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Secrecy and Patents: Evidence from the Uniform Trade Secrets Act

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Abstract

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Keywords: patents, trade secrets, law, discrete technology, complex technology

1 Introduction

A key issue in policy and strategy is how to appropriate the returns from innovations. Innovators can choose among formal intellectual property (patents, trademark, copyright, and design), secrecy, complexity, lead time, and complementary assets (Teece 1986; Cohen et al. 2000; Hall et al. 2014). Importantly, these strategies need not be exclusive and may be used in combination, for instance, a manufacturer may combine patents or secrecy with trademarks, complexity, and lead time (Anton et al. 2006; Somaya and Graham 2006; Jensen and Webster 2009).

Among strategies for appropriation, researchers and policy-makers have given considerable attention to patents (see, for instance, Graham and Hedge (2015), Wagner and Wakeman (2015)). A patent provides an exclusive right for a limited duration and for which the owner must disclose the invention. The disclosure serves to inform others, so that they can avoid infringement, and, if they wish, approach the owner for a license to use the invention. Disclosure of the invention provides the foundation for follow-on invention, but helps competitors to invent around the invention. To qualify for a patent, the invention must be useful, novel, and not obvious (exceed an inventive step).

By contrast with patents, a trade secret can be of unlimited duration. The only requirements for a trade secret are that it have commercial value, not be generally known or readily ascertainable, and be protected against disclosure. In particular, the secret need not meet any threshold of inventive step. However, the law does not protect trade secrets against accidental disclosure or reverse engineering. Competitors may legally reverse engineer the trade secrets of others.

Previous research has tended to focus on patents and secrecy as substitutes (Hussinger 2006; Hall et al. 2014: 388). Certainly, any particular invention can be protected either by a patent or secrecy but not both. Yet the commercialization of a product may combine patents with secrecy in complementary ways. Some technologies may be more difficult to invent around, and so, better protected through patents, while other technologies may be more difficult to reverse engineer, and so, better protected through secrecy. Moreover, commercialization may depend on using specific processes and techniques of production. Such know-how might not meet the inventive step requirement for a patent, and can only be protected by secrecy (Beckerman-Rodau 2002; Jorda 2008), or might be difficult to codify, or if filed in patent applications, would facilitate inventing around by competitors, and so, better protected by secrecy (Arora 1997).

For policy-makers as well as practitioners, it is important to understand the relationships between patents and secrecy. At the most basic, if patents and secrecy are substitutes, then any strengthening of trade secrets law should lead managers to make less use of patents, and any strengthening of patent law should lead managers to make less use of secrecy, while the converse would hold if patents and secrecy are complements. Indeed, during a period when the United States strengthened patent rights, Cohen et al. (2000) observed an increase in the reported effectiveness of secrecy, suggesting that secrecy was complementary with patents.

Here, I exploit differences in the timing of enactment of the Uniform Trade Secrets Act (UTSA) among U.S. states and in the impact on manufacturers with different geographic distribution of R&D to investigate the effect of trade secrets protection on company-level patenting in manufacturing industries. Stronger protection of trade secrets affects patenting in conflicting ways. For simplicity, suppose that innovation begins with R&D, which produces inventions. Then, at the exploitation stage, the business selects inventions to exploit, and decides whether to protect the invention through patent or secrecy, and how to further develop the invention. In the commercialization stage, selected inventions are taken to market through licensing and/or incorporation into products for sale.[1]

Logically, any particular invention can either be patented or kept secret, but not both. Hence, at the exploitation stage, patents and secrecy can only be substitutes, and stronger protection of trade secrets may lead businesses to switch from patents to secrecy (substitution effect). By contrast, at the commercialization stage, stronger protection of trade secrets strengthens exclusivity over products and processes, and raises the return to commercialization. Hence, businesses would choose to commercialize more inventions, which would increase patenting and secrecy at the prior exploitation stage (commercialization effect). Thus, the net outcome on patenting depends on the balance between the substitution and commercialization effects.

[1]Among over 35,000 inventions reported at a large multinational corporation, about half did not meet the standard for a patent, and of those that did, the management filed patents for about 40 percent, while keeping about 10 percent on the shelf for later exploitation. Of the latter, the company subsequently patented about 15 percent (Alexy et al. 2014).

I reason that the balance between the substitution and commercialization effects depends on the nature of the technology. Cohen et al. (2000) distinguish discrete vis-a-vis complex technology products. Discrete technology products apply individual technologies, while complex technology products apply multiple technologies, some of which may be patented and others kept secret (Arora 1997; Graham 2004).

For discrete technology products, the substitution effect will be relatively weak. So long as a product embeds at least one patent, it gets some of the advantages of a patent – exclusivity, publicity, underpinning licensing, and access to federal courts. Manufacturers of discrete technology products would be reluctant to switch the single technology from patent to secrecy and lose those advantages. By contrast, in complex technology products, there will be many patents to convey those advantages, even after substitution of some patents for secrecy. Hence, the substitution effect will be stronger among complex technology products, and so, the effect of stronger trade secrets protection would be more negative.

Empirically, I find that the UTSA was associated with 15.3 percent fewer patents in complex technology industries but no significant effect in discrete technology industries. Further, the UTSA was associated with relatively greater reduction of patenting of major inventions, among larger companies which are technology leaders, and in less competitive industries. These findings are consistent with my theory on the relation between patents and secrecy in exploitation and commercialization. The empirical results suggest that managers take account of the legal protection of trade secrets in deciding how to protect and whether to commercialize their inventions, and that they do so in nuanced ways, depending on circumstances of the technology and business.

2 Previous Research

The relation between patents and secrecy has been the subject of a rich theoretical literature (Hall et al. 2014). Most analyses focus on patents and secrecy as substitutes. Anton and Yao (2006), Kultti et al. (2007), and Mosel (2011) analyze the choice between patents and secrecy by size of invention, reaching differing conclusions depending on assumptions regarding the behavior of potential competitors. A technology leader will choose secrecy as it is more effective in excluding competition, whereas a business with only a moderate lead will choose to protect its inventions through patents (Schneider 2008; Zaby 2010). Henry and Ponce (2011) explain the growth in the reported effectiveness of secrecy against a background of stronger patent law (Cohen et al. 2000) as due to the rise of markets for knowledge (Arora et al. 2001: Chapter 7).

There has been relatively less analysis of patents and secrecy as complements. Arora (1997) draws a distinction in the way that innovators learn and discover. Knowledge based on "inductive and empiricist procedures" might be difficult to codify, or if filed in patent applications, help competitors to invent around, and so, are better protected by secrecy. Innovators can patent the codifiable technologies and keep the remainder secret. Ottoz and Cugno (2008) and Belleflamme and Bloch (2013) analyze complementarity between patents and secrecy in the context of complex technology products.

Empirical research on the relation between patents and secrecy, whether from the economics, management, or legal perspective, is relatively limited (Hall et al. 2014; Risch 2016). The bulk comprises national surveys, in which, fairly consistently, R&D managers report secrecy to be more effective than patents (Cohen et al. 2000; Arundel 2001; National Science Foundation 2008; Jensen and Webster 2009). However, among German businesses, Hussinger (2006) finds that sales of new products are strongly correlated with the use of patents but not secrecy. Among French businesses, Pajak (2010) finds empirical evidence that large inventions are protected by secrecy and smaller ones by patent.

Arora (1997) discusses how the chemical industry combines patents with secrecy. In the late 19th and early 20th centuries, German manufacturers of organic dyestuffs skilfully blocked competitors by patenting the codifiable technologies while maintaining other technologies as secrets. Also taking a historical perspective of the chemical industry, Moser (2012) shows that patenting of chemicals increased as secrecy became less effective.

Two studies focus on the complementary role of secrecy in the U.S. patent application process. Until 1995, inventors could file continuations in the application process while keeping their applications secret, and use such "submarine patents" to hold up competitors using the similar technology (Graham 2004). In 1999, the law was changed to require publication of patent applications, while allowing inventors to keep their applications secret only if they gave up priority in foreign applications. Most applicants opted to disclose their applications, which choice Graham and Hegde (2015) interpret as a way to publicize their inventions.

3 Theory

— Figure 1. Innovation stages —

For simplicity, as Figure 1 illustrates, suppose that innovation comprises three stages – R&D, exploitation, and commercialization.[2] The R&D stage produces new technologies. Here, and as modelled in the Appendix, I focus on the exploitation and commercialization stages, and compare the marginal profit contribution of patents vis-a-vis secrecy and the marginal cost of commercialization.

Patents protect technologies from imitation, while secrecy protects technologies from misappropriation. Patents provide several additional benefits. A patent provides a legally-enforceable exclusive right to the technology. To the extent that the technology is essential to a product, the owner of the patent can legally exclude competitors. Patents help to publicize new technology (Graham and Hegde 2015). Patents underpin licensing of non-patented technology (Arora 1995; Arora et al. 2001: Chapter 5). Further, patents provide automatic access to federal courts, whereas owners of trade secrets can only sue in federal court if the misappropriator is resident in another state. Almeling et al. (2010 and 2011) observed that trade secrets litigation in federal courts has grown much faster than in state courts, suggesting that owners of proprietary knowledge prefer to litigate in federal courts. Moreover, appeals of cases involving patents, even if the subject of the appeal is not patent-related, go to the Court of Appeals for the Federal Circuit (CAFC) which is notably pro-inventor (Henry and Turner 2006).

In the exploitation stage, the business selects which technologies to exploit, and, for each particular technology, decides whether to protect through patent or secrecy. The marginal patented technology balances the marginal profit contribution from patents (in protecting the marginal technology from imitation and providing exclusivity, publicity, underpinning of licensing, and access to federal courts) against the marginal profit contribution from secrecy (in protecting the marginal technology from misappropriation).

In the commercialization stage, the business decides the products to commercialize through licensing and/or incorporation into products for sale (for brevity, I use "product" to encom-

[2] In reality, innovation is much more complex with multiple feedback channels from exploitation and commercialization to R&D (Kline and Rosenberg 1986).

pass both products and processes). For the marginal product, the marginal profit contribution just covers the cost of commercialization.

In general, stronger trade secrets law has two conflicting effects on patenting.

(i) Substitution effect – Fewer patents: At the exploitation stage, stronger trade secrets law encourages substitution from patents to secrecy among technologies that will be commercialized. The extent of the substitution effect depends on the marginal profit contribution from patent vis-a-vis secrecy.

(ii) Commercialization effect – More patents: Stronger trade secrets law raises the expected profit from commercialization, and so leads to the commercialization of marginal products. At the prior exploitation stage, this means that more technologies (those embedded in the marginal product) would be exploited, some of which would be patented and others kept secret.

Importantly, the balance between the substitution and commercialization effects, and so, the relative use of patents and secrecy, depends on characteristics of the technology, invention and business.

Cohen et al. (2000) distinguish discrete technologies, such as chemicals and pharmaceuticals, which are naturally commercialized individually, from complex technologies, such as computers and communications, which are complementary and naturally commercialized as a bundle. In any commercialized product, the embedding of one patented technology provides the benefits of exclusivity, publicity, underpinning of licensing, and access to federal courts. The marginal benefit diminishes with additional patents. To this extent, businesses are likely to embed at least one patented technology in every product.

In a discrete technology product, there is only one technology, and so, it is likely to be patented rather than kept secret. Accordingly, among discrete technology products, stronger trade secrets law would induce relatively little substitution from patents to secrecy. By contrast, among complex technology products, stronger trade secrets law would induce substitution, as the business switches the protection of marginal technologies from patents to secrecy. Assume that the extent of the commercialization effect is the same for discrete and complex technology industries. Then, the main hypothesis is:

Hypothesis 1 *Stronger trade secrets law will reduce patents in complex technology industries relatively more than in discrete technology industries.*

The next factor is the magnitude of the invention. Regarding major inventions, it seems unlikely that they would be embedded in products at the margin of commercialization, and so, stronger trade secrets law would have little commercialization effect. Hence, the main effect of stronger trade secrets law would be substitution from patents to secrecy, and so, reducing patenting. By contrast, with regard to minor inventions, stronger trade secrets law would both increase commercialization (increasing patenting) and induce substitution (reducing patenting). This motivates the next hypothesis:

Hypothesis 2 *Stronger trade secrets law will reduce patenting of major inventions relatively more than minor inventions.*

Next, consider how patenting strategy depends on the size of business. Using the law – whether patents or secrecy – to protect new technologies requires legal work, which can be carried out in-house or outsourced to external lawyers. Establishing in-house expertise in intellectual property will involve substantial fixed costs that give rise to economies of scale. The marginal cost of in-house intellectual property work would be lower than that outsourced to external lawyers.

This applies to both patents and secrecy. Suppose that larger businesses are more likely to set up in-house intellectual property departments, and that the marginal cost of patents relative to secrecy is relatively lower with in-house legal work than outsourcing to external lawyers. Then, larger businesses would make more use of patents (Lerner 1995; Cohen et al. 2000) and less use of secrecy (Lerner 2006). Moreover, in response to stronger legal protection of trade secrets, larger businesses would substitute less from patents to secrecy, i.e., the substitution effect would be smaller.

On the other hand, businesses with in-house intellectual property departments are likely to better informed about changes in the law, and more responsive. Further, as Ziedonis (2003) found in the semiconductor industry, larger businesses may be more likely to enforce intellectual property rights. In the context of the UTSA, this implies that, for larger businesses, the substitution and commercialization effects would be larger in magnitude.

The conflicting arguments motivate opposing hypotheses:

Hypothesis 3

(a) *To the extent that the marginal cost of patents relative to secrecy is lower among larger businesses, stronger trade secrets law will lead larger businesses to reduce patenting relatively less than smaller businesses.*

(b) *To the extent that larger businesses are better informed about changes in the law and more likely to enforce intellectual property rights, stronger trade secrets law will lead larger businesses to adjust patenting relatively more than smaller businesses.*

Further, consider the effect of technology leadership. The patents of a technology leader should be more difficult to invent around and its secrets should be more difficult to reverse engineer. Accordingly, for a technology leader, relatively few products would be at the margin of commercialization, and so, stronger trade secrets law would have little commercialization effect. Hence, the main effect of stronger trade secrets law would be substitution from patents to secrecy. By contrast, among technology laggards, stronger trade secrets law would both increase commercialization and induce substitution. This motivates the hypothesis that:

Hypothesis 4 *Stronger trade secrets law will lead technology leaders to reduce patenting relatively more than technology laggards.*

Finally, consider how patenting strategy depends on industry competition. In a less competitive industry, relatively few products would be at the margin of commercialization, and so, stronger trade secrets law would have little commercialization effect. Hence, the main effect of stronger trade secrets law would be substitution from patents to secrecy. By contrast, in a more competitive industry, relatively more products would be at the margin of commercialization, and so, stronger trade secrets law would induce the commercialization effect as well as the substitution effect. This motivates the hypothesis that:

Hypothesis 5 *Stronger trade secrets law will lead to a greater reduction in patenting in less competitive as compared with more competitive industries.*

4 Trade Secrets Law

Historically, in the United States, trade secrets were governed by common law. The law varied across the states and some states had little or no case law. In 1979, the National Conference of Commissioners on Uniform State Laws published and recommended the Uniform Trade Secrets Act (UTSA) for enactment by the states.

Relative to the prevailing common law, the UTSA strengthened the protection of trade secrets by dropping the requirement that the information be business related and in continuous use, and defining misappropriation to include mere acquisition of the secret. The UTSA also stipulates civil procedure for claims, including time limitations, as well as injunctive and damages remedies for misappropriation (Samuels and Johnson 1990; Pooley 1997: §2.03).

Between 1979 and 2010, forty-four states enacted the UTSA, while four states – Alabama, North Carolina, South Carolina, and Wisconsin – enacted trade secrets statutes that did not conform to the UTSA.[3] Png (2016) develops an index of the effective legal protection of trade secrets to compare the changes in protection before and after the statute and differences across states in the years 1980-1998. The index represents the changes arising from the UTSA in substantive law, time limitations, as well as injunctive and damages remedies.

– Table 1. UTSA (up to 2010) –

– Figure 2. Effective legal protection of trade secrets –

Table 1 extends the trade secrets index up to the year 2010. Figure 2 depicts the evolution of the index in the top six states in the sample of companies by location of R&D analyzed below. The general pattern is an increase in the legal protection of trade secrets as the states enacted the UTSA.

The UTSA changed the legal protection of trade secrets and possibly influenced businesses in several ways. Codifying the law as such would reduce uncertainty. States enacting the UTSA would increase their stock of legal capital by gaining the use of case law of other UTSA states.[4] Moreover, trade secrets legislation would draw attention to the legal protection of

[3]South Carolina enacted the UTSA in 1992 and then, in a substantial revision, deviated from the UTSA in 1997.

[4]Almeling et al. (2010 and 2011) noted an increasing trend of citing statutes rather than common law in trade secrets cases tried by federal district courts and state appelate courts. In a follow up study, Risch (2014) finds that state appelate courts cite UTSA-related case law of other states

trade secrets, and not only among lawyers. Enactment of trade secrets statutes as reported in the general media (for example, *Washington Post* (1986), *New York Times* (1993), and *Crain's Detroit Business* (1999)) might have influenced the broader business community.

5 Empirical Strategy

The essence of my empirical strategy is to exploit differences in the timing of enactment of the Uniform Trade Secrets Act (UTSA) among U.S. states and in the impact on companies with different geographical distribution of R&D. The outcome of interest is the number of patent applications, Y_{it}, by company i in year t, which is a non-negative integer. Following Hall and Ziedonis (2001), I model the production of patents using a Poisson regression as it produces estimated coefficients that are consistent if the mean specification is correct and robust standard errors that are consistent even under misspecification of the distribution.

Formally, suppose that the mean of Y_{it}, conditional on company characteristics, is

$$E(Y_{it} \mid \mathrm{UTSA}_{it}, X_{it}) = \exp(\beta \cdot \mathrm{UTSA}_{it} + \gamma X_{it} + \alpha_i + \alpha_t), \tag{1}$$

where the variables are explained below.

The key issue is the relevant trade secrets law. Referring to Figure 1, at the commercialization stage, trade secrets law helps to protect technologies that are not patented as well as production know-how that cannot be patented. Almeling et al.'s (2010 and 2011) analyses of trade secrets litigation in federal and state courts suggests that the main channel of misappropriation is current and former employees. The employees with closest access to technical trade secrets are those engaged in R&D.

To the extent that a company performs R&D in different locations across multiple states, the relevant trade secrets law is a basket of the laws of the various states in which the company carries out R&D. In the patent production function, (1), the index, UTSA_{it}, represents the change in the effective legal protection of company i's trade secrets in year t due to the UTSA taking effect. As detailed in the following section, I construct the company-level

relatively infrequently.

index, UTSA_{it}, as an average of the state-level indexes (Png 2016) in the states where the company carried out R&D in the preceding year.[5]

The X_{it} comprise company-level factors that vary over time and affect patenting. Among these, the most pertinent is the (prior) common law in effect before the UTSA. Corresponding to the UTSA index, I calculate the index of prior common law as an average of the indexes in the states where the company conducted R&D in the preceding year.

Another important control variable is company-level R&D expenditure. In principle, the depreciated stock of R&D seems to be most pertinent. However, Hall and Ziedonis (2001) show that contemporaneous R&D parsimoniously models the effect of R&D. In addition, the X_{it} include an indicator of company-years with no reported R&D, as previous research shows substantial patenting by companies that do not report R&D (Koh and Reeb 2014).

Further, the parameters, β and γ, are the coefficients of the change in effective legal protection and controls respectively. The α_i are fixed effects for company that account for non-time-varying heterogeneity among companies. The α_t are year fixed effects which account for systematic changes in U.S. patent law and policy that affect all technologies equally, such as the establishment of the U.S. Court of Appeals for the Federal Circuit (Henry and Turner 2006). The errors in the regression model might be serially correlated, and so, I estimate standard errors that are robust to heteroskedasticity and clustered by company.

6 Data

For information on patents, I draw on the Harvard Patent Inventor Database (Li et al. 2014), which covers patents granted up to the year 2010. Since there is a lag between applications for patents and grants (Lerner and Seru 2015), I limit the analysis to applications for patents up to the year 2008. Focusing on applications for patents with a single non-government

[5]By contrast, most prior research into the effect of state laws on patenting simply associates companies with the law of their headquarters state. See, for instance, Acharya et al. (2014) on the effect of wrongful discharge laws, and Dass et al. (2014) on the effect of the UTSA, as characterized by Png's (2016) index.

assignee, I calculate the number of patent applications by assignee (company). Below, for brevity, I simply write of "patents" rather than "patent applications".

Then, using the Kogan et al. (2015) data, I match the patent data by assignee with financial information from Compustat for all companies in manufacturing industries. The financial information are sales revenue, R&D expenditure, expenditure on property, plant, and equipment (PPE), number of employees, and industry (4-digit SIC). I deflate sales revenue by the U.S. GDP deflator, and R&D expenditure by the U.S. deflator for gross private domestic investment (the U.S. Bureau of Economic Analysis publishes state-level deflators only from 1987).

The key explanatory variable is a measure of the change in the legal protection of the company's trade secrets due to the UTSA taking effect. For each company, I construct the index, UTSA_{it}, as a simple average of the state-level UTSA indexes (Png 2016) in the states where the company carried out R&D in the preceding year. The challenge is to identify the locations of the company's R&D facilities, which I do in two ways.

One way uses a data-set compiled from eight volumes of the R.R. Bowker directories (between the 16th edition (1979) and the final 32nd edition (1998)). Based on surveys of organizations that conduct R&D, the directories report the organization name and locations of R&D facilities. Unfortunately, the Bowker directories ceased publication in 1998, and so, the Bowker data is limited to the period 1979-98. The Bowker directories match 32.2 percent of companies in the matched patent-Compustat dataset.[6]

The other way identifies the R&D locations as those from which inventors applied for patents assigned to the company. For each company with more than two patents in the period, 1976-2008, I define a state to be a location of R&D from the first year to the last year that an inventor in that state applied for a patent assigned to the company. Obviously, imputing locations of R&D from patents is less accurate than the Bowker directories, but the advantage of the patent method is that it covers more companies and a longer period of time.

[6] Organizations listed in the Bowker directories may also report the numbers of professional and technical staff at each location. However, of the companies matched among the Bowker directories, Harvard Patent Inventor Database, and Compustat, just 61.7 percent reported complete staff information. Notably, of the top three U.S. patent assignees, IBM, General Electric, and Hewlett-Packard, only Hewlett-Packard reported complete information on staff.

– Table 2. Summary statistics –

I limit the analysis to company-years for which the company financial information are complete, and revenue, R&D, and PPE are non-negative. Table 2 presents summary statistics of the sample with the effective UTSA index constructed from the Bowker directories. In discrete technology industries, the average number of patents is 20.9 per year and the average increase in the effective protection of trade secrets due to the UTSA taking effect is 0.15. In complex technology industries, the average number of patents is 25.67 and the average increase in the effective protection of trade secrets due to the UTSA taking effect is 0.16.

Figure 3 depicts the evolution of patent applications by companies in discrete vis-a-vis complex technology industries. Applications from both discrete and complex technology industries followed similar trends until the late 1980s. From the early 1990s, applications from complex technology industries surged to a peak in the year 2004, when they were about treble the number from discrete technology industries. The apparent decrease in applications from 2005 onward may be an artifact of the Harvard Patent Inventor Database being limited to patents granted up to the year 2010 and lags in processing of patent applications.

– Figure 3. Trends in patent applications –

Figure 2 shows that the states' enactment of the UTSA raised the legal protection of trade secrets over time in almost all states. Superficially, the trends of the raw patent data (Figure 3) appear to be inconsistent with Hypothesis 1 that stronger trade secrets law would reduce patenting relatively more in complex technology industries. However, the graphs of the raw data do not control for confounds, in particular, changes in U.S. patent law and procedure causing an overall increase in patent applications (Henry and Turner 2006) and organic differences in the growth of discrete and complex technology industries. Below, I use multiple regression methods to account for these confounds and more precisely estimate the effect of stronger trade secrets law on patenting in discrete vis-a-vis complex technology industries.

7 Results

As a preliminary, Table 3, column (a), reports a background estimate of the patent production function, (1), without the UTSA index. The coefficient of R&D per employee, 0.345 (s.e. 0.092) is positive and significant, and similar to previous estimates (Hall and Ziedonis 2001; Galasso and Simcoe 2011). The coefficient of no reported R&D is not significant, which is perhaps because almost all companies in this sample did report R&D.

– Table 3. UTSA and patents –

Next, Table 3, column (b), reports the estimate including the UTSA index. The coefficients of the control variables are similar to those in the background estimate. The coefficient of effective UTSA, -0.289 (s.e. 0.261), is negative but not precisely estimated.

Hypothesis 1 predicts that strengthening of the legal protection of trade secrets would induce relatively more substitution of secrecy for patents in complex than discrete technology industries. To test the hypothesis, I estimate the patent production function separately on discrete and complex technology industries.

In the estimate for discrete technology industries (Table 3, column (c)), the coefficient of effective UTSA is positive but not significant. By contrast, in the estimate for complex technology industries (Table 3, column (d)), the coefficient of effective UTSA, -1.032 (s.e. 0.382), is negative and significant. To appreciate the managerial significance of this estimate, I calculate the marginal effect. The average change in the effective UTSA index is associated with 15.3 percent fewer patents, which is a significant difference.[7]

The estimates are consistent with Hypothesis 1. Indeed, the difference between the estimated coefficient of effective UTSA in discrete vis-a-vis complex technology industries is more than two standard errors. Formally, in a regression including all companies, in discrete and complex technology industries, and allowing all coefficients to differ between discrete and complex technology industries, a χ^2 test rejects the null hypothesis that the coefficients are the same, $\chi^2(7) = 30.08, p = 0.0001$) and a t-test rejects the null hypothesis that the coefficients of effective UTSA are the same ($t = -2.88, p = 0.004$).

[7]To calculate the marginal effect, note that the average change in the effective UTSA index in complex technology industries is 0.16 and the regression coefficient is -1.032. Hence, the marginal effect on the mean number of patents is $\exp(-1.032 \times 0.16) - 1 = 0.153$.

Referring to Figure 1, my empirical analysis controls for R&D, and so, focuses on exploitation and commercialization. At the exploitation stage, stronger trade secrets law leads to substitution from patents to secrecy, and at the commercialization stage, stronger trade secrets law increases commercialization of technologies, some of which are patented, and so, increases patenting. Apparently, among discrete technology industries, the commercialization effect somewhat outweighed the substitution effect, and the UTSA was associated with a statistically insignificant increase in patenting. By contrast, among complex technology industries, the substitution effect substantially outweighed the commercialization effect to such an extent that the UTSA was associated with significantly less patenting.

Next, Table 3, columns (f)-(h), replicate the analysis of the effect of the UTSA on patenting, with R&D locations identifed by the addresses of patents assigned to the companies and covering the period 1976-2008. Generally, the results are similar as with R&D locations according to the Bowker directories. As Table 3, column (f) reports, the average effect of the UTSA on companies in all industries is negative and significant. Importantly, consistent with Hypothesis 1, the UTSA is associated with a more negative effect on patenting in complex as compared with discrete technology industries. As between the estimates with R&D location according to the Bowker directories and patents, I prefer the former as the Bowker directories more precisely identify the sites of R&D.

The Supplement reports multiple robustness checks of the negative relation between effective UTSA and patenting. The robustness checks include calculating the company-level protection of trade secrets from a binary indicator of the UTSA, rather than Png's (2016) index of legal protection, weighting the company-level measure of the effective UTSA by the number of professionals in the states, associating each company with the law of the state of its headquarters, estimating the patent production function with a negative binomial and zero-inflated Poisson regressions, and accounting for the possible endogeneity of R&D (to the extent that R&D varies with UTSA, it is a bad control (Angrist and Pischke 2008: Section 3.2.3)).

The negative relation between effective UTSA and patenting is robust to all of these variations except the alternative specifications of the UTSA – the average of binary indicators, weighting the effective UTSA by the number of professionals in the states, and associating each company with the law of just its headquarters state. In the estimates with these alternative specifications, the coefficient of UTSA is negative but not precisely estimated. To the extent that these alternatives are subject to measurement error (binary indicators or law of headquarters state) or smaller sample (weighting by number of professionals), it is reasonable that the estimated effect of the UTSA is less precise.

Apparently, the evidence is quite robust that the UTSA is associated with a more negative effect on patenting in complex as compared with discrete technology industries. I interpret the difference as being due to the substitution effect being relatively weak in discrete technology industries, as businesses prefer to embed at least one patented technology in each product or process.

Yet, the difference in the relation between the UTSA and patenting in complex vis-a-vis discrete technology industries might be due to other reasons. Referring to Figure 1, the UTSA generally raised the legal protection of trade secrets. Hence, if, for some reason, patenting tended to rise faster in discrete as compared with complex technology industries, then statistically, the UTSA would be associated with a more negative effect on patenting in complex than discrete technology industries. However, referring to Figure 2, the raw data suggest that patenting in discrete technology industries grew relatively more slowly than in complex technology industries, which tends to weigh against the alternative explanation.

Another alternative explanation is that revenues and/or R&D of companies in complex technology industries grew faster than those in discrete technology industries. If, relative to the scale of revenues or R&D, patenting in complex technology industries grew relatively more slowly than in discrete technology industries, then the relation between UTSA and patenting might be more negative in complex as compared with discrete technology industries. However, the estimates in Table 3 control for revenues and R&D, so tending to discount this alternative explanation. Moreover, the estimates include year fixed effects. The year fixed effects control, in a very flexible non-parametric way, for any year-by-year differences in patenting between discrete and complex technology industries.

8 Patent Strategy

The estimates in Table 3 suggest that the UTSA was associated with relatively more substitution of secrecy for patents in complex as compared with discrete technology industries. Hypotheses 2-4 propose how changes in the legal protection of trade secrets would affect patent strategy by size of invention, size of business, and technology leadership. In testing these hypotheses, I focus on companies in complex technology industries with R&D locations according to the Bowker directories.

– Table 4. UTSA and patents: Complex technology industries –

Invention Size

Hypothesis 2 predicts that stronger trade secrets law will reduce patenting of major inventions relatively more than minor inventions. Stronger trade secrets law would have little commercialization effect on major inventions as they are not likely to be at the margin of commercialization. Hence, the main effect of stronger trade secrets law would be substitution from patents to secrecy.

A business deciding whether to commercialize a set of technologies would base its decision on ex-ante information. The challenge in testing the effect of invention size on patenting is to find an ex-ante measure of size. Many studies of patents use forward citations, but this is obviously an ex-post measure.

To distinguish inventions by magnitude, I use the OECD database of "triadic" patents, which are families of patents granted in the three major jurisdictions – Europe, Japan, and the United States – to protect the same invention (Dernis and Khan 2004). I classify all other patents as "non-triadic". Wagner and Wakeman (2015) show that the number of offices at which a technology is patented correlates well with other measures of importance, and in particular, forward citations.

The cost of filing patent applications in multiple jurisdictions is higher than filing in just the United States. Moreover, the European Patent Office requires a larger inventive step and applies more rigorous examination than the U.S. Patent and Trademark Office (van Pottelsberghe de la Potterie 2011). Indeed, valuations in mergers and acquisitions suggest that the value of U.S. patents has fallen relative to European patents (Belenzon and Patacconi 2013). It seems likely that U.S. businesses will apply to patent only the major inventions in Europe, Japan, as well as the United States. Accordingly, triadicity seems to be a reasonable ex-ante measure of the size of an invention.

Table 4, columns (b) and (c), present estimates of the patent production function for triadic vis-a-vis non-triadic patents. The coefficient of effective UTSA for triadic patents, -1.601 (s.e. 0.478) is negative and significant. By contrast, coefficient of effective UTSA for non-triadic patents, -0.668 (s.e. 0.379), is not significant, and smaller in magnitude than that for triadic patents. Moreover, a robustness test (reported in the Supplement) defines minor inventions as those with below the median forward citations and finds similar results. These results are consistent with Hypothesis 2.

Business Size and Technology Leadership

Hypothesis 3(a) predicts that stronger trade secrets law will lead larger businesses to reduce patenting relatively less than smaller businesses. The reason is that larger businesses are more likely to carry out legal work internally, and so, their marginal cost of patents relative to secrecy is relatively lower. By contrast, Hypothesis 3(b) predicts that stronger trade secrets law will lead larger businesses to adjust patenting relatively more than smaller businesses. The reason is that larger businesses are better informed about changes in laws and more likely to enforce intellectual property rights.

Here, to operationalize size, I define small companies as those with below the median revenue and large companies as those with above the median revenue. Table 4, columns (d) and (e), present estimates of the patent production function for small vis-a-vis large companies. The coefficient of effective UTSA for small companies, 0.206 (s.e. 0.345), is not significant. The coefficient of effective UTSA for large companies, -1.124 (s.e. 0.414), is negative, significant, and more than two standard deviations different from the coefficient for small companies.[8] These results are consistent with Hypothesis 3(b) that stronger trade secrets law leads larger businesses to adjust patenting relatively more than smaller businesses.

[8]The total number of small and large companies exceeds the total number of companies because some companies grow from small to large, while others shrink from large to small during the sample period.

Hypothesis 4 predicts that stronger trade secrets law will lead technology leaders to reduce patenting relatively more than technology laggards. The essential reason is that technology leaders are less susceptible to inventing around and reverse engineering. Accordingly, stronger trade secrets laws would have little commercialization effect and mainly a substitution effect.

Here, I define companies as technology leaders if their ratio of R&D to sales exceeds the industry median, and other companies as technology laggards. Table 4, columns (f) and (g), present estimates of the patent production function for technology laggards and leaders. The coefficient of effective UTSA for technology laggards, -0.165 (s.e. 0.406), is not significant. The coefficient of effective UTSA for technology leaders, -1.355 (s.e. 0.306), is negative, significant, and more than two standard deviations larger in magnitude than the coefficient for laggards.[9] These estimates are consistent with Hypothesis 4 that stronger trade secrets law will lead technology leaders to reduce patenting relatively more than technology laggards.

In reality, small businesses might overlap with technology laggards and large businesses might overlap with technology leaders, and so, confounding the inference from the estimates for small/large busineses and technology laggards/leaders. To check, the Supplement presents estimates of the patent production function that distinguish small laggards, small leaders, large laggards, and large leaders. The negative association between the effective UTSA and patenting is concentrated among large technology leaders, and the coefficient is an order of magnitude larger than in the other segments – small laggards, small leaders, and large laggards. Accordingly, I draw the conservative inference that stronger trade secrets law leads large businesses that are technology leaders to reduce patenting relatively more than other businesses.

Industry Competition

Hypothesis 5 predicts that stronger trade secrets law will lead to a greater reduction in patenting in less competitive as compared with more competitive industries. The essential

[9] The total number of technology laggards and leaders exceeds the total number of companies because some companies advance from laggards to leaders, while others downgrade from leaders to laggards during the sample period.

reason is that, in less competitive industries, relatively few products would be at the margin of commercialization. Accordingly, stronger trade secrets laws would have little commercialization effect and mainly a substitution effect.

Here, I define industries as less competitive if their Herfindahl-Hirschman Index (HHI) exceeds the industry median, and other industries as more competitive, using the HHI as calculated by Hoberg and Phillips (2010). Table 4, columns (h) and (i), present estimates of the patent production function for less and more competitive industries. The coefficient of effective UTSA in more competitive industries, -0.669 (s.e. 0.456), is not significant. The coefficient of effective UTSA in less competitive industries, -0.993 (s.e. 0.321), is negative and significant.

9 Discussion

Here, I exploit differences in the timing of enactment of the UTSA among the U.S. states and its impact on companies with different geographical distribution of R&D to investigate the effect of stronger legal protection of trade secrets on patenting in manufacturing industries. The UTSA was associated with 15.3 percent fewer patents in complex technology industries but no significant effect in discrete technology industries. Further, the UTSA was associated with a relatively greater reduction in patenting of major inventions, among larger companies which are technology leaders, and in less competitive industries. These heterogeneous effects are consistent with prior studies which find substantial industry differences in the use of secrecy and patents (Cohen et al. 2000).

My results are consistent with managers taking account of the legal protection of trade secrets in deciding which inventions to exploit, and whether to protect the inventions through patents or secrecy. The underlying theory provides guidance to the management of innovation. Patents facilitate commercialization through exclusivity, publicity, underpinning licensing, and access to federal courts. Managers can avail of these benefits by embedding at least one patent in each product. In responding to changes in the legal protection of intellectual property, managers of major inventions, in larger businesses which are technology leaders, and in less competitive industries should focus on the choice between patents and secrecy, and pay less attention to adjusting the margins of commercialization and exploitation.

The empirical evidence of a relation between the UTSA and patenting has further implications for the management of innovation. Patents are widely used to measure innovation, at national, industry, and business levels (Lerner and Seru 2015). To the extent that patents and secrecy are substitutes (as in complex technology industries), then using patents may under-count innovation. Policies and business strategies that shift the means of appropriation away from patents and towards secrecy may be wrongly inferred to reduce innovation.

My findings must be interpreted in light of differences in the geographical scope of laws and size of the economy. In the United States, a patent is a federal right that is effective in all states, while secrecy is a matter of state law, and so, protection in other states depends on how courts interpret conflicts in state laws. Hence, secrecy is a poorer substitute for patents in the United States than in jurisdictions where both patent and secrecy are protected at the national level. However, by contrast with the United States, in smaller economies, patents are relatively less attractive because the disclosure helps competitors worldwide, beyond the jurisdiction of the patent.

The findings here are also subject to limitations of data and methods. To the extent that state trade secrets laws influence the location of R&D, the measure of effective company-level legal protection of trade secrets due to the UTSA based on state location of R&D is endogenous. To mitigate endogeneity, I construct the effective UTSA index using the locations of R&D in the year before the UTSA took effect. Moreover, the Supplement reports estimates showing that enactment of the UTSA is not related to state-level patenting. Nevertheless, the effective UTSA measure must be interpreted with caution.

Finally, I rely on Compustat for company financial data, and so, the analysis is limited to publicly-listed companies. The effects of the UTSA on private businesses, which are typically smaller, may well differ. For instance, smaller businesses may be less aware of changes in trade secrets laws and less likely to enforce intellectual property rights. Nevertheless, my findings would be useful in guiding the managers of small businesses, and, in particular, alerting them to the potential importance of trade secrets law to their management of innovation.

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Appendix

Trade secrets law and patenting

Consider a business introducing a complex technology product based on a set of N technologies, of which it patents n and keeps the remainder secret. Production uses a set of know-how, which is kept secret. There is a single competitor. Every one of the technologies and the know-how are essential in the sense that, to produce a competing product, the competitor must use all of the patented and secret technologies and know-how. Referring to Figure 1, at the commercialization stage, the business will commercialize all products for which the expected profit is positive. Looking forward from the exploitation stage, the business will exploit all technologies embedded in products for which the expected profit is positive.

Let the competitor invent around patented technology i with probability, α_i, misappropriate secret technology i with probability, ρ_i, and misappropriate the secret know-how with probability, ρ_k. (For brevity, I define misappropriation to include reverse engineering.) Order the technologies such that, for $i = 1, \ldots, N$, $\alpha_i \leq \alpha_{i+1}$, $\rho_i \geq \rho_{i+1}$, and $\alpha_1 < \rho_1$ and $\alpha_N > \rho_N$.

The competitor will produce a competing product with probability, $\alpha_1 \ldots \alpha_n \rho_{n+1} \ldots \rho_N \rho_k$. In that event, suppose that the profit contribution of the focal business is zero. The competitor will not produce a competing product with probability, $[1 - \alpha_1 \ldots \alpha_n \rho_{n+1} \ldots \rho_N \rho_k]$. In that event, the focal business will have a monopoly, and suppose that its profit contribution would be $R(n)$. The profit contribution increases with the number of patents, n, because patents legally exclude competitors, help to publicize new technology, facilitate licensing, and provide automatic access to federal courts. Assume that patents yield diminishing marginal profit contribution,

Assumption

$[R(n) - R(n-1)]$ decreases with n, and $\lim_{n\to\infty}[R(n) - R(n-1)] = 0$.

Let the cost of a patent be c_p, the cost of maintaining a trade secret be c_s, the cost of maintaining the know-how as a secret be c_k, and the cost of commercialization be C. Then, the expected profit from patenting technologies $1, \ldots, n$ and keeping the others secret is

$$E_c(\Pi_{pat}) = [1 - \alpha_1 \ldots \alpha_n \rho_{n+1} \ldots \rho_N \rho_k] R(n) - nc_p - [N - n]c_s - c_k - C. \qquad \text{(A1)}$$

The expected profit from patenting technologies $1, \ldots, n-1$ and keeping the others secret is

$$E_c(\Pi_{sec}) = [1 - \alpha_1 \ldots \alpha_{n-1}\rho_n \ldots \rho_N \rho_k]R(n) - [n-1]c_p - [N-n+1]c_s - c_k - C. \qquad \text{(A2)}$$

Define the expected profit, $E_c(\Pi) \equiv \max\{E_c(\Pi_{pat}), E_c(\Pi_{sec})\}$. Suppose that that patenting n technologies maximizes profit. Then, $E_c(\Pi) = E_c(\Pi_{pat}) \geq E_c(\Pi_{sec})$, or, substituting from (A1) and (A2),

$$\begin{aligned} &[1 - \alpha_1 \ldots \alpha_{n-1}\alpha_n\rho_{n+1} \ldots \rho_N\rho_k]\ R(n) - nc_p - [N-n]c_s - c_k - C \\ \geq\ &[1 - \alpha_1 \ldots \alpha_{n-1}\rho_n\rho_{n+1} \ldots \rho_N\rho_k]\ R(n-1) - [n-1]c_p - [N-n+1]c_s - c_k - C, \end{aligned}$$

which simplifies to

$$\begin{aligned} &[1 - \alpha_1 \ldots \alpha_{n-1}\alpha_n\rho_{n+1} \ldots \rho_N\rho_k]\ [R(n) - R(n-1)] \\ &+ \alpha_1 \ldots \alpha_{n-1}\rho_{n+1} \ldots \rho_N\rho_k\ [\rho_n - \alpha_n]\ R(n-1) \geq c_p - c_s. \end{aligned} \qquad \text{(A3)}$$

Since patenting n technologies maximizes profit, the profit from patenting the $[n+1]$th technology must be less than that from keeping it secret,

$$\begin{aligned} &[1 - \alpha_1 \ldots \alpha_n\alpha_{n+1}\rho_{n+2} \ldots \rho_N\rho_k]\ [R(n+1) - R(n)] \\ &+ \alpha_1 \ldots \alpha_n\rho_{n+2} \ldots \rho_N\rho_k\ [\rho_{n+1} - \alpha_{n+1}]\ R(n) < c_p - c_s. \end{aligned} \qquad \text{(A4)}$$

Suppose that trade secrets law strengthens in ways that reduce the probabilities of misappropriation to $\rho_1', \ldots, \rho_N'$, and ρ_k'. This would affect patenting in two ways. First, consider the exploitation stage. If the business continues to patent technologies, $1, \ldots, n$ its expected profit would increase to

$$E_c(\Pi_{pat}') = [1 - \alpha_1 \ldots \alpha_{n-1}\alpha_n\rho_{n+1}' \ldots \rho_N'\rho_k']R(n) - nc_p - [N-n]c_s - c_k - C. \qquad \text{(A5)}$$

However, if it uses secrecy to protect technology n, its expected profit would be

$$E_c(\Pi_{sec}') = [1 - \alpha_1 \ldots \alpha_{n-1}\rho_n'\rho_{n+1}' \ldots \rho_N'\rho_k']R(n-1) - [n-1]c_p - [N-n+1]c_s - c_k - C. \quad \text{(A6)}$$

The focal business would switch technology n from patenting to secrecy ("substitution effect") if $E_c(\Pi'_{pat}) < E_c(\Pi'_{sec})$, or,

$$\begin{aligned}&[1-\alpha_1\ldots\alpha_{n-1}\alpha_n\rho'_{n+1}\ldots\rho'_N\rho'_k]\ [R(n)-R(n-1)]\\&\quad+\alpha_1\ldots\alpha_{n-1}\rho'_{n+1}\ldots\rho'_N\rho'_k\ [\rho'_n-\alpha_n]\ R(n-1)<c_p-c_s.\end{aligned}\tag{A7}$$

Second, at the commercialization stage, the stronger trade secrets law would raise the expected profit from $E_c(\Pi)$ to $E_c(\Pi') \equiv \max\{E_c(\Pi'_{pat}), E_c(\Pi'_{sec})\}$. For technologies such that $E_c(\Pi) < 0$ but $E_c(\Pi') \geq 0$, the stronger trade secrets law would lead to commercialization. At the exploitation stage, technologies $1, \ldots, n-1$ would be patented (and technology n as well if the parameters do not satisfy (A7)). Accordingly, the stronger trade secrets law would be associated with more patents, which is the commercialization effect.

For a discrete technology product, there is a single technology, $N = 1$, which is protected either by a patent or secrecy. Let the competitor invent around the patented technology with probability, β, or misappropriate the technology with probability $\sigma > \beta$, and misappropriate the secret production know-how with probability, σ_k. Then, the expected profit from patenting the technology,

$$E_d(\Pi_{pat}) = [1-\beta\sigma_k]R(1) - c_p - c_k - C,\tag{A8}$$

and the expected profit from keeping the technology secret,

$$E_d(\Pi_{sec}) = [1-\sigma\sigma_k]R(1) - c_s - c_k - C,\tag{A9}$$

Define $E_d(\Pi) \equiv \max\{E_d(\Pi_{pat}), E_d(\Pi_{sec})\}$. To avoid triviality, suppose that the focal business maximizes profit by patenting the technology, $E_d(\Pi_{pat}) \geq E_d(\Pi_{sec})$. Substituting from (A8) and (A9), this implies that

$$[1-\beta\sigma_k]\ [R(1)-R(0)] + [\sigma-\beta]\sigma_k\ R(0) \geq c_p - c_s.\tag{A10}$$

Suppose that trade secrets law strengthens in ways that reduce the probabilities of misappropriation to σ' and σ'_k. Then, the expected profits from patenting the technology and keeping it secret are

$$E_d(\Pi'_{pat}) = [1 - \beta\sigma'_k]\ R(1) - c_p - c_k - C, \tag{A11}$$

and

$$E_d(\Pi'_{sec}) = [1 - \sigma'\sigma'_k]\ R(0) - c_s - c_k - C. \tag{A12}$$

The difference in the expected profit between patenting and secrecy is

$$E_d(\Pi'_{pat}) - E_d(\Pi'_{sec}) = [1 - \beta\sigma'_k]\ [R(1) - R(0)] + [\sigma' - \beta]\ R(0) - [c_p - c_s]. \tag{A13}$$

For technologies such that $E_d(\Pi) < 0$ but $E_d(\Pi') \equiv \max\{E_d(\Pi'_{pat}), E_d(\Pi'_{sec})\} \geq 0$, the stronger trade secrets law would lead to commercialization, and so, at the prior exploitation stage, one more patent if $E_d(\Pi'_{pat}) \geq E_d(\Pi'_{sec})$. This is the commercialization effect.

Generally, strengthening of trade secrets law will lead to both substitution and commercialization effects in discrete as well as complex technology industries. However, the magnitude of the substitution effects differs.

In complex technology industries, by (A4), the difference, $[R(n+1) - R(n)]$, is bounded above. Supposing that the slope of the function, $R(\cdot)$, is not too large, this also bounds the preceding difference, $[R(n)-R(n-1)]$, in (A7). Hence, if the stronger law sufficiently reduces the probabilities of misappropriation, then $E_c(\Pi'_{pat}) < E_c(\Pi'_{sec})$, and the focal business will switch technology n from patenting to secrecy.

By contrast, in discrete technology industries, there is only one technology, and so, there is no upper bound on the difference, $[R(1)-R(0)]$. Referring to (A13), if the difference, $[R(1)-R(0)]$ is sufficiently large, then $E_d(\Pi'_{pat}) \geq E_d(\Pi'_{sec})$, and so, there will be no substitution of secrecy for patents. This motivates Hypothesis 1.

Table 1. UTSA (up to 2010)

State	Year	Common law	UTSA
Alaska	1988	0	0.47
Arizona	1990	0.25	0.22
Arkansas	1981	0.5	-0.10
California	1985	0.22	0.25
Colorado	1986	0	0.77
Connecticut	1983	0	0.47
Delaware	1982	0	0.47
District of Columbia	1989	0	0.47
Florida	1988	0.1	0.37
Georgia	1990	0	0.70
Hawaii	1989	0	0.47
Idaho	1981	0	0.47
Illinois	1988	0	0.70
Indiana	1982	0	0.47
Iowa	1990	0	0.47
Kansas	1981	0	0.47
Kentucky	1990	0	0.47
Louisiana	1981	0	0.40
Maine	1987	0	0.50
Maryland	1989	0.22	0.25
Michigan	1998	0.25	0.15
Minnesota	1980	0	0.47
Mississippi	1990	0	0.57
Missouri	1995	0	0.63
Montana	1985	0	0.57
Nebraska	1988	0	0.43
Nevada	1987	0	0.47
New Hampshire	1990	0.025	0.44
New Mexico	1989	0	0.47
North Dakota	1983	0	0.47
Ohio	1994	0.25	0.28
Oklahoma	1986	0.025	0.44
Oregon	1988	0	0.47
Pennsylvania	2004	0.24	-0.11
Rhode Island	1986	0	0.47
South Carolina	1992	0	0.47
South Dakota	1988	0	0.47
Tennessee	2000	0	0.63
Utah	1989	0	0.47
Vermont	1996	0	0.57
Virginia	1986	0.025	0.44
Washington	1982	0	0.47
West Virginia	1986	0	0.47
Wyoming	2006	0.5	0.00

Notes: Based on Png's (2016) index of the legal protection of trade secrets, updated to 2010. Year: effective year of UTSA; Common law: Strength of legal protection of trade secrets prior to UTSA; Effective statute: Change in legal protection of trade secrets due to UTSA. South Carolina enacted UTSA in 1992 and then changed statute away from UTSA in 1997.

Table 2. Summary statistics

(a) Discrete technology industries

VARIABLE	Unit	Mean	Std dev	Minimum	Maximum
Revenue (real)	$ million	3,798.69	8,602.32	0	129,075
Employees	’000	15.02	27.14	0.003	486
PPE per employee	$’000	170.22	226.73	10.65	3,923.1
R&D (real) per employee	$’000	17.84	91.42	0	4,684.59
No reported R&D	Indicator	0.24	0.43	0	1
Patents	Count	20.9	55.56	0	739
Common law		0.1	0.1	0	0.5
Effective UTSA		0.15	0.20	-0.1	0.77
Observations	5,037				
Companies	456				

(b) Complex technology industries

VARIABLE	Unit	Mean	Std dev	Minimum	Maximum
Revenue (real)	$ million	2,727.24	12,577.28	0	204,238.9
Employees	’000	13.69	51.46	0.01	876.8
PPE per employee	$’000	75.42	53.58	0.79	481.47
R&D (real) per employee	$’000	10.02	13.68	0	217.55
No reported R&D	Indicator	0.07	0.25	0	1
Patents	Count	25.67	96.42	0	2010
Common law		0.12	0.1	0	0.5
Effective UTSA		0.16	0.19	-0.1	0.77
Observations	6,581				
Companies	638				

Notes: Sample with location of R&D according to Bowker directories; Unit of observation is company-year. Panel (a): Companies in discrete technology industries; Panel (b): Companies in complex technology industries.

Table 3. UTSA and patents

VARIABLES	Bowker R&D locations (a) Controls	(b) UTSA	(c) Discrete	(d) Complex	Patent locations (e) Controls	(f) UTSA	(g) Discrete	(h) Complex
Revenue (ln)	0.293	0.287	-0.107	0.608	0.227	0.225	0.075	0.310
	(0.163)	(0.162)	(0.156)	(0.210)	(0.079)	(0.079)	(0.059)	(0.104)
Employees (ln)	0.637	0.638	0.821	0.361	0.617	0.613	0.572	0.547
	(0.209)	(0.207)	(0.188)	(0.306)	(0.101)	(0.100)	(0.114)	(0.126)
PPE per	0.300	0.289	0.287	0.064	0.262	0.260	0.140	0.252
employee (ln)	(0.241)	(0.244)	(0.191)	(0.294)	(0.085)	(0.085)	(0.123)	(0.087)
R&D per	0.345	0.334	0.375	0.277	0.284	0.282	0.168	0.293
employee (ln)	(0.092)	(0.094)	(0.106)	(0.126)	(0.073)	(0.073)	(0.094)	(0.088)
No reported R&D	-0.419	-0.423	-0.613	0.500	0.200	0.202	-0.051	0.468
	(0.614)	(0.615)	(0.573)	(0.187)	(0.205)	(0.204)	(0.247)	(0.155)
Prior common law	-0.269	-0.485	1.914	-2.285	-3.427	-3.892	-1.989	-3.820
	(0.676)	(0.737)	(0.811)	(0.926)	(0.535)	(0.556)	(0.556)	(0.709)
Effective UTSA		-0.289	0.322	-1.032		-0.497	-0.019	-0.617
		(0.261)	(0.273)	(0.382)		(0.236)	(0.308)	(0.305)
Observations	11,618	11,618	5,037	6,581	37,632	37,632	16,044	21,588
Companies	1,094	1,094	456	638	3,386	3,386	1,440	1,946
Ln L	-48,951	-48,886	-17,473	-28,307	-143,007	-142,858	-51,298	-85,159
Company f.e.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year f.e.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Marginal effect		-0.044	0.049	-0.153		-0.083	-0.003	-0.107
p-value		(0.268)	(0.239)	(0.007)		(0.035)	(0.951)	(0.043)

Notes: Estimated by Poisson regression using Stata routine, xtpoisson; dependent variable: number of patents by company and year; robust standard errors clustered by company. Column (a): Background estimate on sample constructed by R&D locations in Bowker directories; Column (b): Including average of effective UTSA in states where company performs R&D; Column (c): Discrete technology industries; Column (d): Complex technology industries; Column (e): Background estimate on sample constructed by R&D locations from patents; Column (f): Including average of effective UTSA in states where company performs R&D; Column (g): Discrete technology industries; Column (h): Complex technology industries.

Table 4. UTSA and patents: Complex technology industries

VARIABLES	(a) All companies	(b) Triadic patents	(c) Non-triadic patents	(d) Small companies	(e) Large companies	(f) R&D laggards	(g) R&D leaders	(h) More competitive industries	(i) Less competitive industries
Revenue (ln)	0.608	0.642	0.655	0.245	0.644	0.407	0.477	0.640	0.043
	(0.210)	(0.288)	(0.213)	(0.140)	(0.254)	(0.371)	(0.244)	(0.252)	(0.206)
Employees (ln)	0.361	0.306	0.290	0.526	0.322	0.269	0.595	0.422	0.416
	(0.306)	(0.425)	(0.293)	(0.466)	(0.348)	(0.476)	(0.345)	(0.338)	(0.296)
PPE per employee	0.064	-0.424	0.230	0.013	0.058	-0.656	0.199	0.452	-1.004
(ln)	(0.294)	(0.371)	(0.296)	(0.106)	(0.332)	(0.398)	(0.348)	(0.284)	(0.323)
R&D per employee	0.277	0.072	0.323	0.257	0.255	-0.056	0.330	0.344	0.323
(ln)	(0.126)	(0.198)	(0.124)	(0.088)	(0.137)	(0.327)	(0.183)	(0.156)	(0.170)
No reported R&D	0.500	-0.259	0.629	-0.220	0.496	0.313		0.610	0.699
	(0.187)	(0.493)	(0.234)	(0.380)	(0.204)	(0.372)		(0.306)	(0.344)
Prior common law	-2.285	-2.149	-2.140	0.732	-2.431	1.472	-3.749	-2.979	0.819
	(0.926)	(0.982)	(1.046)	(0.853)	(0.995)	(1.310)	(1.383)	(1.488)	(0.670)
Effective UTSA	-1.032	-1.601	-0.668	0.206	-1.124	-0.165	-1.355	-0.669	-0.993
	(0.382)	(0.478)	(0.379)	(0.345)	(0.414)	(0.406)	(0.306)	(0.456)	(0.321)
Observations	6,581	5,085	6,504	3,245	3,268	3,217	3,234	4,754	1,739
Companies	638	454	627	394	336	351	385	512	207
Ln L	-28,307	-13,530	-23,501	-4,294	-23,244	-10,481	-14,900	-16,678	-8,238
Company f.e.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year f.e.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Marginal effect	-0.153	-0.229	-0.101	0.032	-0.170	-0.023	-0.216	-0.108	-0.129
p-value	(0.007)	(0.001)	(0.078)	(0.550)	(0.007)	(0.684)	(0.000)	(0.143)	(0.002)

Notes: Estimated by Poisson regression using Stata routine, xtpoisson; dependent variable: number of patents by company and year; robust standard errors clustered by company. Column (a): Preferred estimate for companies in complex technology industries from Table 3, column (f); Column (b): Dependent variable is number of triadic patents (applied to European, Japan, and United States patent offices); Column (c): Dependent variable is number of non-triadic patents (total number of observations in triadic and non-triadic estimates exceeds number of observations in preferred estimate because some companies apply for both triadic and non-triadic patents); Column (d): Companies with below median revenue; Column (e): Companies with above median revenue (total number of small and large companies exceeds total number of companies because some companies grow from small to large and others shrink during the sample period); Column (f): Companies with below industry median ratio of R&D to sales; Column (g): Companies with above industry median ratio of R&D to sales (total number of technology laggards and leaders exceeds total number of companies because some companies advance from laggards to leaders and others downgrade during the sample period); Column (h): Companies in industries with below median HHI; Column (i): Companies in industries with above median HHI.

Figure 1. Innovation stages

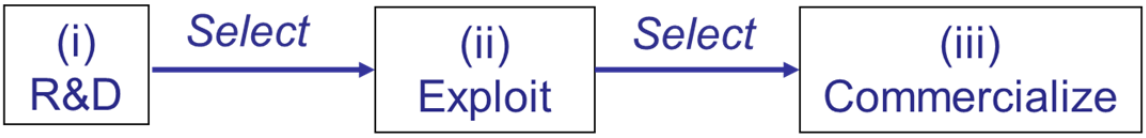


Figure 2. Effective legal protection of trade secrets

Notes: Figures depict the evolution of the effective legal protection of trade secrets by industry for the top six industries in the sample. The measure of legal protection is based on the Png (2016) index weighted by state-level value added.

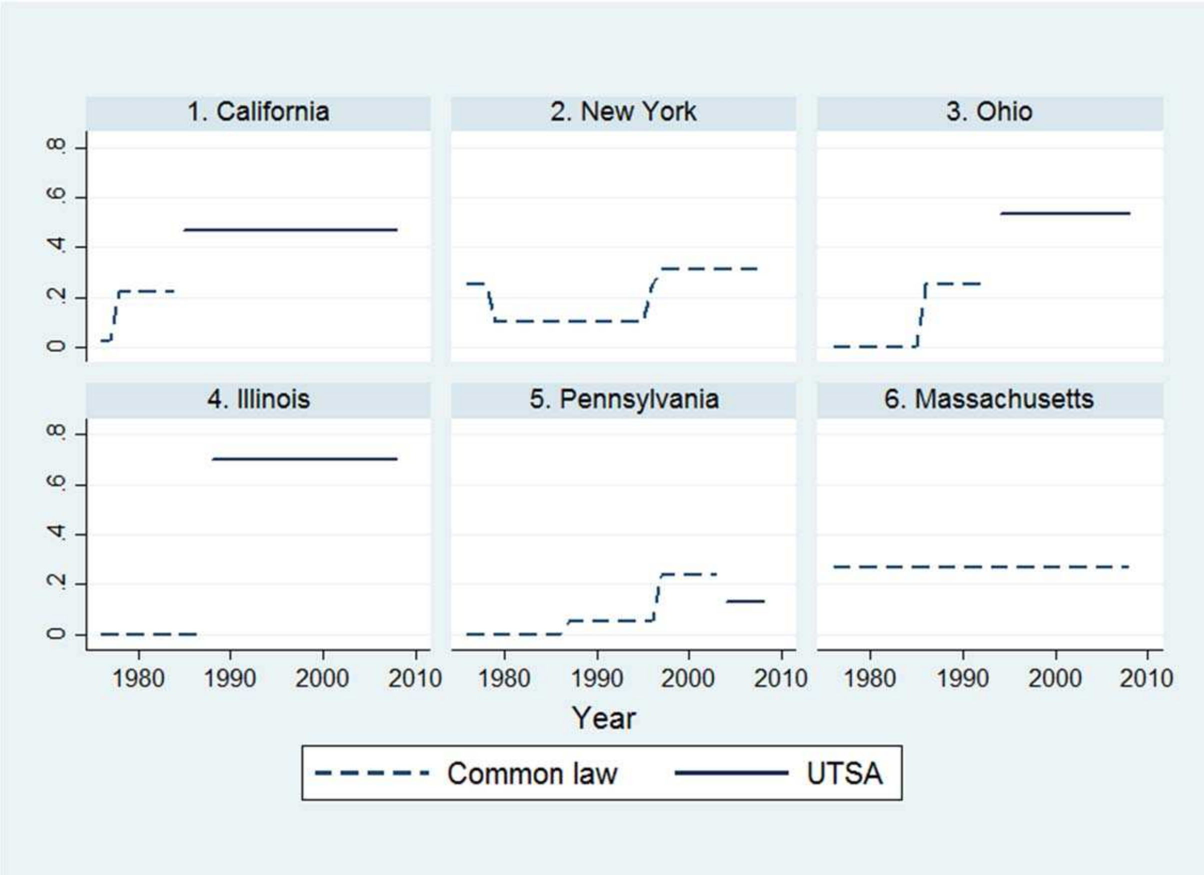
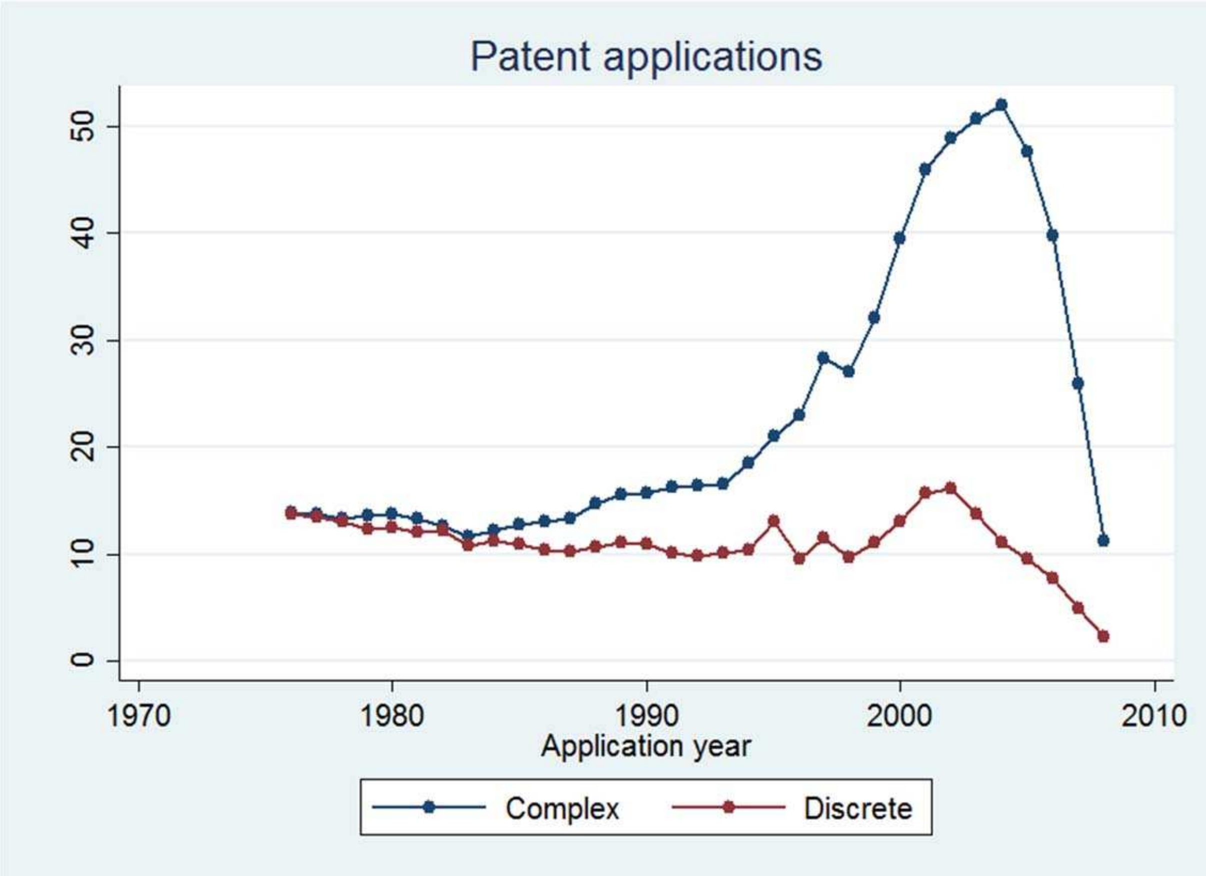


Figure 3. Trends in patent applications



Notes: Each graph depicts the number of patent applications per company in year as recorded in the Harvard Patent Inventor Database (Li et al. 2014).