
	[1]		[2]		[3]		[4]	
	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
LEO	**0.162**	***1.69***	**0.139**	***1.99***	**0.659**	***3.81***	**0.959**	***4.23***
LEO*IDD	-0.141	*-1.00*	-0.071	*-1.40*	**-0.380**	***-1.85***	**-0.734**	***-2.53***
IDD	-0.086	*-1.80*	-0.041	*-0.68*	0.010	*0.12*	0.120	*1.22*
Log sales	0.061	*9.00*	0.059	*6.36*	0.051	*4.62*	0.034	*2.23*
MB	-0.003	*-1.71*	0.005	*1.98*	0.011	*3.49*	0.014	*3.58*
ROA	-0.057	*-4.66*	-0.026	*-1.64*	-0.016	*-0.78*	0.006	*0.23*
Log PPE	0.051	*5.81*	0.057	*4.70*	0.058	*4.05*	0.053	*2.70*
HHI	-0.010	*-0.13*	-0.007	*-0.07*	0.325	*2.51*	0.251	*1.48*
Year F.E.	Yes		Yes		Yes		Yes	
Firm F.E.	Yes		Yes		Yes		Yes	
R-squared	0.77		0.83		0.67		0.73	
No. observations	26128		21079		26128		21079	

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Table 1. Descriptive statistics and correlation

The sample includes all firm-years during the period of 1997 to 2009, where data are available to calculate local employment opportunities (LEO) and to calculate patent amounts and citations. We exclude firms in the utility (SIC 4900-4999) and financial (SIC 6000-6999) industries. Panel A reports descriptive statistics, in which we present the un-logged values of Sales, PPE/EMP, Patents, and Citations. Innovation variables are from year t+1, while other variables including LEO are from year t. Panel B reports Pearson correlation coefficients among main variables. LEO and firm characteristics are measured in year t, whereas innovation variables are measured in years t+1 or years t+1, t+2, and t+3. All variables are winsorized at the 1 and 99 percentiles of their distributions, except LEO. All variables are defined in the Appendix A. In Panel B, italicized faces are p-values.

Panel A. Descriptive statistics

	Obs.	Mean	Std. Dev.	25th Pctl.	50th Pctl.	75th Pctl.
LEO	26,128	0.316	0.105	0.247	0.301	0.368
Sales	26,128	2517.140	12906.130	28.163	165.303	937.641
MB	26,128	2.743	3.242	1.205	1.715	2.860
ROA	26,128	-0.157	0.543	-0.154	0.018	0.071
PPE/EMP	26,128	68.345	129.149	16.810	32.282	64.400
HHI	26,128	0.140	0.141	0.057	0.084	0.166
Patents (t+1)	26,128	11.198	88.744	0.000	0.000	2.000
Citations (t+1)	26,128	50.888	623.736	0.000	0.000	3.000
Patents (t+1 to t+3)	21,079	28.054	240.510	0.000	0.000	5.000
Citations (t+1 to t+3)	21,079	110.613	1479.590	0.000	0.000	6.000
Originality (t+1)	9,047	0.461	0.208	0.346	0.480	0.609
Generality (t+1)	5,627	0.225	0.227	0.000	0.198	0.391

Table 1. Continued

Panel B. Pearson correlations

	1	2	3	4	5	6	7	8	9	10	11	12
1. *LEO*	1.000											
2. *Log sales*	0.086	1.000										
	0.00											
3. *MB*	-0.011	-0.364	1.000									
	0.07	*0.00*										
4. *ROA*	0.047	0.521	-0.485	1.000								
	0.00	*0.00*	*0.00*									
5. *Log PPE*	-0.030	0.346	-0.177	0.176	1.000							
	0.00	*0.00*	*0.00*	*0.00*								
6. *HHI*	-0.049	0.178	-0.098	0.090	0.041	1.000						
	0.00	*0.00*	*0.00*	*0.00*	*0.00*							
7. *Log patents (t+1)*	0.101	0.330	-0.010	0.091	0.212	-0.042	1.000					
	0.00	*0.00*	*0.11*	*0.00*	*0.00*	*0.00*						
8. *Log citations (t+1)*	0.128	0.210	0.031	0.066	0.141	-0.053	0.836	1.000				
	0.00	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*					
9. *Log patents (t+1 to t+3)*	0.100	0.330	0.007	0.094	0.229	-0.042	0.972	0.867	1.000			
	0.00	*0.00*	*0.30*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*				
10. *Log citations (t+1 to t+3)*	0.123	0.230	0.030	0.071	0.162	-0.048	0.819	0.980	0.880	1.000		
	0.00	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*			
11. *Originality (t+1)*	0.047	-0.062	0.044	-0.028	-0.012	0.001	0.017	0.061	0.015	0.042	1.000	
	0.00	*0.00*	*0.00*	*0.01*	*0.25*	*0.96*	*0.11*	*0.00*	*0.17*	*0.00*		
12. *Generality (t+1)*	0.087	-0.147	0.089	-0.012	-0.104	-0.009	-0.128	0.081	-0.121	0.095	0.243	1.000
	0.00	*0.00*	*0.00*	*0.36*	*0.00*	*0.50*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	

Table 2. LEO and innovation quantity

This table reports OLS regressions of innovation quantity on local employment options (LEO), control variables, and fixed effects. In Panel A, *Log patents (t+1)* is defined as the natural logarithm of one plus the total number of patents filed in year t+1. In Panel B, *Log patents (t+1 to t+3)* is defined as the natural logarithm of one plus the total number of patents filed over years t+1, t+2, and t+3. All variables are winsorized at the 1 and 99 percentiles of their distributions, except for LEO. Standard errors are clustered by firm. An intercept is included and unreported.

Panel A. Patents in year t+1

	Log patents (t+1)							
	[1]		[2]		[3]		[4]	
	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
LEO	**0.546**	***3.27***	**0.770**	***4.85***	**0.799**	***8.05***	**0.437**	***4.84***
Log sales	0.183	*16.73*	0.234	*20.94*	0.235	*48.65*	0.243	*57.57*
MB	0.041	*10.27*	0.039	*10.85*	0.040	*11.70*	0.037	*12.86*
ROA	-0.162	*-7.31*	-0.227	*-10.28*	-0.230	*-10.35*	-0.228	*-12.13*
Log PPE	0.123	*7.95*	0.143	*9.01*	0.144	*14.12*	0.133	*15.15*
HHI	-0.766	*-6.10*	-0.119	*-0.91*	-0.131	*-1.58*	-0.062	*-0.92*
Year F.E.	Yes		Yes		-		Yes	
Industry F.E.	-		Yes		-		Yes	
Industry x Year F.E.	-		-		Yes		-	
State F.E.	-		-		-		Yes	
R-squared	0.22		0.33		0.34		0.35	
No. observations	26,128		26,128		26,128		26,128	

Table 2. Continued

Panel B. Patents over years t+1, t+2, and t+3

	Log patents (t+1 to t+3)							
	[1]		[2]		[3]		[4]	
	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
LEO	**0.661**	***2.85***	**1.004**	***4.59***	**1.058**	***7.36***	**0.526**	***4.04***
Log sales	0.234	*16.39*	0.306	*21.25*	0.307	*43.68*	0.318	*51.95*
MB	0.066	*11.91*	0.063	*12.83*	0.065	*13.42*	0.061	*15.06*
ROA	-0.154	*-5.02*	-0.249	*-8.10*	-0.250	*-7.81*	-0.249	*-9.21*
Log PPE	0.191	*8.59*	0.216	*9.51*	0.217	*14.44*	0.202	*15.69*
HHI	-1.017	*-5.61*	-0.144	*-0.78*	-0.155	*-1.25*	-0.079	*-0.77*
Year F.E.	Yes		Yes		-		Yes	
Industry F.E.	-		Yes		-		Yes	
Industry x Year F.E.	-		-		Yes		-	
State F.E.	-		-		-		Yes	
R-squared	0.22		0.34		0.35		0.36	
No. observations	21,079		21,079		21,079		21,079	

Table 3. LEO and innovation quality

This table reports OLS regressions of innovation quality on local employment options (LEO), control variables, and fixed effects. In Panel A, *Log citations (t+1)* is the natural logarithm of one plus the total citations a given patent receives in year t+1. In Panel B, *Log citations (t+1 to t+3)* is the natural logarithm of one plus the total citations a given patent receives over years t+1, t+2, and t+3. All variables are winsorized at the 1 and 99 percentiles of their distributions, except for LEO. Standard errors are clustered by firm. An intercept is included and unreported.

Panel A. Citations in year t+1

	Log citations (t+1)							
	[1]		[2]		[3]		[4]	
	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
LEO	**0.883**	***4.50***	**1.083**	***5.65***	**1.120**	***8.36***	**0.637**	***5.19***
Log sales	0.178	*15.52*	0.225	*19.35*	0.227	*34.77*	0.237	*41.30*
MB	0.055	*10.61*	0.054	*11.31*	0.056	*12.07*	0.052	*13.25*
ROA	-0.124	*-4.51*	-0.196	*-7.18*	-0.197	*-6.59*	-0.198	*-7.76*
Log PPE	0.117	*6.87*	0.160	*8.73*	0.159	*11.54*	0.148	*12.39*
HHI	-0.864	*-6.48*	-0.127	*-0.93*	-0.223	*-1.99*	-0.056	*-0.60*
Year F.E.	Yes		Yes		-		Yes	
Industry F.E.	-		Yes		-		Yes	
Industry x Year F.E.	-		-		Yes		-	
State F.E.	-		-		-		Yes	
R-squared	0.25		0.32		0.34		0.33	
No. observations	26,128		26,128		26,128		26,128	

Table 3. Continued

Panel B. Citations over years t+1, t+2, and t+3

	Log citations (t+1 to t+3)							
	[1]		[2]		[3]		[4]	
	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
LEO	**1.024**	***3.94***	**1.348**	***5.37***	**1.394**	***7.70***	**0.765**	***4.62***
Log sales	0.225	*15.40*	0.291	*19.69*	0.292	*32.99*	0.306	*39.30*
MB	0.074	*11.12*	0.073	*12.03*	0.075	*12.40*	0.070	*13.66*
ROA	-0.138	*-3.82*	-0.236	*-6.58*	-0.233	*-5.77*	-0.239	*-6.94*
Log PPE	0.171	*7.22*	0.224	*8.90*	0.223	*11.79*	0.208	*12.72*
HHI	-1.098	*-5.84*	-0.147	*-0.77*	-0.219	*-1.40*	-0.064	*-0.49*
Year F.E.	Yes		Yes		-		Yes	
Industry F.E.	-		Yes		-		Yes	
Industry x Year F.E.	-		-		Yes		-	
State F.E.	-		-		-		Yes	
R-squared	0.25		0.34		0.35		0.35	
No. observations	21,079		21,079		21,079		21,079	

Table 4. LEO in high-tech industries

This table examines whether the effect of local employment options (LEO) on innovation is different for high-tech industries. We use OLS regressions of innovation output on LEO, control variables, and fixed effects. *High tech* is a dummy equal to one if a firm's industry is listed as high tech in Eckbo et al. (2018), and zero otherwise. *Log patents (t+1)* is defined as the natural logarithm of one plus the total number of patents filed in year t+1. *Log patents (t+1 to t+3)* is defined as the natural logarithm of one plus the total number of patents filed over years t+1, t+2, and t+3. *Log citations (t+1)* is the natural logarithm of one plus the total citations a given patent receives in year t+1. *Log citations (t+1 to t+3)* is the natural logarithm of one plus the total citations a given patent receives over years t+1, t+2, and t+3. All variables are winsorized at the 1 and 99 percentiles of their distributions, except for LEO. Standard errors are clustered by firm. An intercept is included and unreported.

	Log patents (t+1)		*Log patents (t+1 to t+3)*		*Log citations (t+1)*		*Log citations (t+1 to t+3)*	
	[1]		[2]		[3]		[4]	
	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
LEO*High tech	**1.207**	***3.97***	**1.778**	***4.26***	**1.602**	***4.35***	**2.101**	***4.36***
LEO	0.145	*0.76*	0.122	*0.46*	0.270	*1.18*	0.316	*1.05*
High tech	-0.108	*-1.06*	-0.212	*-1.49*	-0.201	*-1.67*	-0.292	*-1.83*
Log sales	0.238	*21.39*	0.312	*21.73*	0.230	*19.82*	0.297	*20.16*
MB	0.038	*10.82*	0.062	*12.76*	0.053	*11.28*	0.071	*11.96*
ROA	-0.233	*-10.52*	-0.258	*-8.37*	-0.203	*-7.40*	-0.246	*-6.83*
Log PPE	0.149	*9.50*	0.223	*9.96*	0.167	*9.19*	0.231	*9.32*
HHI	0.048	*0.37*	0.077	*0.42*	0.052	*0.38*	0.083	*0.43*
Year F.E.	Yes		Yes		Yes		Yes	
Industry F.E.	Yes		Yes		Yes		Yes	
R-squared	0.34		0.35		0.33		0.34	
No. observations	26,128		21,079		26,128		21,079	

Table 5. LEO and high startup costs

This table examines whether the effect of local employment options (LEO) on innovation is different for high startup costs industries. We use OLS regressions of innovation output on LEO, control variables, and fixed effects. In Panel A, *Capital intensive* is a dummy equal to one if the ratio of net property, plant, and equipment (PPENT) to the number of employees (EMP) is above the median in year t, and zero otherwise. In Panel B, *Irreversible* is a dummy equal to one if the asset specificity provided by Kim and Kung (2016) is above the median in year t, and zero otherwise. *Log patents (t+1)* is defined as the natural logarithm of one plus the total number of patents filed in year t+1. *Log patents (t+1 to t+3)* is defined as the natural logarithm of one plus the total number of patents filed over years t+1, t+2, and t+3. *Log citations (t+1)* is the natural logarithm of one plus the total citations a given patent receives in year t+1. *Log citations (t+1 to t+3)* is the natural logarithm of one plus the total citations a given patent receives over years t+1, t+2, and t+3. All variables are winsorized at the 1 and 99 percentiles of their distributions, except for LEO. Standard errors are clustered by firm. An intercept is included and unreported.

Panel A. Capital intensity

	Log patents (t+1)		*Log patents (t+1 to t+3)*		*Log citations (t+1)*		*Log citations (t+1 to t+3)*	
	[1]		[2]		[3]		[4]	
	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
LEO*Capital intensive	**0.516**	***1.98***	**0.520**	***1.64***	**0.793**	***2.47***	**0.792**	***1.89***
LEO	**0.518**	***3.17***	**0.745**	***3.13***	**0.701**	***3.42***	**0.963**	***3.41***
Capital intensive	0.056	*0.62*	0.144	*1.14*	-0.005	*-0.04*	0.073	*0.50*
Log sales	0.233	*20.99*	0.305	*21.3*	0.224	*19.36*	0.290	*19.72*
MB	0.038	*10.66*	0.063	*12.67*	0.053	*11.15*	0.072	*11.90*
ROA	-0.222	*-10.06*	-0.241	*-7.83*	-0.190	*-6.93*	-0.228	*-6.31*
Log PPE	0.068	*3.27*	0.108	*3.61*	0.076	*3.18*	0.110	*3.34*
HHI	-0.118	*-0.91*	-0.146	*-0.79*	-0.125	*-0.91*	-0.148	*-0.78*
Year F.E.	Yes		Yes		Yes		Yes	
Industry F.E.	Yes		Yes		Yes		Yes	
R-squared	0.33		0.34		0.32		0.34	
No. observations	26,128		21,079		26,128		21,079	

Table 5. Continued

Panel B. Irreversibility

	Log patents (t+1)		*Log patents (t+1 to t+3)*		*Log citations (t+1)*		*Log citations (t+1 to t+3)*	
	[1]		[2]		[3]		[4]	
	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
LEO*Irreversible	**0.870**	***2.72***	**1.197**	***2.70***	**1.042**	***2.68***	**1.393**	***2.72***
LEO	0.269	*1.57*	0.294	*0.91*	**0.433**	***1.74***	0.469	*1.55*
Irreversible	-0.109	*-0.96*	-0.180	*-1.13*	-0.051	*-0.38*	-0.125	*-0.70*
Log sales	0.238	*20.08*	0.312	*20.41*	0.230	*18.59*	0.298	*18.99*
MB	0.038	*10.24*	0.062	*12.17*	0.052	*10.71*	0.070	*11.38*
ROA	-0.229	*-10.13*	-0.253	*-8.00*	-0.203	*-7.24*	-0.245	*-6.63*
Log PPE	0.142	*8.33*	0.218	*8.94*	0.162	*8.19*	0.229	*8.44*
HHI	-0.007	*-0.04*	0.020	*0.08*	0.066	*0.38*	0.104	*0.43*
Year F.E.	Yes		Yes		Yes		Yes	
Industry F.E.	Yes		Yes		Yes		Yes	
R-squared	0.33		0.34		0.33		0.34	
No. observations	23,286		18,788		23,286		18,788	

Table 6. LEO and innovation features

This table examines the effect of local employment options (LEO) on innovation features. We use OLS regressions of innovation features on LEO, control variables, and fixed effects. *Originality* is defined as one minus the Herfindahl index (HHI) of the citations made by the patent across technology classes. *Generality* is defined as one minus the HHI of the citations received by the patent across technology classes. All variables are winsorized at the 1 and 99 percentiles of their distributions, except for LEO. Standard errors are clustered by firm. An intercept is included and unreported.

	Originality (t+1)				*Generality (t+1)*			
	[1]		[2]		[3]		[4]	
	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
LEO	**0.086**	***2.88***	**0.053**	***1.74***	**0.157**	***5.03***	**0.105**	***3.47***
Log sales	-0.004	*-2.66*	-0.005	*-3.24*	-0.003	*-2.22*	-0.006	*-3.60*
MB	0.002	*1.84*	0.001	*0.89*	0.003	*2.87*	0.002	*2.21*
ROA	0.006	*0.70*	0.009	*1.06*	0.016	*1.72*	0.014	*1.57*
Log PPE	0.004	*1.12*	0.007	*1.79*	-0.007	*-1.87*	0.004	*0.96*
HHI	0.027	*1.05*	0.061	*2.08*	0.007	*0.29*	0.059	*2.25*
Year F.E.	Yes		Yes		Yes		Yes	
Industry F.E.	-		Yes		-		Yes	
R-squared	0.03		0.07		0.24		0.29	
No. observations	9,047		9,047		5,627		5,627	

Table 7. Inevitable disclosure doctrine

This table examines the effect of local employment options (LEO) on innovation output around the adoption of inevitable disclosure doctrine (IDD). We obtain the year of IDD adoption/rejection across states from Klasa et al. (2018). In Panel A, we include industry and year fixed effects. In Panel B, we include state, industry, and year fixed effects. *IDD* is a dummy equal to one if the state of the firm's headquarters has adopted the IDD by the year, and zero otherwise. We use OLS regressions of innovation output on LEO, control variables, and fixed effects. *Log patents (t+1)* is defined as the natural logarithm of one plus the total number of patents filed in year t+1. *Log patents (t+1 to t+3)* is defined as the natural logarithm of one plus the total number of patents filed over years t+1, t+2, and t+3. *Log citations (t+1)* is the natural logarithm of one plus the total citations a given patent receives in year t+1. *Log citations (t+1 to t+3)* is the natural logarithm of one plus the total citations a given patent receives over years t+1, t+2, and t+3. *Originality* is defined as one minus the Herfindahl index (HHI) of the citations made by the patent across technology classes. *Generality* is defined as one minus the HHI of the citations received by the patent across technology classes. All variables are winsorized at the 1 and 99 percentiles of their distributions, except for LEO. Standard errors are clustered by firm. An intercept is included and unreported.

	Log patents (t+1)		*Log patents (t+1 to t+3)*		*Log citations (t+1)*		*Log citations (t+1 to t+3)*		*Originality (t+1)*		*Generality (t+1)*	
	[1]		[2]		[3]		[4]		[5]		[6]	
	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
LEO	**0.896**	***4.64***	**1.302**	***5.56***	**1.239**	***4.65***	**1.683**	***5.44***	0.045	*1.44*	**0.130**	***3.54***
LEO*IDD	**-0.554**	***-2.05***	**-0.926**	***-2.79***	**-0.951**	***-2.57***	**-1.316**	***-3.02***	0.012	*0.20*	**-0.079**	***-1.69***
IDD	0.083	*0.97*	0.149	*1.46*	0.145	*1.22*	0.213	*1.56*	-0.008	*-0.36*	0.027	*1.21*
Log sales	0.235	*21.01*	0.227	*19.44*	0.308	*21.35*	0.294	*19.81*	-0.005	*-3.17*	-0.006	*-3.57*
MB	0.039	*10.62*	0.054	*11.07*	0.063	*12.62*	0.072	*11.82*	0.001	*0.88*	0.002	*2.15*
ROA	-0.226	*-10.21*	-0.195	*-7.14*	-0.247	*-8.02*	-0.234	*-6.52*	0.009	*1.06*	0.014	*1.57*
Log PPE	0.142	*9.00*	0.159	*8.71*	0.214	*9.52*	0.222	*8.90*	0.007	*1.79*	0.004	*0.93*
HHI	-0.114	*-0.88*	-0.118	*-0.87*	-0.133	*-0.72*	-0.131	*-0.69*	0.060	*2.06*	0.061	*2.31*
Year F.E.	Yes		Yes		Yes		Yes		Yes		Yes	
Industry F.E.	Yes		Yes		Yes		Yes		Yes		Yes	
State F.E.	-		-		-		-		-		-	
R-squared	0.33		0.32		0.34		0.34		0.07		0.29	
No. Obs.	26,128		21,079		26,128		21,079		9,047		5,627	

Table 7. Continued

Panel B. State-fixed effects

	Log patents (t+1)		*Log patents (t+1 to t+3)*		*Log citations (t+1)*		*Log citations (t+1 to t+3)*		*Originality (t+1)*		*Generality (t+1)*	
	[1]		[2]		[3]		[4]		[5]		[6]	
	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
LEO	**0.571**	***6.78***	**0.797**	***6.48***	**0.941**	***8.22***	**1.218**	***7.80***	**0.057**	***1.96***	**0.153**	***4.51***
LEO*IDD	**-0.361**	***-2.77***	**-0.704**	***-3.76***	**-0.811**	***-4.58***	**-1.175**	***-4.94***	-0.012	*-0.24*	**-0.106**	***-1.80***
IDD	0.088	*1.80*	0.178	*2.50*	0.178	*2.66*	0.291	*3.23*	0.001	*0.06*	0.050	*2.14*
Log sales	0.243	*74.78*	0.318	*67.45*	0.236	*53.62*	0.305	*51.00*	-0.005	*-4.49*	-0.005	*-3.56*
MB	0.037	*16.67*	0.061	*19.51*	0.052	*17.16*	0.070	*17.68*	0.001	*1.16*	0.002	*2.28*
ROA	-0.228	*-15.80*	-0.250	*-12.00*	-0.199	*-10.14*	-0.239	*-9.06*	0.009	*1.36*	0.015	*1.89*
Log PPE	0.132	*19.66*	0.201	*20.35*	0.147	*16.07*	0.207	*16.47*	0.007	*2.54*	0.004	*0.98*
HHI	-0.056	*-1.07*	-0.064	*-0.82*	-0.042	*-0.59*	-0.040	*-0.40*	0.055	*2.77*	0.062	*2.49*
Year F.E.	Yes		Yes		Yes		Yes		Yes		Yes	
Industry F.E.	Yes		Yes		Yes		Yes		Yes		Yes	
State F.E.	Yes		Yes		Yes		Yes		Yes		Yes	
R-squared	0.35		0.36		0.34		0.35		0.08		0.30	
No. obs.	26,128		21,079		26,128		21,079		9,047		5,627	

Table 8. Excluding multi-location firms

This table excludes wholesale (NAICS 42), retail (NAICS 44-45), and transportation (NAICS 48) industries and examines the effect of local employment options (LEO) on innovation output. We use OLS regressions of innovation output on LEO, control variables, and fixed effects. *Log patents (t+1)* is defined as the natural logarithm of one plus the total number of patents filed in year t+1. *Log patents (t+1 to t+3)* is defined as the natural logarithm of one plus the total number of patents filed over years t+1, t+2, and t+3. *Log citations (t+1)* is the natural logarithm of one plus the total citations a given patent receives in year t+1. *Log citations (t+1 to t+3)* is the natural logarithm of one plus the total citations a given patent receives over years t+1, t+2, and t+3. *Originality* is defined as one minus the Herfindahl index (HHI) of the citations made by the patent across technology classes. *Generality* is defined as one minus the HHI of the citations received by the patent across technology classes. All variables are winsorized at the 1 and 99 percentiles of their distributions, except for LEO. Standard errors are clustered by firm. An intercept is included and unreported.

	Wholesale, retail, and transportation industries are excluded											
	Log patents (t+1)		*Log patents (t+1 to t+3)*		*Log citations (t+1)*		*Log citations (t+1 to t+3)*		*Originality (t+1)*		*Generality (t+1)*	
	[1]		[2]		[3]		[4]		[5]		[6]	
	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
LEO	**0.805**	***5.00***	**1.056**	***4.74***	**1.133**	***5.81***	**1.412**	***5.52***	**0.050**	***1.74***	**0.104**	***3.44***
Log sales	0.241	*21.08*	0.315	*21.38*	0.232	*19.45*	0.300	*19.77*	-0.006	*-3.56*	-0.006	*-3.84*
MB	0.039	*10.68*	0.063	*12.65*	0.054	*11.08*	0.072	*11.8*	0.001	*0.94*	0.002	*2.15*
ROA	-0.238	*-10.58*	-0.262	*-8.37*	-0.208	*-7.49*	-0.249	*-6.84*	0.009	*1.04*	0.015	*1.61*
Log PPE	0.143	*8.73*	0.216	*9.21*	0.159	*8.39*	0.222	*8.53*	0.008	*1.95*	0.004	*0.90*
HHI	-0.134	*-0.99*	-0.159	*-0.83*	-0.147	*-1.03*	-0.162	*-0.82*	0.066	*2.26*	0.064	*2.40*
Year F.E.	Yes		Yes		Yes		Yes		Yes		Yes	
Industry F.E.	Yes		Yes		Yes		Yes		Yes		Yes	
R-squared	0.33		0.34		0.32		0.34		0.07		0.29	
No. Obs.	25097		20227		25097		20227		8,839		5,497	