Inventor Mobility, Human Capital, and the Propensity to Patent[1]

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ABSTRACT

Using 1975-1992 patent data this article untangles two opposing effects of knowledge spillovers: increasing productivity of invention (encouraging higher-quality patents) and increasing trade secret leakage to competitors (encouraging lower-quality patents). Using geographic labor mobility to predict the former and industry labor mobility in the latter, we find that doubling the rate of industry level labor mobility of scientists and engineers decreases patent quality. Results from doubling the rate of regional level mobility are mixed, but suggest an increase in patent quality.

Keywords: patents; labor mobility; knowledge spillover; patent quality

JEL Codes: C01; K29; D83

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Introduction

Technology workers (engineers and scientists) moving between jobs have opposing impacts on a firm's propensity to patent. On one hand, new workers bring potentially synergistic knowledge that improves the hiring firm's research and development productivity. Greater technological progress leads to more and better breakthroughs and thus more and better patents.[2] On the other hand, new workers also bring information about their old employer's trade secrets. Old employers, fearing they might be aiding competitors through ex-employee knowledge leaks, patent trade secrets to defend against corporate espionage. Firms patent more often and, because these are developments they otherwise would not be patenting, the new patents are of lower quality. This article empirically untangles these two effects of labor mobility on the propensity to patent.

We refer to patenting due to fruitful knowledge spillovers as "productive patenting." Such patents are the result of genuinely new technology. Although they add to the patent system, they also add to the body of invention and reflect the welfare-maximizing goal of the patent system. We refer to patenting that secures trade secrets as "defensive patenting." These patents do not add to social totals because they replicate what already exists but, like productive patents, create more patents around which future inventors have to navigate. The motivations for patenting between the two types are quite distinct and their effects on social totals have clear tendencies.

Engineers and scientists moving to areas outside of their expertise are much more likely to encourage productive patenting. In his 1996 article Weitzman writes

> ….if ideas allow creation of new ideas by a process akin to cross-pollination, then a researcher creates positive externalities for other researchers by increasing the number of potential ideas. (p 354)

[2] There is a large literature in economics and entrepreneurship on patents, knowledge spillovers, and growth. See, for example, Glaeser et al (1992), Wong et al. (2005), Ellison et al. (2010), and Acs and Sanders (2012). This work motivate the importance of better understanding how inventor mobility affects patent quality.

But those same individuals moving *within* an industry are more likely to spill trade secrets than novel insights: the amount of technical knowledge the incoming worker possesses is largely redundant compared to the knowledge he possesses on his previous employer’s established and guarded processes.

By examining patent quality and labor mobility of industrial sectors and of geographic regions, we untangle these opposing forces on patent quality. We find mixed evidence for positive knowledge spillover from labor mobility and consistent evidence of defensive patenting due to labor mobility.

The Patenting Decision

Firms patent to secure intellectual property. In exchange for full public disclosure, the firm gains a monopoly to the invention which, by paying the patent office renewal fees, lasts twenty years (though various legal actions can be taken to extend that period, which require spending more legal fees). Even though competitors cannot invent, copy, or use a technology due to infringement laws, they will be allowed to when the patent runs out. In theory, this disclosure is supposed to enhance technological diffusion. By making the details of an invention open to the public, other inventors can easily build off of that technology. In practice this rarely happens because it puts the inventing firm at risk to patent infringement. Proving the difficult task that your firm was *not* aware of previous work (i.e. the firm independently invented) becomes notably easier when there is a policy of not examining the patent record. (Roin 2005; Lemley and Tangri 2003; and Chiang 2007)

To qualify for a patent, an invention must be novel, non-obvious, and have utility. Novelty implies something new, non-obvious means the invention would not be evident to a person with “ordinary skill in the art,” and utility implies that there is a use for the invention (35 U.S.C. §§ 101-103). The patenting process is expensive, takes years to complete, requires various application, maintenance, and legal fees, and may not be successful. The United States Patent and Trademark Office grants about 64% of utility applications: rejection usually stems from a failure to meet the legally cryptic “non-obvious" clause. [3] Even if the patent is approved, litigation could result in the patent being overturned. Moreover, damages awarded from infringement can be small compared to the actual damage to the firm and some patents are easy to invent around. It is therefore unsurprising that few firms consider the marginal profit from patenting greater than the marginal profit of an alternative method of monetizing invention such as a first mover advantage (Cohen et al. Walsh 2000; Hall and Ziedonis 2001; Mansfield 1986).

Alternatively, a firm could transform an idea into a trade secret. Trade secrets do not require legal action nor disclosure. Firms maintain trade secrets for as long as they can keep them hidden and technology remains relevant. Although they don't suffer any legal costs and application fees, they must spend resources to keep their secrets from spilling out to current and potential competitors. This includes expenses to make reverse engineering more difficult, which is why trade secrets are more effective if applied to process innovations compared to a product which is sold to the general public.[4] Trade secrets are also subject to infringing on a competitor's patent, even if the patent application occurred long after the trade secret technology was perfected. Consequently, firms will patent if they fear a rival will invent the same insight. Like patents, trade secrets allow firms to reap monopoly profits until the technology becomes obsolete, a timeframe which can easily be less than the twenty years of patent protection. Thus if trade secrets can remain protected and a rival does not patent the trade secret, they offer the same level of *de facto* protection as a patent but at a lower cost.[5] Patents, however, protect against independent invention which trade secrets have no protection against.

[3] This number was arrived at using the data on the USPTO website and the NBER database of patents covering 1963-2006. Data on application date is not available for patents granted before 1967; we only include patents up to the application year of 2001 to allow sufficient time for examination.
[4] Trade secrets regarding products still exist, however, such as the formula for Coca-Cola.
[5] This calculus largely depends on the cost of patenting and enforcing the patent relative to the cost of securing the trade secret. A notable difference is that the cost of protecting intellectual property via patents is largely marginal although the cost of protecting trade secrets is largely fixed.

Because the cost of patenting is fixed, high-value inventions will more often tend to be patented compared to low-value patents. If the patent is low-value, then the cost a rival is willing to incur to obtain it is comparatively low and the costs the inventing firm needs to expend to protect the trade secret are low as well. High value patents mean the cost a rival is willing to pay to obtain it are high as well and the cost the inventing firm must pay to protect the technology increases. When the cost to protect is greater than the fixed cost of obtaining a patent, the firm should rely on patents to protect their intellectual property, effectively using the government to pay for the security of their invention. Holding benefits constant, as long as the cost of protecting trade secrets is lower than the cost of establishing a patent, firms will rely on trade secrets to protect their innovative advances (Friedman et al. 1991).

This has important efficiency implications. Firms, fearing corporate espionage, have less incentive to rely on trade secrets and are more likely to go through the expensive task of patenting technology when they otherwise wouldn't. These defensive patents hamper derivative innovation because other firms interested in building off of this technology must negotiate a license agreement with the patent holder. If multiple firms hold related patents, the transaction costs become prohibitively high, preventing the new technology from developing. This "tragedy of the anti-commons" is often countered with patent pools. This technique has mixed success (Lerner et al. 2003). Although a trade secret also holds up the derivative invention process, such secrets only remain obfuscated until the controlling firm deems the costs of stealth outweigh the benefits, usually occurring after the technology's original purpose becomes obsolete. Especially true in the world of biotechnology and computing technology, this term of obsolesce can be less than the patent's fixed term of twenty years.

Labor Mobility and Knowledge Spillover

Labor mobility is not exactly the same thing as knowledge spillover but empirical work backs the intuition that employees will share their knowledge with their new firm. Møen (2000) found that early in their career, technical staff earns low wages in return for the knowledge they accumulate on the job, which translates into high wages later. Trajtenberg et al. (2007) compiled a large dataset on patent citations and found that inventors who changed jobs more often were cited more often. Hoisl (2007) examines survey data of German inventors to find that skilled inventors are more productive if they regularly change jobs. Singh and Agrawal (2010) found that firms drastically increase their use of inventions a new hire developed in the past, taking greater advantage of the scientist's tacit knowledge concerning those inventions.

But precisely because knowledge spills over, greater labor mobility increases the cost of protecting trade secrets. If an employee is more likely to be hired away by a rival firm, the firm must take additional steps to protect its trade secrets if it wishes to maintain the same level of secrecy. This desire for secrecy might manifest as obvious expenses such as biometric locks or as subtle costs in the form of a lost opportunity to improve a product. For example, restricted areas require employees to wait to meet with the engineers who work in the restricted area; restricted access to classified files reduces the number of fresh eyes and thus valuable suggestions for improvements. Patenting as a defense against information leakage potentially has a major impact on U.S. patenting trends. Kim and Marschke (2005) find that increased labor mobility increase the tendency for firms to apply for patents. They explain their result with concerns for trade secrets leaking out to competitors—firms are creating defensive patents—and credit 4-17% of the increase in patenting during the years from 1975 to 1992 to changes in labor mobility.

It is difficult to separate the two potential reasons behind increased patenting. If an employee changes jobs, how does one know how much of what he shares facilitates the productive cross fertilization envisioned by Weitzman (1998) and how much of it reflects the unproductive espionage-like sharing? We solve this problem by noting that firms are more likely to implement the trade secrets of their competitors compared to the trade secrets of their non-competitors because those firms have the infrastructure and expertise to replicate and utilize such trade secrets. When an engineer arrives at a rival company, his technical knowledge isn't as useful because his new colleagues already possess such information, but his knowledge of trade secrets is new and valuable. Thus when turnover within an industry is high, the incentives for defensive patents are also high and the potential benefit from knowledge spillover is quite low. When an engineer changes industries, the reverse is true: the engineer's value to the firm come more from technical knowledge (and thus a high chance of novel cross-fertilization) paired and less from knowledge of trade secrets which the new firm is not in a position to put to profitable use if copied. Inventor productivity increases more than the danger of industrial espionage.

By exploiting differences in industry level and regional level labor mobility, we are able to untangle the conflicting effects. An employee moving to a new firm in the same industry will, on average, witness more resources being dedicated to protecting trade secrets than one moving to a firm in the same geographic area but may not be in the same industry. It is not a perfect distinction but it proves sufficient enough to untangle the two effects.

Empirical Data

Because we are interested in the motivations of why firms patent, patent quality is meant in the private sense. The more valuable a firm feels the invention is—regardless of its social value—the more likely it will patent it. The less valuable the firm feels the patent is, the more likely it will favor relying on trade secrets as a cheaper (though less reliable) method of protecting technology. We use patent citations and patent claims to capture invention quality. By law, every approved patent must cite all relevant precursors, the so-called “prior art.” The prior art, established by the applicant and then added to by a specialist at the patent office, helps determine if the invention can be patented and helps constrain the scope of the granted patent. The legal importance of an exhaustive citation suggests such citations are robust and complete. Because the applicant has a vested interest in the number of citations and is policed by the patent office, the federal court system, and other companies who can trigger legal action, their use for determining quality likely correlates with the level of private value the applicant puts on that inventions.

Citations correlate with knowledge spillover. If patent A cites patent B, then some knowledge contained in patent B is reflected in knowledge contained in patent A much like a citation in an academic article. The more patents a patent cites, the more knowledge that patent contains which implies that the patent is more valuable. Similarly, the more patents which cite a patent the more useful the knowledge in the cited patent is and thus the more valuable the cited patent is. More claims (declarations of what the invention does) on the patent also suggest that the advancement is more valuable as it indicates a higher level of complexity and/or flexibility with the invention. For applicants, adding claims is not a costless affair—it requires additional work on behalf of the patent applicant and delays the patent’s approval because each claim must be evaluated. Again, claims as a proxy for quality reflect the applicant’s private value of the patent (Lanjouw and Schankerman 1999; Jaffe et al. 1998; Jaffe and Trajtenberg 1996; Jaffe et al. 1993; and Trajtenberg 1990).

We use data from the National Bureau of Economic Research’s patent data set, Compustat’s data on firm information, and the National Democratic Survey’s Annual Democratic File (ADF) on labor mobility rates. The NBER dataset includes: the patent number; its assignee; its application year; number of times the patent was cited; the number of patents the patent cites; number of claims the patent has;

and constructed measures of *generality* and of *originality*.[6] Both indices use a Herfindahl index, measuring citation concentration across patent classes instead of production concentration across firms. The generality measure for the *i*th patent ($Generality_i$) is as follows:

$$generality_i = 1 - \sum_j^{n_i} s_{ij}^2 \tag{1}$$

Where s_{ij} indicates the percent of citations patent *i* received from a patent class, *j*, squared and summed across n_i patent classes. Patents cited by a small variety of patent classes will show a large concentration and thus a low *Generality* score; only certain classes of inventions find this patent important enough to cite. Patent being cited by different classes of inventions indicate many different classes of patents find this patent important; the generality measure reflects this with a relativity high value. *Originality* is constructed in a similar fashion but measures citations made, not received. A patent citing across only a few patent classes suggests it closely follows from previous work compared to a patent drawing on inventions from various patent classes. Because this follows from citations as a whole, which reflects private value, *Originality* and *Generality* also reflect a patent's private value.

Although citations and claims correlate with quality (Table 1), it is a noisy relationship. Improvements in information technology could cause more citations for later patents and fluctuations in evaluation times and application fees could influence the claims on a patent (Lanjouw and Schankerman 1999; Johnson and Popp 2003).

Table 1 - Correlation Values of Original Variables

N= 501,375	*Originality*	*Generality*	*Citations Made*	*Citations Received*
Originality	1			
Generality	0.2854	1		
Citations Made	0.3102	0.0022	1	
Citations Received	0.0878	0.3071	0.0745	1
Claims	0.0928	0.1796	0.1069	0.1524

[6] These variables were constructed by Hall et al. (2001) compilation of the NBER dataset and are based on the work of Trajtenberg et al. (1997).

To generate a less noisy measure of patent quality, these measures along with NBER's measure of *Originality* and *Generality* need to be combined into a composite variable. The result will be a less noisy variable for patent quality because each component originates from a different aspect of patent data. For example, an increase in information technology makes it easier to find patents to cite (biasing made and received citations upward overtime) but would not affect the number of claims on a patent. However, *Generality* follows directly from *Citations Received* and *Originality* follows directly from *Citations Made*, and therefore both pairs of variables tend to be positively correlated (Table 1). To mitigate the problem from double counting, we construct four variables to measure invention quality, labeled *Patent Quality 1, Patent Quality 2*, *Patent Quality 3*, and *Patent Quality 4*.

The first measure of quality, *Patent Quality 1*, is the sum of *Citations Made*, *Citations Received*, and *Claims*, divided by the maximum value of the sum of the three (714). *Patent Quality 2* equals *Originality,* while *Patent Quality 3* equals *Generality*. *Patent Quality 4* is the sum of *Patent Quality 1, 2, and 3* divided by the maximum value of 2.175. Each measure is multiplied by 1,000 for ease of interpretation. This ensures each value has the same bounds (between zero and 1,000), enabling easy comparison between different measures. We analyze each measure independently and emphasize the results, which are roughly consistent across all quality measures.

The USPTO-Compustat data capture 4,800 firms from 1967 to 1995. Because we are measuring how greater mobility encourages or discourages technology quality holding research constant, we include the firm's R&D expenditures (*Firm R&D)*. We include the firm's capital-to-labor ratio (*Firm Capital to Labor Ratio*), since firms with higher concentrations of capital may pursue higher quality inventions. *Firm Sales* are included as an indicator of firm size, since large firms have greater economies of scale and may produce better technologies more easily than small firms (Henderson and Cockburn 1996; Hall and Ziedonis 2001; Sørensen and Stuart 2000). Henderson and Cockburn (1996) also find that research productivity in the pharmaceutical industry increases as the firm's patent portfolio (*Firm Patent*

Portfolio at Time of Patent Application) increases due to economies of scope derived from diverse portfolios.

The ADF (March supplements) data compiled by the U.S. Census contains information on whether the respondent changed jobs within the past year as well as their job category, industry, location, age, ethnicity, and gender. Compiled by Kim and Marschke (2005), data used here include only scientists and engineers (with an average of 2,600 a year between 1975 and 1997) and sorts by industry and by region. Both turnover measures represent the portion of the sample which changed jobs in the last year. The data are restricted to the years of 1992 and before because many applications in the last two years of the dataset were still under review. Age is used because older workers tend to be less mobile (Hall 1982). We matched this data to the NBER-Compustat database based on the 1979-1988 universe of firms using a database provided by Bronwyn Hall from Hall et al. (2005). This dataset provides statistics on a firm's patent portfolio (thus regressions using that variable will be restricted to the years between 1979 and 1988). All data are restricted to U.S. firms.

Industry Labor Mobility measures labor mobility of the industries the firm is located in. Table 2 defines the industries. *Regional Labor Mobility* measures the proportion of technology workers who changed jobs in the past year in the region the firm is located in.[7] Like Kim and Marschke (2005), we note that industry-specific capital encourages technology workers to stay within their own industry and this metric may be interpreted as the level of turnover within the industry, although it also includes workers entering the industry from other industries. The variance in *Regional Labor Mobility* reflect natural differences in geography (e.g. size of cities, proximity of cities, education levels, number of industries represented) as well as economic changes in the regional economy. Because these regional differences encourage or discourage mobility both within an industry and across industries, we assume

[7] We have 9 regions: New England, Middle Atlantic, Northeast Central, Northwest Central, South Atlantic, Southeast Central, Southwest Central, Mountain, and Pacific.

interdisciplinary fertilization will be more strongly represented with this type of labor mobility. Moreover, there is little redundancy between the two measures. The correlation between *Industry Labor Mobility* and *Regional Labor Mobility*, despite their similar descriptions, is low: 0.1353 (218,336 observations); a random geographical region has some industries with a great deal of turnover and some with a relatively stable labor force and industries are located in areas of high turnover and low turnover. Because the threat of leaking trade secrets is more systematic in industries with high levels labor mobility than geographical regions with high levels of labor mobility, we can reasonably untangle the influences of protecting trade secrets and cross-pollination on patent quality.

Table 2 - Industry Classification

Industry 1: Food and tobacco	Industry 9: Electrical machinery
Industry 2: Paper and paper products	Industry 10: Electrical instruments and communication equipment
Industry 3: Chemical products	
Industry 4: Plastics and rubber products	Industry 11: Transportation equipment
Industry 5: Primary metal products	Industry 12: Motor vehicles
Industry 6: Fabricated metal products	Industry 13: Optical and medical instruments
Industry 7: Machinery and engines	Industry 14: Pharmaceuticals
Industry 8: Computers and computing equipment	Industry 15: Misc. manufacturing

The United States Census using the Longitudinal Business Database (LBD) compiles another source of labor mobility. The Business Dynamics Statistics (BDS) compiles, among other variables, data on the reallocation rate of jobs in each US state and the District of Columbia. We employ this variable *Reallocation Rate for Patent's Region* in robustness checks.

Because the dependent variable is bounded between 0 and 1,000, we use the Tobit model for this analysis. We estimate the following equations (one for each measure of Quality) for the ith patent:

$$Patent\ QualityX_i = \beta_0 + \beta_1 Industry\ Labor\ Mobility_{i-1} + \beta_2 Regional\ Labor\ Mobility_i + \beta_3 Controls_i + \lambda_r + \theta_t + u_i \quad (2)$$

where X varies between 1-4 (the four different measures of patent quality), *Industry Labor Mobility*$_{i-1}$ is the labor mobility for the patent's industry lagged by one year to account for the possibility of a delayed reaction of defensive patenting in response to increasing worker disclosure, *Regional Labor Mobility* is the labor mobility for the patent's geographical area, λ_r is the regional random effect, and θ_t is the year random effect. We use random effects instead of fixed effects because we are interested in the *between* firm variation as well as the within firm variation.[8] Because *Regional Labor Mobility* is merged based on region and year, it is not included when both random effects are used. Table 3 provides descriptive statistics.

The controls are natural log of *Firm R&D*, *Firm Sales, Firm Capital to Labor Ratio*; *Average Age of Inventors by Industry*, *Average Age of Inventors by Region*, and the *Firm Patent Portfolio at Time of Patent Application*. Finally, we include demographic controls: *% of Technology Workers Who Are White by Industry*, *% of Technology Workers Who Are White by Region*, *% of Technology Workers Who Are Male by Industry*, and *% of Technology Workers Who Are Male by Region*. Table 3 provides descriptive statistics for all variables.

[8] A Hausman test also indicates that random effects are appropriate.

Table 3 - Descriptive Statistics

Variable	N	Mean	Std. Dev	Min	Max
Year of Patent Application	1,217,262	1984.217	5.233	1975	1992
Firm R&D	318,253	385.017	710.943	0	4,194.355
Firm Sales	318,253	10,455.63	17,642.98	0.001004	125,172.3
Firm Capital to Labor Ratio	292,973	26,982.52	241,024.7	0.0000768	5,684,984
Industry Labor Mobility	318,253	0.1079	0.0458	0.00	0.24
Regional Labor Mobility	218,336	0.1282	0.0203	0.05102	0. 22093
Reallocation Rate for Patent's Region	218,363	0.2993	0.0213	0.23333	0.39675
Average Age of Inventors by Industry	318,253	38.537	1.871	33.2	45.5
Average Age of Inventors by Region	218,336	37.796	0.630	34.7	40.8
% of Technology Workers Who Are Male by Industry	318,253	0.837	0.100	0.428571	1
% of Technology Workers Who Are Male by Region	218,336	0.753	0.030	0.67647	0.830
% of Technology Workers Who Are White by Industry	318,253	0.914	0.046	0.75	1
% of Technology Workers Who Are White by Region	218,336	0.886	0.029	0.76524	0.975
Firm Patent Portfolio at Time of Patent Application	326,776	3.145	3.275	0	16.725
Citations Made	632,475	7.838	7.474	0	226
Citations Received	632,475	7.519	10.069	0	631
Claims	631,510	13.006	11.142	1	868
Originality	608,676	0.368	0.280	0	0.9407
Generality	567,894	0.380	0.281	0	0.9286
Patent Quality 1	631,510	27.838	18.491	0.9813543	1,000
Patent Quality 2	608,676	367.929	280.208	0	940.7
Patent Quality 3	567,894	379.731	281.125	0	928.6
Patent Quality 4	548,665	289.415	167.496	1.089264	1,000

Empirical Results

The results consistently show that industries with greater labor mobility patent inventions with lower quality, suggesting they are more willing to patent technology they previously held as a trade secret. *Regional Labor Mobility* results are mixed, but favor increasing patent quality. Tables 4-7 summarize the results. We indicate standard errors in parenthesis below the coefficient. While the models without random effects have robust errors, a random effects tobit model requires i.i.d. normal errors independent of normal random effects and thus cannot correct for heteroscedasticity. As a result, significance of coefficients in the random effect models may be notably overstated.

Table 4 -The Effect of Inventor Mobility on Patent Quality as Measured by Patent Quality 1

Variable	1	2	3	4
Industry Labor Mobility (lagged)	-3.48*** (1.022)	-3.56 (5.474)	-3.82 (5.788)	-3.21 (4.956)
Regional Labor Mobility	34.48*** (2.433)	3.33 (12.763)	41.78*** (1.643)	—
Firm R&D (ln)	0.55*** (0.055)	0.07 (0.126)	0.64 (0.754)	0.16 (0.238)
Firm Sales (ln)	-1.74*** (0.063)	-1.40*** (0.147)	-1.83 (1.209)	-1.51*** (0.335)
Firm Capital to Labor Ratio (ln)	0.46*** (0.022)	0.52*** (0.053)	0.46** (0.212)	0.51*** (0.080)
Average Age of Inventors by Industry	-0.19*** (0.026)	-0.33* (0.141)	-0.17 (0.103)	-0.29* (0.134)
Average Age of Inventors by Region	0.45*** (0.082)	-0.51 (0.347)	0.69*** (0.188)	—
Firm Patent Portfolio at Time of Patent Application	0.13*** (0.021)	0.15** (0.055)	0.14 (0.195)	0.21*** (0.063)
Constant	23.06*** (3.229)	67.59*** (16.013)	12.22* (5.342)	47.28*** (5.235)
Region RE	No	No	Yes	Yes
Year RE	No	Yes	No	Yes
Obs	179,489	179,489	179,489	179,489
P-value	0.0000	0.0000	0.0000	0.0000

Notes: * significant at the 5% level, ** significant at the 1% level, *** significant at the 0.1% level. *Patent Quality 1* is defined as the sum of *Citations Made, Citations Received*, and *Claims,* divided by 714. See text for more detail.

Table 5 - The Effect of Inventor Mobility on Patent Quality as Measured by *Quality 2*

Variable	1	2	3	4
Industry Labor Mobility (lagged)	-182.34*** (19.680)	-144.34** (44.943)	-147.77* (59.749)	-132.62** (42.587)
Regional Labor Mobility	354.96*** (50.141)	-90.11 (100.118)	314.79*** (68.127)	—
Firm R&D (ln)	-0.44 (1.154)	-4.91** (1.673)	-0.17 (7.733)	-5.35 (2.699)
Firm Sales (ln)	-15.01*** (1.237)	-8.01*** (1.638)	-11.25 (7.475)	-7.93** (2.522)
Firm Capital to Labor Ratio (ln)	5.89*** (0.469)	4.91*** (1.046)	4.20*** (0.671)	4.75*** (1.042)
Average Age of Inventors by Industry	9.40*** (0.515)	6.20*** (1.886)	7.58*** (0.844)	6.53*** (1.560)
Average Age of Inventors by Region	14.33*** (1.648)	3.16 (4.514)	8.15*** (1.507)	—
Firm Patent Portfolio at Time of Patent Application	8.61*** (0.431)	6.67*** (0.736)	6.14*** (1.318)	6.91*** (0.848)
Constant	-537.72*** (64.524)	92.70 (203.234)	-190.00** (72.086)	189.01** (63.681)

	1	2	3	4
Region RE	No	No	Yes	Yes
Year RE	No	Yes	No	Yes
Obs	174,981	174,981	174,981	174,981
P-value	0.0000	0.0000	0.0000	0.0000

Notes: * significant at the 5% level, ** significant at the 1% level, *** significant at the 0.1% level. *Patent Quality 2* is *Originality* from Hall, Jafee, and Trajtenberg (2001). The measure captures the extent to which a patent's citations made are from a narrow selection of patent classes or cite more broadly. See text for more detail.

Table 6 - The Effect of Inventor Mobility on Patent Quality as Measured by *Patent Quality 3*

Variable	1	2	3	4
Industry Labor Mobility (lagged)	-112.15***	-115.83*	-93.02**	-119.10*
	(21.219)	(57.977)	(31.604)	(59.427)
Regional Labor Mobility	-47.57	250.30*	-132.13***	—
	(52.820)	(118.778)	(30.799)	
Firm R&D (ln)	27.45***	21.99***	16.97	20.07***
	(1.235)	(3.478)	(9.678)	(3.621)
Firm Sales (ln)	-36.36***	-28.09***	-24.09*	-26.45***
	(1.308)	(2.202)	(9.755)	(3.429)
Firm Capital to Labor Ratio (ln)	5.16***	3.31***	3.78***	3.42***
	(0.506)	(0.845)	(0.909)	(0.894)
Average Age of Inventors by Industry	-5.47***	-1.13	-2.97***	-1.38
	(0.547)	(1.649)	(0.889)	(1.328)
Average Age of Inventors by Region	-26.60***	-0.37	-22.96***	—
	(1.746)	(3.249)	(2.94)	
Firm Patent Portfolio at Time of Patent Application	5.15***	3.95***	4.37*	4.42***
	(0.452)	(0.839)	(1.989)	(0.923)
Constant	1669.84***	508.39**	1466.68***	530.55***
	(68.185)	(168.126)	(122.739)	(54.718)
Region RE	No	No	Yes	Yes
Year RE	No	Yes	No	Yes
Obs	160,843	160,843	160,843	160,843
P-value	0.0000	0.0000	0.0000	0.0000

Notes: * significant at the 5% level, ** significant at the 1% level, *** significant at the 0.1% level. *Patent Quality 3* is *Generality* from Hall, Jafee, and Trajtenberg (2001). The measure captures the extent to which the citations received by a patent are from a narrow selection of patent classes or are more general in nature. See text for more detail.

Table 7 - The Effect of Inventor Mobility on Patent Quality as Measured by *Patent Quality 3*

Variable	1	2	3	4
Industry Labor Mobility (lagged)	-107.41*** (9.348)	-112.73** (35.383)	-106.61** (36.243)	-108.47** (37.647)
Regional Labor Mobility	96.46*** (23.206)	82.48 (47.153)	92.24*** (27.73)	—
Firm R&D (ln)	7.26*** (0.530)	6.85*** (1.553)	6.79 (6.366)	5.98** (2.096)
Firm Sales (ln)	-14.44*** (0.560)	-14.14*** (1.091)	-13.92* (6.629)	-13.44*** (2.171)
Firm Capital to Labor Ratio (ln)	3.11*** (0.219)	3.15*** (0.630)	3.09*** (0.575)	3.09*** (0.693)
Average Age of Inventors by Industry	1.65*** (0.241)	1.96 (1.181)	1.83** (0.610)	2.08* (0.880)
Average Age of Inventors by Region	-3.21*** (0.763)	0.77 (2.652)	-5.46*** (1.056)	—
Firm Patent Portfolio at Time of Patent Application	4.01*** (0.199)	3.97*** (0.428)	3.88*** (1.058)	4.19*** (0.481)
Constant	404.32*** (29.864)	244.36 (123.537)	481.72*** (40.861)	276.92*** (36.133)
Region RE	No	No	Yes	Yes
Year RE	No	Yes	No	Yes
Obs	156,851	156,851	156,851	156,851
P-value	0.0000	0.0000	0.0000	0.0000

Notes: * significant at the 5% level, ** significant at the 1% level, *** significant at the 0.1% level. *Patent Quality 4* is defined as *Patent Quality 1 + Patent Quality 2 + Patent Quality 3* divided by the maximum value of 2.175. See text for more detail.

Another interpretation of the results is a confounding variable: technological uncertainty. When there is uncertainty within an industry concerning which technology will prove profitable (e.g. Blue Ray versus HD DVD), the expected value of what turns out to be the winning technology falls and the expected value of what turns out to be the losing technology increases. Firms are more willing to patent technology which later turns out to be a loser and they are less willing to patent technology which later turns out to be a winner. If there are more losers than winners (as if often the case), average patent quality will fall. At the same time, technological uncertainty encourages labor mobility as technology workers are constantly revising which technological approach holds the most promise.

Suppose this interpretation is correct and the relationship between industry-level technology worker mobility and patent quality is entirely due to an underlying variable.[9] To test this theory, it is worth considering a case where labor mobility should still cause patenting due to espionage without being connected to technological uncertainty. Because technological uncertainty in one industry is likely uncorrelated with uncertainty in other industries, it is unsurprising that region-level technology worker mobility usually had a fundamentally different impact on patent quality than industry-level. We explain this as evidence of knowledge spillover.

Instead of measuring just technology workers for a region, consider measuring the mobility of *all* workers. It is hard to believe that managers, administrative assistants, factory workers, accountants, and other occupations have the same positive impact on technological inquiry as scientists and engineers. Such jobs have (varying) access to trade secrets but little to no technical knowledge to share—if firms are patenting to assuage espionage, greater mobility of all workers should reduce patent quality. And because this mobility is by region rather than by industry, technological uncertainty should not be an underlying cause if there is a relation between the two variables.

Regions differ widely in their capacity to generate and copy technology—industry concentration, population density, education levels, taxes, regulations, availability of capital, and quality of local talent all play important roles in determining not just how well technology is created and copied, but also how easily workers can change jobs. Again, regional random effects are employed to adjust for this unobserved heterogeneity.

[9] There is room for both interpretations to be correct but untangling which has a larger impact is beyond the scope of this article and is a task I leave to future research.

The level of overall labor mobility uses data made available through BDS. It measures state-level reallocation rates for all occupations and will serve as the measure of overall turnover. A state's reallocation rate is defined as:

$$\left(\frac{Job\ creation + Job\ destruction}{Employment} - \left|\frac{Job\ creation - Job\ destruction}{Employment}\right|\right) * 100 \tag{3}$$

By subtracting the absolute value of the net job creation rate, the reallocation rate measures simultaneous instances of job creation and job destruction. This is much closer to the mobility of workers than simply dividing the sum of gross creation and gross destruction by gross employment as it removes changes in the rate of employment.

If technological uncertainty was a major issue and fear of espionage was not, then the results using *Reallocation Rate for Patent's Region* should be similar to the results using *Regional Labor Mobility*. Geographic concentration of industry should play an even greater role in technological espionage as the proximity of similar firms would ease the ability of non-technical workers to find competitors (because these worker are less likely to be able to utilize the technology workers' networking avenues for purposes of finding a buy for their trade secrets).

As the data show, reallocation exhibits virtually the opposite trend seen for technology workers as a whole when using regional random effects. Like the measure of technology worker mobility, the results are mixed but favor defensive patenting. According to these results, doubling the rate of reallocation decreases patent quality. The trend from Tables 4-6 persist as well: doubling the rate of industry level labor mobility of technology workers decreases patent quality. Half of all models are significant and negative. Three are insignificant and one is significant and positive with this latter instance for the model without random effects. Table 8 summarizes the results (controls are not reported). All errors are robust and are reported below the estimated coefficient.

Table 8 - The Effect of Inventor Mobility on Patent Quality Using *Reallocation Rate* Instead of *Regional Labor Mobility*

FE	*Variable*	*Patent Quality 1*	*Patent Quality 2*	*Patent Quality 3*	*Patent Quality 4*
No RE	*Industry Labor Mobility (lagged)*	-2.83**	-101.42***	-79.82***	-65.60***
		(1.057)	(20.458)	(21.670)	(9.613)
	Reallocation Rate for Patent's Region	-29.79***	-118.18**	185.81***	2.56
		(2.058)	(43.454)	(45.317)	(19.951)
	F-Stat	161.89	130.35	199.43	156.06
	Obs	181,616	177,056	162,800	158,760
Regional RE	*Industry Labor Mobility (lagged)*	-2.42	-86.41	-76.20***	-68.87*
		(4.361)	(52.887)	(13.380)	(28.601)
	Reallocation Rate for Patent's Region	-8.50**	-123.80**	-69.09	-70.34
		(2.809)	(38.274)	(87.580)	(53.471)
	F-Stat	283048.72	53046.24	272805.62	135542.97
	Obs	181,616	177,056	162,800	158,760

Notes: * significant at the 5% level, ** significant at the 1% level, *** significant at the 0.1% level. Estimated using Tobit. *Firm R&D (ln)*, *Firm Sales (ln)I*, *Firm Capital to Labor Ratio (ln)*, *Average Age of Inventors by Industry*, *Average Age of Inventors by Region*, *Firm Patent Portfolio at Time of Patent Application*, and *Constant* included but not reported.

Extensions

Our analysis captures the lower bound of the degree of defensive patenting. This is because our dataset only examines granted patents and all of the quality measures (save the number of claims) manifest only if the application is approved by the USPTO. A rejected patent application isn't cited by other patents, cites no patents, and has no assignee. Therefore, rejected patents are not included in the dataset and the average quality of patent applications is biased upwards. This causes the quality of defensive patents to be understated though this understatement is likely not drastic. Patent applications are expensive and time-consuming and the requirements of patenting mean low-quality applications have a higher rate of rejection. If a firm fears increased labor mobility will expose a trade secret, and the trade secret is of low enough quality that its patent application approval is unlikely, the firm will probably not apply for a patent at all and, following the proliferation of the development, begin adapting to its new market position. This is especially likely because applying for a patent requires the applicant to detail the invention for public consumption, increasing the risk of exposure with little or no benefit. Analyzing patent quality based solely on claims (thus allowing the inclusion of rejected patents) would provide a useful, if noisy, metric to better ascertain the impact of regional and industry level labor mobility on patent applications.

The geographic regions we use for our dataset are quite large, crossing several states. This implies that if many technology workers in San Francisco changed jobs last year, then firms in Los Angeles, Seattle, and Portland should produce higher quality inventions. Clearly this is not the case. In contrast, Jaffe et al. (1993) follow patent citations (a proxy for knowledge spillover instead of patent quality) across Metropolitan Statistical Areas. An improved analysis would reflect the role of cities in this regard, but would require a much larger dataset to provide an adequate sample for each of the United States' 362 MSAs (plus an additional eight in Puerto Rico). These are tasks for future research.

Conclusion

Our analysis supports the theory that departing technology workers will encourage defensive patenting and weakly supports the existence of knowledge spillovers. That the knowledge spillovers are difficult to detect might be explained by the size of the regional areas, though reallocation rates for all workers have a predictably negative impact on patent quality despite the large regions. When technology workers of a particular industry change jobs, the gains from knowledge transfer are small compared to the costs of the threat to trade secrets. Exactly how much is wasted in protecting trade secrets is unknown, but it is clear that firms tend to apply for low quality patents as a result of increased industry level labor mobility.

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