Trade Secrets, Non-Competes, and Inventor Mobility: Empirical Evidence

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Abstract

As they change jobs, scientists and engineers carry knowledge from one employer to another. Spillovers of knowledge, and so, innovation and economic growth, depend on institutions that influence professional mobility.

Here, I investigate the impact of U.S. state-level trade secrets law on the movement of inventors among employers within states. Using patent assignments to track inventor moves, I find that mobility was negatively associated with the stock of trade secrets cases, but not the enactment of a trade secrets statute or the stock of cases on covenants not to compete. Specifically, a 1% larger stock of trade secrets cases was associated with 0.3% (±0.1%) lower inventor mobility. The empirical findings were robust to differences in the rate of depreciation of legal cases and the measure of change of employer, and various falsification tests.

My results have implications for the degree of knowledge spillovers between established organizations as well as the rate of entrepreneurial start-ups, and ultimately, the overall economy-wide rate of innovation and economic growth.

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1 Introduction

In the fall of 1999, three employees left semiconductor manufacturer, Intel, to join Broadcom, a semiconductor manufacturer that specializes in communications devices.[1] They were Greg Young, product manager for Fast Ethernet and gigabit MAC products, Steven Lindsay, described as the "chief architect" of software for gigabit MAC products, and Martin Lund, an engineering manager. In March 2000, Intel engineer, Brad Gunther, approached Broadcom Chief Executive Officer, Henry T. Nicholas III, for a job.

Intel sued Broadcom and the four engineers for misappropriation of trade secrets. Further, claiming that the engineers would "inevitably disclose" Intel's trade secrets, Intel applied for an injunction to bar each of them from working on gigabit Ethernet for Broadcom, pending trial. Judge William F. Martin of the California Superior Court refused to grant the injunction against Messrs Young, Lindsay, and Lund. However, Judge Martin described Mr Gunther as "not trustworthy" and enjoined him from working for Broadcom in any role.

Intel's suit against Broadcom and the four engineers illustrates several issues of importance to public policy and managerial practice. Scientists and engineers who move between employers bring technical knowledge from one organization to another. Spillovers of knowledge play a central role in innovation and economic growth. Accordingly, it is important for policy-makers and managers to understand the institutions that influence professional mobility.

Png (2011) showed that state enactment of trade secrets laws was associated with less R&D among low-tech companies and less patenting in industries where patents are useful in protecting processes. However, his research did not investigate the mechanism by which trade secrets laws affected corporate innovation.

Intel's suit suggests one answer – trade secrets law affected corporate innovation by inhibiting the movement of technical professionals among employers. Indeed, more than 75% of trade secrets cases in state courts and over half of cases in federal courts involved an existing or former employee (Almeling et al. 2010 and 2011). To the extent that fewer professionals move from one employer to another, less knowledge would spill over from one employer to another. This would affect the return from and incentive for expenditure on R&D.

[1] The following case study of the dispute between Intel and Broadcom is based on *Los Angeles Times* (2000a and 2000b) and Hyde (2003), 26-27.

In the United States, trade secrets are a state matter and the law comprises both statute (in all but four states) and case law. So, the relevant questions are whether trade secrets law affected the mobility of technical professionals, and if so, whether through statute or case law.

Intel's suit indirectly raises another important issue. The information and communications technology industry germinated in both Silicon Valley, Northern California, and along Route 128, Massachusetts. However, Silicon Valley eventually eclipsed Route 128. Saxenian (1994) famously attributed the Valley's relative success to a culture of job-hopping and vertically specialized businesses. In turn, Gilson (1999) ascribed the easy worker mobility to a California statute that prohibits covenants not to compete (CNCs). However, trade secrets law, working through the doctrine of "inevitable disclosure", could effectively serve to enforce CNCs (Gilson 1999; Hyde 2003; Graves and DiBoise 2006).

So, to what extent did professional mobility and Silicon Valley's success depend on the law of trade secrets vis-a-vis the law of CNCs? By contrast with trade secrets, the bulk of the law on CNCs is case law, rather than statute. Hence, the empirical issue is to compare the effects of trade secrets statute and case law with CNC case law.

Here, I draw on data from multiple sources to investigate the effect of three sets of legal institutions on the mobility of technical professionals:

- Trade secrets statutes,
- Case law on trade secrets, and
- Case law on covenants not to compete (CNCs).

Focusing on employed U.S. inventors who filed patents, I use the U.S. Patent Inventor Database, as published by the Harvard Institute of Quantitative Social Science (Lai et al. 2011), to track the movement of inventors between employers. To represent trade secrets statutes, I use Png's (2011) chronology of the Uniform Trade Secrets Act (UTSA) and supplement with the histories of the North Carolina and South Carolina Trade Secrets Acts. To represent trade secrets case law, I use the Lexis-Nexis database to compile the stocks of trade secrets cases for each state from 1960 onward. Likewise, to represent state law on CNCs, I use the Lexis-Nexis database to compile the stocks of CNC cases.

I find that inventor mobility was negatively associated with the stock of trade secrets cases. Specifically, if the stock of trade secrets cases was 1% higher, inventor mobility was 0.3% (±0.1%) lower. This empirical finding was robust to differences in the sample, the measure of change of employer, the rate of depreciation of legal cases, and various falsification tests. I also find that inventor mobility was not significantly associated with the enactment of a trade secrets statute. Further, trade secrets case law had a more significant and larger effect on inventor mobility than CNC case law.

My findings have obvious implications for public policy and managerial practice. To the extent that trade secrets law affects the mobility of technical professionals, it would affect innovation and economic growth through the rate of spin-outs as well as spillovers of knowledge among established organizations. Within organizations, the reduced mobility of technical professionals would affect the incentives of the organization and the employees themselves to invest in training and development. Finally, the reduced mobility would also affect compensation policy: to the extent that employees have less opportunity to work elsewhere, organizations might them pay them less (because they need not worry so much about retention) or more (because the organization no longer provides a training ground for better opportunities elsewhere).

2 Law

In the United States, trade secrecy and covenants not to compete are matters of state rather than federal jurisdiction. Historically, trade secrets were governed by common law. In 1939, the Restatement (First) of Torts, in its consolidation of the common law of torts, included section 757 on trade secrets, and defined a trade secret to "consist of any formula, pattern, device or compilation of information which is used in one's business, and which gives him an opportunity to obtain an advantage over competitors who do not know or use it".

Then, in 1979, the National Conference of Commissioners on Uniform State Laws approved and recommended the Uniform Trade Secrets Act to the states for two reasons.[2] One reason was that many states did not have extensive case law on trade secrets. The other reason, even for states with substantial case law, was to clarify the parameters of trade secret protection and the appropriate remedies for misappropriation. Substantively, the UTSA expanded the definition of a trade secret. Compared with the Restatement (First) of Torts, the UTSA does not require that the secret be business related or in continuous use. So, the UTSA encompasses negative information, work in

[2] "Uniform Trade Secrets Act Prefatory Note", *Uniform Laws Annotated*, Vol. 14.

progress, and one-off information (Lydon 1987: 430; Samuels and Johnson 1990: 62-63; Pooley 1997- : 2.03[2]). Further, the UTSA clarified injunctive and damages remedies, and the statute of limitations (Samuels and Johnson 1990: 53). Png (2011), Table 1, presents a chronology of the UTSA in the various states.

At the time of writing, 44 states and the District of Columbia had enacted the UTSA. North Carolina and South Carolina enacted trade secrets statutes that differ substantially from the UTSA. Four states – Massachusetts, New Jersey, New York, and Texas – had not enacted any trade secrets statute and rely completely on common law. Obviously, case law is key for states without a trade secrets statute. However, even in the states that have enacted UTSA or some other trade secrets statute, the law continues to evolve through litigation.

The stronger is trade secrets law, the stronger would be the intellectual property rights of an employer over its proprietary information, including technical knowledge such as designs, formulas, algorithms, and processes. To the extent that an employer has stronger rights over technical knowledge, its scientific and engineering professionals would be more constrained in the information that they can bring to other employers. So, the scientists and engineers would be less attractive to other employers, and fewer of them would move.

A CNC may be part of a contract between a business and a shareholder, employee, vendor, distributor, franchisee, or consultant. The CNC serves to protect the employer's interest, which, among other things, could be a trade secret, confidential information, or goodwill. Although CNCs may extend beyond employees, they are generally the subject of employment law. In deciding whether to enforce CNCs, courts balance the employer's interest against an individual person's right to practise her trade or profession. Depending on the employee's work and skills, courts may limit the enforcement of CNCs by geography (to a particular distance or geographical unit such as city or county), and by time (in months or years).

Historically, CNCs were governed by common law. State laws on CNCs vary on multiple dimensions, including the interest that an employer can protect through a CNC, the permitted scope in geography and time, what constitutes sufficient consideration for a CNC, the available injunctive and damages remedies, and procedures for civil action.

Some states have enacted statutes concerning CNCs. For instance, the California Business and Professions Code, Section 16600, provides, "Except as otherwise provided in this chapter, every contract by which anyone is restrained from engaging in a lawful profession, trade, or business of any kind is to that extent void".[3] However, by contrast with the subject of trade secrets, there is no uniform statute on CNCs across the states. Hence, there is considerable variation among the states in their substantive law regarding CNCs.

3 Implications for Mobility

Both trade secrets law and CNC law possibly influence the mobility of professionals between employers. Referring to figure 1, the scope of trade secrets and CNC law is defined, in part, by the closeness of technology and customers. In addition, CNCs may be limited in geography and time.

For instance, a chemical engineer developing alternative fuels who quits to write software for a social media website is not likely to misappropriate any trade secrets or infringe any CNC. By contrast, a software engineer who leaves a computer manufacturer to join a bank might misappropriate trade secrets but would only infringe any CNC if the bank was a customer of the manufacturer. A surgeon trained at a cardiac clinic that developed a new technique who joins a clinic in another city might misappropriate trade secrets but is unlikely to infringe any CNC.

Many legal scholars have analyzed how the laws of trade secrets and CNCs inhibit the mobility of workers, and so reduce innovation and entrepreneurship (Gilson 1999; Hyde 2003; Graves and DiBoise 2006). They particularly criticized the doctrine of "inevitable disclosure" in trade secrets law. By this doctrine, an organization can seek an injunction to prohibit a former employee from working for a competitor, on the ground that she would inevitably disclose trade secrets. While the doctrine originated in the late 19th century, it gained renewed significance in the *PepsiCo* decision by the U.S. Court of Appeals for the 7th Circuit.[4] Graves and DiBoise (2006) argued that the doctrine of "inevitable disclosure" suppresses worker mobility and innovation, and they exhorted courts to reject the theory out of hand.

However, regardless of the law, the employer and employee could contract around the law to achieve the economically efficient outcome – whether it be that the employee

[3] This law was first enacted in 1872 as California Civil Code section 1673. The California Supreme Court recently affirmed that the law must be construed broadly, to void any noncompetition agreement even it only restrains the employee from practicing part of her profession, trade, or business (Trossen 2009).

[4] *PepsiCo, Inc. v. Redmond*, 54 F.3d 1262, 1269 (7th Circuit 1995).

remain with the current employer or leave to use the current employer's proprietary knowledge elsewhere. Suppose, for instance, that the law strongly protects trade secrets. If the economically efficient outcome is that the employee leave, then the employee could pay her current employer to use its proprietary knowledge at another organization. With such efficient contracting, the law would only affect the division of profit between employer and inventor.

The law should affect the outcome only to the extent of market imperfections that impede efficient contracting around the law. The possible imperfections include the actions of the employee and/or employer being not contractable (Motta and Ronde 2001; Garmaise 2011), asymmetry of information between employee and employer about outside opportunities (Franco and Mitchell 2008), and limits on the amount that the employee can borrow (Fosfuri and Ronde 2004).

Thus, to the extent of market imperfections that impede efficient contracting, laws that provide stronger protection of trade secrets would lead to lower mobility of employees.

4 Empirical Strategy and Data

To study the impact of trade secrets laws on inventor mobility, I applied an empirical strategy similar to those in recent studies of the impact of enforcement of CNCs on innovation (Garmaise 2011; Marx et al. 2010; Samila and Sorensen 2011). Essentially, the research design is one of difference in differences (Bertrand et al. 2004). The law of trade secrets evolved in the various states differently over the years. Accordingly, panel estimation of the following specification implements differences in differences in a setting of multiple treatment groups over multiple years:

$$\Pr(M_{ist}|Z_{ist}) = \beta_i + \beta_t + \beta \cdot X_{ist} + \gamma_1 \cdot \mathrm{TSA}_{st} + \gamma_2 \cdot \mathrm{TS\ cases}_{st} + \epsilon_{ist}. \tag{1}$$

In (1), M_{ist} is an indicator of whether inventor i changed employer in state s in year t, Z_{ist} represents the collective of the explanatory variables, X_{ist} represents time-varying characteristics, and ϵ_{ist} is idiosyncratic error. Further, $\mathrm{TSA}_{st} = 1$ for any year t in which state s had a trade secrets statute in effect and zero otherwise, and TS cases_{st} represents the stock of trade secrets cases. The β_i, β_t are inventor and year fixed effects, while β and γ_i are the coefficients of the time-varying controls and the laws and cases respectively.

To represent trade secrets statutes, I used Png's (2011) chronology of the Uniform Trade Secrets Act, supplemented with the histories of the North Carolina and South Carolina Trade Secrets Acts. To represent trade secrets case law, I constructed the stock of reported legal cases in the following way. I searched the Lexis-Nexis legal database for all federal and state cases from 1960 onward including "trade secret" in the headnote. Although civil actions in trade secrecy are a state matter, cases involving parties from different states may be tried in federal court.[5] Using the cases, I then constructed the stock of federal and state cases for each state for each year, starting from 1960. For each state, the federal cases comprised those decided by District Courts in the state, the Court of Appeals with jurisdiction over the state, the Supreme Court, as well as federal courts with functional rather than territorial jurisdiction, including the Tax Court, and Courts of Appeals for the DC and Federal Circuits. For each state, the state cases comprised cases at all levels of the judicial system.

In measuring stocks of capital, a key issue is the rate of depreciation over time. In a sample of U.S. federal cases decided in the 1960s and 1970s, Landes and Posner (1996) found that Court of Appeal decisions on the common law of torts and contracts depreciated at the rate of 4.0%, which was more than twice the depreciation rate of Supreme Court cases, 1.8%. The depreciation of cases decided by courts of first instance (the level below the Court of Appeal) would be even faster. Further, in a study of all decisions by 99 U.S. Supreme Court justices between 1793 and 1991, Kosma (1998) produced a depreciation rate of 6.5%, which was higher than the estimates of Landes and Posner (1996).

Among the trade secrets cases reported by Lexis-Nexis, most were decided by courts of first instance, and a minority of cases were appeals. Accordingly, it seemed reasonable to use 10% as the main specification, with 7.5% in robustness checks. I constructed the initial stock in 1960 as the average number of cases a year in the period 1960-69.[6]

It is worth stressing an obvious limitation of my measure of case law. The stocks of cases, as constructed, were pure numerical measures, without any analysis of the content of the decisions. A case could relax trade secrets protection by creating more exceptions

[5] Federal courts also try criminal trade secrets cases under the federal Economic Espionage Act of 1996.

[6] In their study of economic growth across countries, Hall and Jones (1999) constructed the initial stock of capital as the investment in the first year divided by the sum of the average growth rate of investment and the depreciation rate. However, in the present context, in the early years, most states had zero or one case, so the growth of cases fluctuated between −100%, 0% and 100%. Hence, it did not seem reasonable to use the Hall and Jones method.

or it could strengthen protection by closing loopholes. However, a legal analysis of the case law was beyond the scope of this study.

To compare the effect of trade secrets vis-a-vis CNC law, I also compiled the stocks of reported cases on CNCs. I searched the Lexis-Nexis legal database for all federal and state cases from 1960 onward including "covenant not to compete" in the headnote. In the same way as for the stock of trade secrets cases, I then constructed stocks of federal and state cases for each state for each year from 1960 onward, with alternative depreciation rates of 10% and 7.5%.

Garmaise (2011) took a different approach, building an index of CNC case law based on a periodic survey of substantive state CNC law by the American Bar Association, Section of Labor and Employment Law. Using the fourth edition of the survey (Malsberger et al. 2004), Garmaise (2011) compiled a zero-one score for each of twelve dimensions of the enforcement of CNC law in the states, and added the twelve items to create an overall score. However, Garmaise's (2011) index covered only the period 1992-2004 and varied over time in only three states – Florida, Louisiana, and Texas, thus presenting a challenge to a study over a longer period and accounting for unobserved heterogeneity across states with fixed effects. Accordingly, I preferred to use the stock of CNC cases compiled from Lexis-Nexis, which covered all years from 1960 onward, and which varied both by time within state and across states.

An immediate question regarding the specification (1) is whether the enactment of a trade secrets statute would affect the number of trade secrets cases. Indeed, one of the Uniform Law Commissioners' justifications for the UTSA was that some states did not have much case law. So, by clarifying the law, the enactment of a statute could reduce the extent of subsequent litigation. Then, the stock of cases would be a bad control (Angrist and Pischke 2008: Section 3.2.3).

Table 1 reports regressions of the number of trade secrets cases by state and year on the enactment of a trade secrets statute and various controls. Apparently, the enactment of a statute had no significant effect on the number of trade secrets cases decided by state courts, a marginally significant negative effect on the number of trade secrets cases decided by federal courts, and no significant effect on the total of state and federal cases. Nevertheless, to be conservative, in the regressions of inventor mobility on trade secrets law, I use either the statute or the stock of cases as an explanatory variable but not both.

The U.S. Patent and Trademark Office (USPTO) publishes records of all patents issued. Applying a Bayesian supervised learning algorithm, Lai et al. (2011) matched inventors across all utility patents that the USPTO granted between 1975 and 2010 to build the U.S. Patent Inventor Database. I used their database to track the movement of inventors between employers in the thirty year period 1975-2004. Patents granted in 2010 took an average of 35.3 months from application to grant (USPTO 2010). Hence, to avoid selection bias, I limited the study to patents filed before 2005. I further limited the sample to inventors residing in the United States (ignoring foreign inventors) and patents with assignees (excluding inventions of self-employed persons).

The data covered 848,236 inventors. About half filed just one patent in their lifetime and so could not provide any record of employer changes, leaving 431,968 inventors with a median of 555 days between patents. Dropping inventor-years with more than 1080 days (about the 90th percentile) between patents and with movements across state boundaries left a sample of 356,918 inventors.[7] For most of the analyses, I focused on the top 2% of inventors (as I explain below, their frequent patenting would support an accurate indicator of employer changes). The top 2% accounted for almost 18% of the sample data. I did consider the entire sample of inventors in robustness checks.

Previous research (Almeida and Kogut 1999; Rosenkopf and Almeida 2003; Marx et al. 2009; Marx et al. 2010) identified an inventor as changing employment if the assignee on one patent differed from the assignee on the previous patent. This measure would be less accurate with a longer the time between patents. So, to control measurement error, I limited the sample to inventor-years with less than 1080 days between patents and further limited to the top 2% of inventors by lifetime patents.

Even so, the difference in assignee between consecutive patents would wrongly flag inventors who work as consultants for multiple clients as changing employers.[8] Further, the U.S. Patent Inventor Database (Lai et al. 2011) wrongly classified fathers and sons with the same basic name, distinguished only by the suffix, "Jr" or "III", as the same person.[9] So, a difference in assignee between consecutive patent applications by father

[7]The longer is the interval between patents, the greater would be the error in identifying changes in employment by differences in patent assignee. Below, I explain why I limit the analyses to inventor-years without movement across states.

[8]For example, in the period 2000-2003, Dov Z. Glucksman of Wenham, Massachusetts (identifier 03877897-1) was granted patents that he variously assigned to Appliance Development Corporation, Windmere Corporation, Homedics Inc, Whirlpool Corporation, and Bojour Inc. An Internet search revealed that Mr Glucksman is an employee of Appliance Development Corporation, which specializes in developing consumer electrical appliances.

[9]For instance, the U.S. Patent Inventor Database lists both Theodore S. Zajac of Bay Village, OH, and Theodore S. Zajac, Jr., of Elyria, OH, as the same person, with identifier 03862587-1.

and son with the same basic name would be wrongly identified as a change of employer.

To avoid misclassification due to inventors working for multiple employers, and father and son inventors with the same basic name, it seemed reasonable to check the assignees of previous and subsequent patents. Since the median time between patents was 555 days, I defined an inventor as having changed employer if the assignee on the focal patent application differed from the assignee on the previous patent application, *and* the previous assignee was not among the assignees of the patent applications in the following 540 days, *and* the focal assignee was not among the assignees of the patent applications in the previous 540 days. I defined an inventor as not having changed employer if any of the three conditions was not satisfied.[10]

Given the central importance of this measure, I constructed two alternatives for use in robustness tests. Both were similar to the primary measure, but with shorter windows, of 360 and 180 days respectively, and so, less stringent. With the 360 day windows measure, I defined an inventor as having changed employer if there was a difference in assignee, *and* the previous assignee was not among the assignees of the patent applications in the following 360 days, *and* the focal assignee was not among the assignees of the patent applications in the previous 360 days. The 180 day windows measure was constructed similarly.

As Table 2 reports, the three measures of change of employer were highly correlated. Relative to the 540-day measure, the 360-day measure produced 16,067 more changes of employer (7.3% more), while the 180-day measure produced 29,097 more changes of employer (13.2%). Table 2 also compares the 540-day measure with a simple measure, based simply on the difference in assignee. Relative to the 540-day measure, it produced 34,522 more changes of employer (15.7% more).

I then matched the data on trade secrets statutes and case law and CNC case law with the inventor records. Since trade secrets and CNCs are governed by state law, inventors changing employers across states would possibly face conflicts of laws. There is no general rule in conflicts of law regarding trade secrets or even CNCs, not even for people moving to California (Wardwell 2009). So, for inventors changing employers across states, there is no clear rule as to which law – that of the state from which the person moves, or the state to which the person moves, or the state in which the person's previous employer is located, or the state in which the person's new employer is located, or a state specified by employment contract – would apply.

[10] Among workers in California, the median job tenure was three years (*Economist*, 2000).

To avoid conflicts of laws issues, I limited the sample to changes of employer *within states*. These comprised about 80% changes of employer in the sample. Table 3 presents summary statistics of the data, and the Data Appendix details the variables including sources and construction.

For a first look, Figure 2 depicts the trends over time of the flow and stock of trade secrets cases and the rate of inventor mobility (number of inventors who moved in the year divided by the number of active inventors), averaged over all states. Apparently, the number of cases grew over the years, with the result that the stock of cases steadily increased. The rate of inventor mobility fluctuated around a rising trend.

Since both inventor mobility and the stock of trade secrets cases increased with time, they might exhibit a spurious correlation due to the time trends. Accordingly, I considered the *residuals* from regressions of inventor mobility and the stock of trade secrets cases on time trends. As Figure 2 shows, the residuals seemed to have been negatively correlated. In the late 1970s, the residuals of the stock of cases were positive while the residuals of inventor mobility were negative. Then, from the early 1990s onward, the residuals of the stock of cases were negative while the residuals of inventor mobility were positive. However, in the mid to late 1980s, both series of residuals were positive.

5 Results

I estimated (1) using the linear probability model, for ease of interpretation and ready implementation of clustered standard errors. Since the treatment variables were state-level, it was important to cluster the estimated standard errors by state (Bertrand et al. 2004). Accordingly, I organized the data as a panel by inventor-state and year, treating an inventor who moved state as a different individual in each state.[11]

All estimates included real gross state product, the number of times that the inventor had moved state, as well as inventor-state and year fixed effects as controls. Real gross state product accounted for changes in the macro-economy that would affect the movement of inventors between employers. The number of state moves controlled for the sample being limited to changes of employer within state. The inventor-state fixed effects accounted for non time-varying differences across inventors such as inherent loyalty to employer and across states such as labor laws affecting changes of employer,

[11]Since inventors moved across states, in a panel organized by inventor and year, the inventors would not nest within states, and so the estimation of standard errors could not be clustered by state.

while the year fixed effects accounted for changes over time that affected all inventors in all states, such as changes in federal laws on employment and patents.[12] Other than indicator variables (including fixed effects), all variables were specified in logarithm. For brevity, in discussing the results, I do not mention the logarithm.

The first specification focused on a trade secrets statute being in effect. As reported in Table 4, column (1), the coefficient of trade secrets statute, $0.003(\pm 0.011)$, was not significant. This empirical result suggested that enactment of a statute did not have a significant effect on inventor mobility.

The second specification considered both trade secrets case law. As reported in Table 4, column (2), the coefficient of the stock of trade secrets cases, $-0.076(\pm 0.026)$, was negative and significant. Apparently, the evolution of trade secrets case law was associated with lower inventor mobility. An increase in the case law by 1% was associated with the expected number of changes of employers per year being 0.00076 lower, or almost 0.3% of the mean probability, 0.244. So, the elasticity of the probability of changing employer with respect to the stock of trade secrets cases was about 0.3.

The stock of cases was a pure numerical measure of case law that did not take any account of the substance of the cases. The litigated cases could strengthen trade secrets protection by closing loopholes or weaken protection by carving out new exceptions. My empirical finding suggests that the trend in the case law was to tighten protection, and so, associated with lower inventor mobility.

The third specification explored differences in the effect of all (federal and state) trade secrets cases as compared with state cases. As reported in Table 4, column (3), the coefficient of the stock of state trade secrets cases was negative, small, and not significant. By contrast, as reported in Table 4, column (4), the coefficient of the stock of federal trade secrets cases was negative and significant. However, Apparently, it was the combination of cases decided by federal and state courts that affected inventor mobility, while cases decided by state courts by themselves had no significant effect.

The fourth specification considered the effect of CNC case law. As reported in Table 4, column (4), the coefficient of the stock of CNC cases, $-0.037(\pm 0.021)$, was negative and marginally significant. Apparently, the evolution of CNC case law was associated with lower inventor mobility. Interestingly, the impact of CNC case law was less than that of trade secrets case law. Specifically, comparing the results in Table 4, columns (2) and (4), the coefficient of the stock of trade secrets cases was double the coefficient

[12] With inventor-state fixed effects, state fixed effects could not be separately identified.

of CNC cases.

In the fifth specification, I ran a contest between the stocks of trade secrets vis-a-vis CNC. As reported in Table 4, column (5), consistent with the stocks of trade secrets and CNC cases being correlated, the coefficients of both decreased in magnitude relative to the estimates with each alone. The coefficient of the stock of trade secrets cases, $-0.071(\pm 0.033)$, was negative and significant, and close to that in the estimate including only the stock of trade secrets cases. By contrast, the coefficient of the stock of CNC cases, $-0.010(\pm 0.027)$, was negative and not significant. Moreover, it was substantially smaller than in the estimate including only the stock of CNC cases. Accordingly, it seemed reasonable to infer that trade secrets case law had more effect on inventor mobility than CNC case law.

Including CNC case law as an explanatory variable added a variable that was not significant, served to inflate the standard error of trade secrets case law, which was a significant variable, and did not improve the explanatory power (the R^2 was 0.261 in both estimates). Accordingly, I preferred the specification with just trade secrets statute and case law, as reported in Table 4, column (2).

I checked the robustness of my findings to the specification, sample, measure of employer change, and depreciation rate of legal cases, and also conducted several falsification tests. For easy comparison, Table 5, column (1), presents the preferred estimate from Table 3, column (2).

First, I checked robustness to the subject matter of the patent. Inventors might differ in mobility as they switch field of work. Table 5, column (2), reports an estimate including fixed effects for patent class (the first class if the patent was granted in multiple classes). The results were quite similar to the preferred estimate. The sample size was slightly reduced by patents for which the class was missing or in design classifications.

Next, I checked robustness to the sample. Most of the analyses focused on the top 2% of inventors. Table 5, column (2), reports an estimate including all inventors. The coefficient of the stock of trade secrets cases, $-0.054(\pm 0.025)$, was smaller in magnitude than the preferred estimate, but still negative and significant.

The next three estimates checked robustness to the measure of employer change. The preferred estimate used a definition that checked for the same patent assignees within 540 day windows. One alternative used less stringent windows of 360 days, another used even less stringent windows of 180 days, while the third alternative did not check for the same assignee in other patents at all. As reported in Table 4, columns (4)-(6), the estimate with 360 day windows was close to the preferred estimate, while the estimates with 180 day windows and ignoring other patents were negative, but smaller and not precisely estimated. These results are consistent with my initial concern with error in identifying changes of employer by a difference in patent assignee.

Next, I checked sensitivity to the rate of depreciation of legal cases. Instead of 10% per year, the robustness check applied the alternative rate of 7.5%, which was a slower rate of depreciation. As Table 5, column (7) reports, the estimated coefficient of the stock of trade secrets cases, $-0.082(\pm 0.029)$, was negative and significant, and even larger in magnitude than the preferred estimate.

Finally, I conducted several falsification tests. The first also served to address the possibility of endogeneity. The concern is that both movements of inventors and trade secrets litigation were caused by an unobserved factor, or that movements of inventors generated trade secrets litigation. (Regarding the latter hypothesis, Almeling et al. (2010 and 2011) found that 70% of state trade secrets cases and 48% of federal cases involved internal information such as customer lists, while 36% of state cases and 58% of federal cases involved technical information.)

Under either theory, inventor mobility would be related to the current *flow* of trade secrets cases rather than the *stock* of cases. Table 6, column (2), reports a regression of inventor mobility on the year-by-year flow of trade secrets cases. The coefficient, $-0.009(\pm 0.005)$, was negative, very small, and insignificantly different from zero. This result serves to confirm that inventor mobility was related to the stock rather than the flow of trade secrets cases.

In another falsification test, I regressed inventor mobility on the stock of federal and state cases involving the law of limited partnership. In the United States, the main user of limited partnerships has been the real estate industry, which is far removed from the world of patent-filing inventors. However, the law of limited partnership is like that of trade secrets in two ways. It is a state matter and most states have adopted a uniform act (the Revised Uniform Limited Partnership Act) that was published in the late 1970s. Accordingly, limited partnership cases seemed a reasonable candidate for falsification. I compiled the stock of limited partnership cases from Lexis-Nexis in the same way as for the stock of trade secrets cases. As reported in Table 5, column (3), the coefficient of the logarithm of the stock of limited partnership cases was far from significant.

6 Discussion

Posner (2011) famously argued that the evolution of common law, through the adversarial process of litigation between plaintiff and defendant, would produce legal rules that would induce economically efficient behavior. His hypothesis was implicitly predicated on the assumption that the rules produced by litigation would actually affect economic behavior – the choices and actions of organizations and individuals.

Here, in the context of the movements of U.S. patent-filing inventors between employers within states, I found that, indeed, the accumulation of legal cases affected economic behavior. Specifically, a 1% larger stock of trade secrets cases was associated with 0.3% lower inventor mobility. This finding was robust to specification, sample, definition of employment changes and stock of cases, and also to falsification tests. This study might well be the first to show an effect of case law on economic behavior.

Further, I found that state enactment of trade secrets statutes was not significantly associated with inventor mobility. By contrast, a previous study showed that the UTSA was associated with lower company-level R&D but only in low-tech industries (Png 2011). Note that it is high-tech businesses that invest in patents. So, the present findings represent the behavior of technical professionals in high-tech companies and need not be inconsistent with Png's (2011) earlier results.

I also found that the trade secrets case law had a larger impact on inventor mobility than CNC case law. This result should not be interpreted as meaning that CNC law did not affect the movement of inventors between employers. Indeed, Marx et al. (2009) found that an accidental change in Michigan law that struck out an earlier prohibition of CNCs was associated with significantly lower inventor mobility. Rather, the empirical finding suggests that trade secrets law was more influential.

My findings on the impact of trade secrets case law have important ramifications for public policy and business practice. Apparently, the evolution of trade secrets case law, as represented by the stock of legal cases, has tended to strengthen the protection of trade secrets. To this extent, recruiting a competitor's scientists and engineers would be less rewarding. They would be more limited in the degree to which they may legally transfer knowledge from their previous employer. Consequently, the movement of technical personnel between established organizations fell.[13]

[13]As illustrated by Intel's suit against the four engineers, trade secrecy can substitute for CNCs as a way to protect an employer's technical knowledge from spilling over to competitors (Hyde 2003). So, while California famously does not enforce CNCs except with narrow exceptions, employers in the state

One implication could be slower diffusion of technical knowledge. Technical knowledge that is explicit can be shared through joint ownership and licensing. However, the spread of technical knowledge of a tacit nature depends relatively more on the movement of scientists and engineers. With less mobility, spillovers of knowledge among employers would be reduced.

Another implication would be fewer spin-outs and start-ups. A key advantage for employees leaving established organizations to start new businesss is the knowledge that they acquired in their previous employment. To the extent that they are more constrained in using such knowledge, their expected profit from starting a new businesss would be lower. So, trade secrets law would result in fewer spin-outs and start-ups.[14]

These implications should be balanced against the effect on longer-term incentives. If employees are less likely to quit for other opportunities, employers would realize a greater return on investment in development and training of their employees. So, stronger trade secrets protection might foster more employer investment in their employee's human capital.

An interesting related question is how the trade secrets protection would affect the employees' own incentive to invest in their human capital. They might be induced to invest more in themselves, since their external market value would depend more on their own capabilities and less on knowledge that they bring from previous employers. On the other hand, they might be induced to invest less since they would have fewer external opportunities to realize the return on that investment.

Another related issue is the impact on compensation policies. In the short term, employers might pay their employees less, as their outside opportunities would be less attractive. On the other hand, in the long term, the reduction in outside opportunities may imply that their employers must pay more to attract talent. With weaker trade secrets protection, employees might be willing to trade off lower salaries for the opportunity to acquire knowledge and then capitalize on that knowledge with another employer or a start-up.[15] By reducing such outside opportunities, trade secrets law might force employers to increase compensation.

can and do protect their technical knowledge through trade secrets law.

[14]Using Garmaise's (2011) index, Samila and Sorensen (2011) showed that states which enforced CNCs more strongly had fewer start-ups.

[15]Moen (2005) studied the careers of technical workers in the Norwegian machinery and equipment industries during the period, 1986-95. Early in their careers, workers accepted lower earnings while they accumulated knowledge. Later in their careers, they received higher earnings which compensated them for their earlier investment.

Finally, it would be interesting and important to study the effect of trade secrets protection on professional interaction among scientists and engineers. Here, I have shown that the evolution of trade secrets case law served to inhibit the movement of inventors. Trade secrets protection would also inhibit professional interaction at meetings, conferences, and trade shows. Of course, the challenge to studying these effects would be to procure measures of such interaction.

My study was based on data on employed inventors with utility patents from the U.S. Patent Inventor Database (Lai et al. 2011). Employed inventors with utility patents are a subset of all employed inventors, who, in turn, are a subset of all employed technical professionals. To the extent that employers can protect their technical knowledge through patents, the movement of inventors with patents should be relatively less sensitive to trade secrets law. Hence, my findings should apply with greater force to the mobility of technical professionals who gain knowledge that their employers *cannot* fully appropriate through patents.

To the extent that trade secrets law affects the expected return from patenting, changes in trade secrets law would affect applications for patents. Since I used patents to identify changes of employers, changes in the law that affect patenting would affect the observability of changes of employer. However, I believe that any effect would be biased against my empirical finding. I found that the evolution of trade secrets cases was associated with lower inventor mobility and interpreted the result as the trend in cases as increasing trade secrets protection. To the extent that stronger trade secrets protection leads to reduced patenting, I would observe *fewer* changes of employer. Thus, the evolution of case law biases against my finding a reduction in inventor mobility.

Finally, it is worth reiterating that my measure of case law was purely numerical, with no regard for the legal substance of the cases. Obviously, it would be better to construct a more precise representation of case law based on substantive legal analysis. The challenge, however, is how to carry out such analyses on large scale, for multiple states over a long period of time.

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Data Appendix

Period of study: 1975-2004.

State-level variables

S1 Trade secrets statute in the state by year. Indicator variable: = 1 if statute in effect; = 0 otherwise. Sources: Png (2011), Pooley (1977-).

S2 Stock of trade secrets cases (10% depreciation) by state and year. Compiled from Lexis-Nexis, Federal and State Cases database, all cases with "trade secret" in headnote from 1960-2004. The federal cases comprised those decided by District Courts in the state, the Court of Appeals with jurisdiction over the state (the United States is divided into eleven territorial circuits), the Supreme Court, and all federal courts with functional rather than territorial jurisdiction, including the Court of International Trade, Tax Court, the Court of Appeal for the DC Circuit, and the Court of Appeal for the Federal Circuit. Stock of cases in initial year, 1960 = average of cases in years, 1960-69. Stock in following years calculated by perpetual inventory method with 10% depreciation, i.e., stock in year $t+1$ = stock in year $t \times 0.90$ + cases in year $t+1$. Specified as logarithm of one plus the number of cases. Source: Lexis-Nexis, Federal and State Cases database.

S3 Stock of trade secrets cases (7.5% depreciation) by state and year. Constructed by a method similar to that for stock with 10% depreciation.

S4 Stock of state trade secrets cases (10% depreciation) by state and year. Constructed by a method similar to that for stock of all (federal and state) cases but including only state cases.

S5 Stock of federal trade secrets cases (10% depreciation) by state and year. Constructed by a method similar to that for stock of all (federal and state) cases but including only state cases.

S6 Stock of CNC cases (10% depreciation) by state and year. Compiled from Lexis-Nexis, Federal and State Cases database, all cases with "covenants not to compete" in headnote from 1960-2004. Constructed by a method similar to that for the stock of trade secrets cases. Source: Lexis-Nexis, Federal and State Cases database.

S7 Stock of limited partnership cases (10% depreciation) by state and year. Compiled from Lexis-Nexis, Federal and State Cases database, all cases with "limited partnership" in headnote from 1960-2004. Constructed by a method similar to that for the stock of trade secrets cases. Source: Lexis-Nexis, Federal and State Cases database.

S8 Gross state product. Source: Bureau of Economic Analysis.

Inventor-level variables

I1 Change of employer (540 day windows). Indicator variable: = 1 if the assignee on the focal patent application differed from the assignee on the previous patent application, *and* the previous assignee was not among the assignees of the patent applications in the following 540 days, *and* the focal assignee was not among the assignees of the patent applications in the previous 540 days; = 0 otherwise. Source: Compiled from U.S. Patent Inventor Database (Lai et al. 2011).

I2 Change of employer (360 day windows). Constructed by a method similar to that for the change of employer (540 day windows). Source: Compiled from U.S. Patent Inventor Database (Lai et al. 2011).

I3 Change of employer (180 day windows). Constructed by a method similar to that for the change of employer (540 day windows). Source: Compiled from U.S. Patent Inventor Database (Lai et al. 2011).

I4 Number of moves across state boundary. Specified as logarithm of one plus the number of state moves. Source: Compiled from U.S. Patent Inventor Database (Lai et al. 2011).

Figure 1. Scope of trade secrecy and CNC

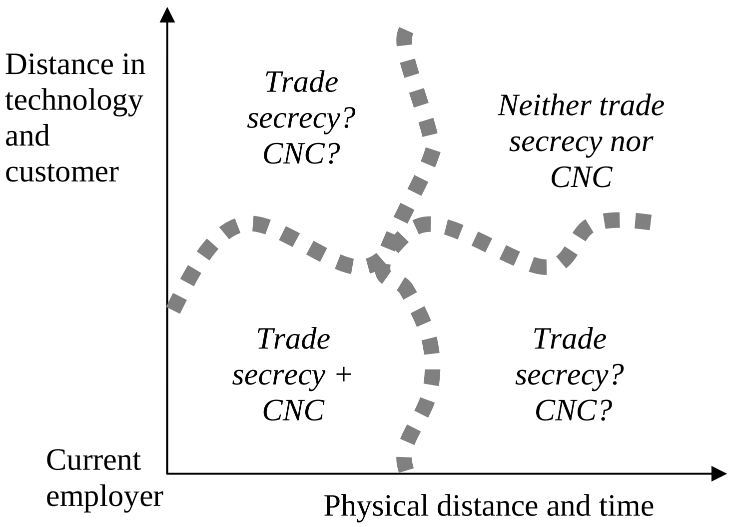

Figure 2. Trade secrets cases and inventor moves

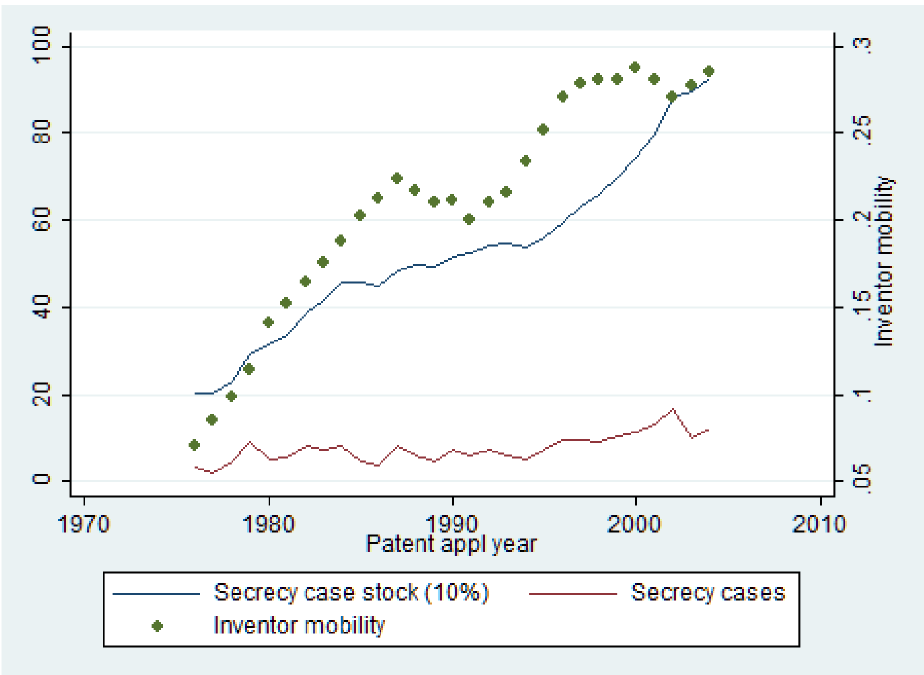

Figure 3. Trade secrets cases and inventor moves
(residuals of regressions on year fixed effects)

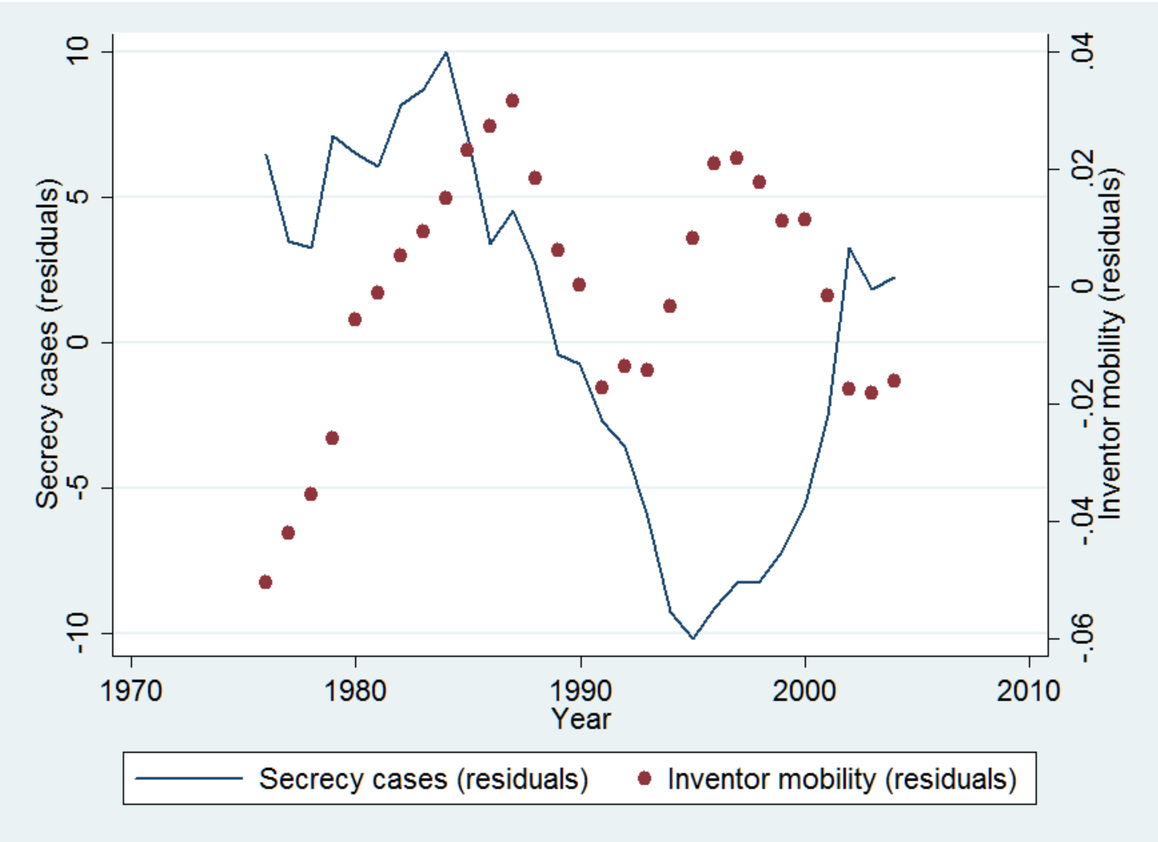

Table 1. Case law

VARIABLES	(1) State secrecy cases	(2) Federal secrecy cases	(3) All secrecy cases
Trade secrets	-0.045	-0.057*	-0.029
statute	(0.078)	(0.033)	(0.042)
Gross State	0.036	-0.010	0.004
Product (ln)	(0.170)	(0.057)	(0.070)
Constant	-0.085	0.549*	0.284
	(1.003)	(0.318)	(0.406)
State f.e	Yes	Yes	Yes
Year f.e.	Yes	Yes	Yes
Observations	2,295	2,250	2,160
R-squared	0.200	0.875	0.854
Number of state	51	50	50

Notes: Estimated by ordinary least squares; (1) Dependent variable: State trade secrets cases; (2) Dependent variable: Federal trade secrets cases; (3) Dependent variable: All trade secrets cases; Standard errors clustered by state in parentheses (*** p<0.01, ** p<0.05, * p<0.1).

Table 2. Change of employer: Alternative definitions

Employer changes (540 day windows)	Employer changes (360 day windows) 0	1	Total
0	755,394	16,067	771,461
1	0	219,796	219,796
Total	755,394	235,863	991,257

Employer changes (540 day windows)	Employer changes (180 day windows) 0	1	Total
0	742,364	29,097	771,461
1	0	219,796	219,796
Total	991,257	991,257	991,257

Employer changes (540 day windows)	Employer changes (0 day windows) 0	1	Total
0	736,939	34,522	771,461
1	0	219,796	219,796
Total	736,939	254,318	991,257

Table 3. Summary statistics

Variable	Observ-ations	Mean	Std. Dev.	Min	Max
Employer changes (540 day windows)	991,257	0.244	0.429	0	1
Employer changes (360 day windows)	991,257	0.263	0.440	0	1
Employer changes (180 day windows)	991,257	0.280	0.449	0	1
Employer changes (0 day windows)	991,257	0.288	0.453	0	1
State moves	991,257	0.18	0.74	0	64
Trade secrets statute	991,257	0.57	0.49	0	1
Stock of secrecy cases (10% deprec)	990,751	93.56	49.49	12.24	240.83
Stock of secrecy cases (7.5% deprec)	990,751	111.12	58.99	13.75	293.05
Stock of state secrecy cases (10% deprec)	991,257	20.03	16.52	0.00	65.39
Secrecy cases by year	990,751	13.65	7.70	1.00	38.00
Stock of CNC cases (10% deprec)	990,751	35.723	14.884	13.46	87.86
Stock of limited partnership cases (10% deprec)	990,751	43.264	18.892	4.803	98.52
Real Gross State Product ($ billion)	991,257	5.1503	4.328	0.091	15.89

Table 4. Inventor mobility

VARIABLES	(1) Statute	(2) Secrecy cases	(3) State cases	(4) Federal cases	(5) CNC cases	(6) Secrecy and CNC
Trade secrets	0.003					
statute	(0.011)					
Secrecy case stock		-0.076***				-0.071**
(10%)(ln)		(0.026)				(0.033)
State secrecy case			-0.005			
stock (10%)(ln)			(0.007)			
Federal secrecy case				-0.066**		
stock (10%)(ln)				(0.027)		
CNC case stock					-0.037*	-0.010
(10%)(ln)					(0.021)	(0.027)
State moves	-0.002	-0.003	-0.002	-0.003	-0.002	-0.003
(ln)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Real GSP	-0.006	-0.009	-0.002	-0.020	-0.020	-0.013
(ln)	(0.039)	(0.038)	(0.039)	(0.039)	(0.035)	(0.035)
Constant	0.095	0.373	0.072	0.410	0.321	0.415
	(0.302)	(0.291)	(0.299)	(0.319)	(0.266)	(0.256)
Inventor-state f.e.	Yes	Yes	Yes	Yes	Yes	Yes
Year f.e.	Yes	Yes	Yes	Yes	Yes	Yes
Observations	176,803	176,776	176,803	176,776	176,776	176,776
R-squared	0.261	0.261	0.261	0.261	0.261	0.261

Notes: Estimated by linear probability model, with the dependent variable being at least one change of employer in the year, defined by patents in forward and backward windows of 540 days; (1) Regression on trade secrets statute in effect; (2) Preferred specification: Regression on stock of trade secrets cases, depreciated at annual rate of 10%; (3) Regression on stock of state trade secrets cases, depreciated at annual rate of 10%; (4) Regression on stock of federal trade secrets cases, depreciated at annual rate of 10%; (5) Regression on stock of CNC cases, depreciated at annual rate of 10%; (6) Horse race: Regression on stocks of trade secrets and CNC cases, depreciated at annual rate of 10%; Standard errors clustered by state in parentheses (*** p<0.01, ** p<0.05, * p<0.1).

Table 5. Robustness

VARIABLES	(1) Preferred spec	(2) Patent class f.e.	(3) All inventors	(4) Empr chg 360	(5) Empr chg 180	(6) Empr chg 000	(7) 7.5% deprectn
Secrecy case stock	-0.076***	-0.079***	-0.054**	-0.070**	-0.051	-0.046	
(10%)(ln)	(0.026)	(0.026)	(0.025)	(0.029)	(0.043)	(0.049)	
Secrecy case stock							-0.082***
(7.5%)(ln)							(0.029)
State moves (ln)	-0.003	-0.002	-0.043***	0.003	0.009	0.010	-0.003
	(0.008)	(0.008)	(0.009)	(0.011)	(0.012)	(0.013)	(0.008)
Real GSP (ln)	-0.009	-0.011	0.042	-0.003	0.018	0.036	-0.010
	(0.038)	(0.038)	(0.044)	(0.042)	(0.045)	(0.046)	(0.039)
Constant	0.373	0.363	-0.164	0.324	0.124	-0.017	0.406
	(0.291)	(0.301)	(0.298)	(0.297)	(0.318)	(0.330)	(0.296)
Inventor-state f.e.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year f.e.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Patent class f.e.	No	Yes	No	No	No	No	No
Observations	176,776	175,780	990,751	176,776	176,776	176,776	176,776
R-squared	0.261	0.264	0.519	0.297	0.343	0.370	0.261

Notes: Estimated by linear probability regression, with the dependent variable being at least one change of employer in the year; (1) Preferred specification with employer changes defined by patents in forward and backward windows of 540 days; (2) Including fixed effects for patent class; (3) Sample of all inventors; (4) Dependent variable: Employer changes defined by patents in windows of 360 days; (5) Dependent variable: Employer changes defined by patents in windows of 180 days; (6) Dependent variable: Employer changes without regard for previous or subsequent patents; (7) Stock of trade secrets cases, depreciated at annual rate of 7.5%; Standard errors clustered by state in parentheses (*** p<0.01, ** p<0.05, * p<0.1).

Table 6. Falsification

VARIABLES	(1) Preferred spec	(2) Falsifi-cation	(3) Falsifi-cation
Secrecy case stock (10%)(ln)	-0.082***		
	(0.029)		
Secrecy cases by year (ln)		-0.009	
		(0.005)	
Limited partnership case stock (10%)(ln)			0.015
			(0.028)
State moves (ln)	-0.003	-0.002	-0.002
	(0.008)	(0.008)	(0.008)
Real GSP (ln)	-0.010	-0.003	-0.004
	(0.039)	(0.038)	(0.038)
Constant	0.406	0.091	0.050
	(0.296)	(0.296)	(0.301)
Inventor-state f.e.	Yes	Yes	Yes
Year f.e.	Yes	Yes	Yes
Observations	176,776	176,776	176,776
R-squared	0.261	0.261	0.261

Notes: Estimated by linear probability regression, with the dependent variable being at least one change of employer in the year. (1) Preferred specification with regression on stock of trade secrets cases, depreciated at annual rate of 10%; (2) Falsification: Regression on flow of trade secrets cases in the year; (3) Falsification: Regression on stock of limited partnership cases, depreciated at annual rate of 10%. Standard errors clustered by state in parentheses (*** p<0.01, ** p<0.05, * p<0.1).