Trade Secrets Laws and Technology Spillovers

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Abstract

This article examines whether and to what extent the Uniform Trade Secrets Act (UTSA) affects technology spillovers between focal firms (i.e., receivers of spillovers) and peers (i.e., senders of spillovers). I find that technology spillovers from peers located in states adopting the UTSA are 27% to 51% lower than technology spillovers from peers located in states not adopting the UTSA. Focal firms whose peers come from the UTSA states have fewer migrant inventors than firms whose peers come from non-UTSA states.

JEL classification: O30; O38; K22; G31
Keywords: Technology spillovers; R&D spillovers; Trade secrets laws; UTSA.

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This article examines whether and to what extent the Uniform Trade Secrets Act (UTSA) affects technology spillovers between focal firms (i.e., receivers of spillovers) and peers (i.e., senders of spillovers). I find that technology spillovers from peers located in states adopting the UTSA are 27% to 51% lower than technology spillovers from peers located in states not adopting the UTSA. Focal firms whose peers come from the UTSA states have fewer migrant inventors than firms whose peers come from non-UTSA states.

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1. Introduction

Technology spillovers are one of most important research topics in economics and innovation since 1980s and continue to attract the attention of researchers.[1] Research and development investment benefits not only own-firms but also other firms because of existence of involuntary know-how leakage, and technology spillovers allow the receivers to generate new inventions at lower cost. To maintain R&D appropriability and reinforce the technology advantages of innovative companies, trade secret protections are used. Many researchers argue that protecting trade secrets could reduce technology spillovers.[2] However, no previous article directly examines whether and to what extent trade secret protection may reduce technology spillovers. Thus, I explore the economic impact of the trade secret protections on the technology spillovers of firms by focusing on trade secrets laws in United States.

Trade secrets laws are legal protections that protect intellectual property that is a company secret. Such properties include formulas, processes, customer details, or compilations of information with commercial value. Innovative firms can sue for trade secret thefts (for example, by departing employees) whenever their intellectual property rights are infringed. This legal protection increases the cost of stealing and prevents technology spillovers (Hall, Helmers, Rogers, and Sena, 2014; Png, 2017a). The reward theory explains the negative relationship between the trade secret legal protection and the technology spillovers. Under the reward theory, patent system offers the innovators monopoly rent in exchange of the disclosure of their unobserved knowledges (e.g., Liebhafsky, 1963; Kitch, 1977; Friedman, et al., 1991; Sichelman, 2010). By contrast, trade

[1] See, for example, Jaffe (1986; 1989), Bernstein and Nadiri (1989), Cohen and Levinthal (1990), Griliches (1991), Audretsch and Feldman (1996), Henderson and Cockburn (1996), Beise and Stahl (1999), David, Hall, and Toole (2000), Cassiman and Veugelers (2002), Cohen, et al., (2002), Cabrer-Borras and Serrano-Domingo (2007), Bloom, Schankerman, and Van Reenen (2013), Liang (2017), and Ugur, Churchill, and Luong (2020).

[2] See, for example, Png and Samila (2015), Png (2017a), Glaeser (2018), Li, Lin, and Zhang (2018), and Chen, Hsu, Officer, and Wang (2020).

secrets reduce the chance that a focal firm can learn peer firms' unobserved know-how and inventions. Namely, when firms decide to protect their technologies by trade secrets, the innovators do not earn legal monopoly rent of the specific technologies but keep the know-how as a secret, reducing the degree of technology spillovers. However, some scholars also argue that trade secrets laws may not necessarily reduce technology spillovers. For example, Fosfuri and Rønde (2004) build a simple model and suggest that stronger trade secret protection reduces the wages that workers receive, which, in turn, reduces the costs of clustering. When firms are likely to cluster, technology spillovers are more likely. Therefore, this article addresses two empirical questions: (1) whether trade secrets laws reduce technology spillovers, and (2) if they do, to what extent trade secrets laws reduce technology spillovers.

In this article, I use the staggered passage of the Uniform Trade Secrets Act (UTSA) to explore the effect of trade secrets laws on technology spillovers.[3] State governments began passing the UTSA in 1980. To date 48 states and District of Columbia have adopted the UTSA. The cross-sectional and time-series heterogeneities of the UTSA adoptions allow this article to examine the effect of the UTSA on technology spillovers. I estimate the technology spillovers in the spirit of Jaffe (1986) and Bloom, Schankerman, and Reenen (2013), where I regress the number of patents and R&D intensity of the firm on the pool of technology spillovers to gauge to what extent the focal firm (i.e., receiver of spillovers) may receive R&D spillovers from its peers (i.e., senders of spillovers), enabling the focal firm to improve its innovation and firm performance. The pool of technology spillovers indicates R&D investments made by a firm's peers, which are identified by the closeness in technology space between any two firms using the information on patenting activities across patent technological fields.

[3] As I will also discuss in later part, the US government signed into law the Defend Trade Secrets Act in 2016, which is a federal civil law for protecting the trade secrets of companies.

In particular, I separate the pool of technology spillovers into the spillover pools from peers located in states adopting the UTSA and the spillover pools from peers located in states *not* adopting UTSA. Using US listed firms between 1980 and 2015, I find that about 16% of peers come from the state in which the focal firm is located, which in part supports the notion that R&D spillovers are related to geographical clustering of innovative firms (Audretsch and Feldman, 1996), even though the other 49 states explain a majority of the incoming spillovers (roughly 84%). Potential infringed firms, i.e., the sender of spillovers in this study, can accuse other firms of trade secrets theft in the state court with jurisdiction, which usually depends on whether or not the plaintiffs operate and/or conduct commercial activities in the state (Almeling, Snyder, Sapoznikow, and McCollum, 2010; Effron, 2016). Therefore, I focus on the UTSA status of states of peers because it is more relevant to the technology spillovers than the UTSA status of states of focal firms.

My results show that the number of patents and R&D intensity are higher for firms with a greater pool of technology spillovers from peers, confirming the existence of technology spillovers documented in the literature. I further find that the effect of spillover pools on patent counts is 27% lower for the firms whose peers are located in states with the UTSA than for firms whose peers are located in states without the UTSA, suggesting that technology spillovers (outflowing from peers to the focal firm) decrease 27% due to trade secrets laws. I also find that technology spillovers decrease 51% after the adoption of the UTSA when I estimate spillovers by regressing firm's R&D intensity on spillover pools. These results suggest that trade secrets laws impede knowledge spillovers and reduce technology spillovers by economically significant amounts.

Moreover, several past articles suggest that migration of inventors contributes to know-how and technology spillovers (Møen, 2005; Agarwal, Ganco, and Ziedonis, 2009). The trade secrets laws, which increase the cost of departure of inventors moving to new companies, could prevent migrant inventors from being hired by firms that plan to enjoy the technology spillover benefits. I confirm this conjecture and find that there are fewer migrant inventors to firms if their spillover senders are located in states adopting the UTSA. Finally, I study how the focal firm's state adopting the UTSA may affect technology spillovers, in particular whether the UTSA status of the state of the focal firm is also relevant because of its legal practices. I uncover the evidence that the spillover effect is stronger when the focal firm is located in a state not adopting the UTSA, though the economic impact of the UTSA is moderate in this test.

This article contributes to the economics and innovation literature. First, this article is the first study that directly estimates whether and to what extent trade secrets laws reduce technology spillovers. Although the idea that trade secrets laws prevent spillovers has been discussed in the literature (Hall, Helmers, Rogers, and Sena, 2014; Yeganegi, Laplume, Dass, and Huynh, 2016; Png, 2017a; Klasa, Ortiz-Molina, Serfling, and Srinivasan, 2018), the magnitude of the economic impact on technology spillovers is unclear. Knowing the magnitude of this economic impact is vital for policymakers when legislating trade secret protections because great reductions in knowledge spillovers can hurt economic growth, employment creation, and international competitiveness (Griliches, 1991; Agarwal, Audretsch, Sarkar, 2007). Second, this paper echoes the reward theory in the law and economic literature (e.g., Liebhafsky, 1963; Kitch, 1977; Friedman, et al., 1991; Sichelman, 2010; Anderson, 2011). Under the reward theory, when intellectual property rights are protected by trade secrets, innovators do not earn legal monopoly rent of the technologies. Accordingly, innovators are not responsible for disclosing their technology secrets. Hence, their technologies will not spread out to the public sector and technology spillovers will be reduced. Third, the findings of this paper may be aligned with the institutional theory (Meyer and Rowan, 1977; DiMaggio and Powell, 1983). For example, corporate policy (e.g., philanthropic donations) may be driven by peer pressures (Marquis and Tilcsik, 2016). Therefore, the innovation activity of a focal firm could be affected by its peers' R&D activities through spillover channels. Fourth, this article enriches our understanding of the real effects of the UTSA in the literature. The UTSA is a hot topic in domains in which researchers are interested in how trade secrets laws may affect corporate decisions (Png, 2017a, Glaeser, 2018). This article studies the UTSA and technology spillovers and enables scholars to better understand the real effect of latest developments in trade secrets laws in the U.S.

The remainder of this article is organized as follows. Section 2 presents the background and literature reviews. Section 3 discusses the data and research design. Section 4 provides empirical analyses of technology spillovers and migrant inventors. Section 5 includes the discussion. Section 6 concludes.

2. Background and Literature Reviews

2.1 Trade Secrets Laws in US

Trade secrets laws are distinct from patent laws because they usually encourage multiple independent development whereas patent laws discourage it (Milgrim, 1971; Jager, 1985; Pooley, 2015). In US, trade secrets laws were governed by common law, which is the accumulated stock of case precedents (Png, 2017a; Hou, Png, Xiong, 2022). In 1979, the National Conference of Commissioners on Uniform State Laws approved the Uniform Trade Secrets Act (UTSA) and recommended its enactment for all states. To date, 48 states (exceptions: Massachusetts and New York) and the District of Columbia have adopted the UTSA with the 1979 version of the UTSA or with the 1985 amended version of the UTSA. Appendix Table A1 presents the year of enactment of the UTSA for each state. The UTSA defines a trade secret as information, including a formula, pattern, compilation, program, device, method, technique, or process, that:

(i) derives independent economic value, actual or potential, from not being generally known to, and not being readily ascertainable by proper means by, other persons who can obtain economic value from its disclosure or use, and

(ii) is the subject of efforts that are reasonable under the circumstances to maintain its secrecy.[4]

Under Section 2 of the UTSA, the owner has a legal claim for trade secret misappropriation to obtain injunctive relief, where misappropriation means disclosure or use of a trade secret by the defendant to the plaintiff's detriment (Li, Lin, and Zhang, 2018). The UTSA is thus intended to protect trade secrets that are appropriated by improper means. The UTSA clearly states that the legal term "improper" extends beyond illegal activities to include "otherwise lawful conduct which is improper under the circumstances; e.g., an airplane overflight used as aerial reconnaissance to determine the competitor's plant layout during construction of the plant. E. I. du Pont de Nemours & Co., Inc. v. Christopher, 431 F.2d 1012 (CA5, 1970), cert. den. 400 U.S. 1024 (1970). Because the trade secret can be lost through public knowledge, the unauthorized disclosure of a trade secret is also a misappropriation." The UTSA also states that improper means does not include reverse engineering (Glaeser, 2018).

Potential infringed firms (i.e., the sender of spillovers in this paper) could accuse other firms of trade secrets theft (i.e., the receiver of spillovers in this paper) in the state court with jurisdiction, which usually depends on whether or not the plaintiffs operate and/or conduct commercial activities in the state (Almeling, Snyder, Sapoznikow, and McCollum, 2010; Effron, 2016). Therefore, it is very likely that the plaintiff would file a complaint with the court near the state that

[4] https://www.law.cornell.edu/wex/trade_secret

the plaintiff or defendant is located. The court in the state where the plaintiff operates and runs the business usually has the jurisdiction. The court in the state that the defendant is located can also have the jurisdiction because of the "*actor sequitur forum rei*"[5], or because the right to claim compensation for damages caused by infringing act can be applied to the law of the place where the infringement occurred. However, the choice between courts in the locations of the plaintiff and defendant depends on many factors. For example, if the state of the plaintiff does not pass the UTSA but the state of the defendant does, then the plaintiff would sue for trade secrets infringement upon the UTSA in the court of the defendant's state. Other factors affecting the choice between the courts in the locations include the creation of the jurisdiction diversity (Almeling, Snyder, Sapoznikow, and McCollum, 2010), whether a jury is desired (Malin, 2003), employment protection policy of the state (Lang, 2003) and so on. Of course, *ceteris paribus*, the distance is also expected to a factor that the plaintiff could sue for trade secret infringement in the state court to save transportation costs. Overall, the choice of which court is most suitable for a litigation case is complex (Malin, 2003), but the courts in the states where the plaintiff and defendant are located are very relevant.[6]

In 2016, Congress passed the Defend Trade Secrets Act (DTSA), which authorizes a civil action in federal court for the misappropriation of trade secrets. Although the UTSA and DTSA both formulate the elements of the tort of trade secret misappropriation and derive private remedies

[5] The "*actor sequitur forum rei*" means "the plaintiff follows the forum of the property in suit or the forum of the defendant's residence." This principle applies to both civil and criminal torts. See https://openjurist.org/law-dictionary/actor-sequitur-forum-rei

[6] The litigation case of TechForward, Inc. (plaintiff) versus Best Buy Co., Inc. (defendants) is an example, where TechForward sued Best Buy Co. in United States District Court, C.D. California because TechForward is located in California though Best Buy Co. is located in Minnesota. See https://www.leagle.com/decision/infdco20130128620. However, in another case of Global Advanced Metals, Inc. versus Kemet Blue Powder Corp, the plaintiff, Global Advanced Metals that is located in Massachusetts, sued for various tort and unfair competition and trade secrets claims as preempted by the UTSA in United States District Court, Nevada, where the defendant, Kemet Blue Powder Corp, is located.
See https://www.casemine.com/judgement/us/5914e65dadd7b0493490dbec.

for it (Dole Jr, 2017), unlike the USTA, the DTSA creates a uniform standard for trade secret protections across states by following the Economic Espionage Act of 1996 (which provides criminal penalties) but provides a federal civil remedy for trade secret misappropriation. The owner who has a legal claim for trade secret misappropriation can sue for redress in federal court under the DTSA.[7] However, the UTSA is not preempted by the DTSA: plaintiffs can sue in state court (under the UTSA), federal court (under the DTSA), or both.[8]

2.2 Technology Spillovers and Trade Secrets Laws

Technology spillovers, which are also known as R&D spillovers, R&D externalities, or knowledge spillovers, occur when firms cannot fully appropriate the benefits of their own R&D investment. Technology spillovers lower the costs of firms that receive know-how from the R&D investment of other firms and enhance their own performance and productivity (Jaffe, 1986; Bernstein and Nadiri, 1989; Bloom, Schankerman, and Van Reenen, 2013; Chen, Chen, Liang, and Wang, 2013). To prevent outgoing spillovers and maintain R&D appropriability, firms may file patents or use trade secrets protection to protect their know-how.[9]

In this version of the paper, I propose that the reward theory to explain the relationship between the trade secret legal protection and the technology spillovers. The reward theory indicates

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[7] https://www.tradesecretslaw.com/2016/04/articles/dtsa/what-does-the-passage-of-the-defend-trade-secrets-act-mean-for-your-business/

[8] Several states rely on the Inevitable Disclosure Doctrine (IDD) to protect trade secrets, which has also been studied in recent articles (Klasa, Ortiz-Molina, Serfling, and Srinivasan, 2018; Li, Lin, and Zhang, 2018). This doctrine allows the state court to find that a former employee who works at a competitor under the principle that the employee would inevitably disclose trade secrets of his former employer. How state courts apply the Inevitable Disclosure Doctrine varies across states, leading to highly heterogeneous impacts of this trade secrets protection even within those states adopting this doctrine. Further, prior to 2015, almost all US states adopted the UTSA, whereas less than half of all states recognize the IDD (Guernsey, John, and Litov, 2017). The IDD has recently become less influential, because the DTSA implicitly rejects inevitable disclosure and is in favor of employee mobility (Bohrer, 2016).

[9] I do not discuss the spillover from public sectors in this article, for example governments and universities (e.g., Belenzon and Schankerman, 2013; Chen, Chen, Liang, and Wang, 2020).

that protection of intelligent property rights through patent system offers the innovators monopoly rent for several years in exchange of the disclosure of their new and unobserved knowledges (e.g., Liebhafsky, 1963; Kitch, 1977; Friedman, et al., 1991; Sichelman, 2010). The innovators who disclose their knowledge through the patent system are rewarded in order to encourage more inventions in a society (Lemley, 1996-1997). By contrast, under a regime of trade secret protection, the focal firm might not learn peer firms' processes, and would not know peer firms' technology incorporated in new products until they are commercialized (Kitch, 1977). Reward theory justifies the patent system as a means to induce the disclosure of new and useful inventions; without the significant profits from a patent, the reward theory also predicts that innovators would rely on trade secrets to protect their intelligent property rights (Anderson, 2011). Namely, when firms decide to protect their technologies by trade secrets, the innovators do not earn legal monopoly rent of the specific technologies but retain the know-how as a secret. Accordingly, the technologies would not disseminate out to the public under the trade secret system because the innovators, who are not rewarded by the legal system, are not responsible for disclosing their secrets, reducing the degree of technology spillovers from spillover senders to receivers.

The idea that trade secrets protection reduces technology spillovers has been documented in the literature, though it is not empirically tested. Fosfuri and Rønde (2004) use a theoretical model and suggest that technology spillovers arise through labor mobility and discuss the role of trade secrets protection on profits, industry clustering, and technology spillovers. They suggest that stronger trade secret protection reduces the wages that workers receive, which, in turn, reduces the costs of clustering. When firms are likely to cluster, technology spillovers are more likely, an idea similar to Alcácer and Chung (2007) who suggest that firms locate to maximize their net spillovers with determinants of locations' knowledge activity, their own capabilities, and competitors' anticipated actions. Yeganegi, Laplume, Dass, and Huynh (2016) study the trade secrets protection and spinouts by employees, and find that trade secret protections (mainly the non-compete and non-disclosure agreements in their study) impede spinouts. Png (2017a) studies the UTSA and firm innovation. He argues that there are two effects of trade secrets on innovation performance. First, trade secrets protection raises appropriability and leads to better return on R&D investments, incentivizing corporate innovation activities. Second, stronger protection reduces spillovers from peers, which might increase or decrease the return on R&D investments depending on whether own and spillover R&D are substitutes or complements. Glaeser (2018) argues that trade secrets laws in part substitute for filing patents to increase the degree of R&D appropriability, leading to lower patenting rates of firms. Because the proprietary information is protected by trade secrets laws (which are private information) but not patents (which are public information), technology spillovers are less possible. The contention that trade secrets protections reduce technology spillovers has also been discussed in other studies (Møen, 2005, Klasa, Ortiz-Molina, Serfling, and Srinivasan, 2018; Li, Lin, and Zhang, 2018).

To the best of my knowledge, however, none of these studies directly examines the extent to which trade secret protection may reduce technology spillovers. Thus, I study the economic impact of the trade secrets laws on technology spillovers. Knowing the magnitude of this economic impact is important. Trade secrets laws stimulate the R&D investments of firms, which contribute to economic growth. Yet, extensive reduction in knowledge spillovers resulting from strong trade secrets protection can hurt economic growth, employment creation, and international competitiveness (Griliches, 1991; Agarwal, Audretsch, Sarkar, 2007). Given this, policymakers should consider the pros and cons of trade secret protections.

3. Data and Methods

3.1 Data

The sample of this study consists of U.S. listed firms covered in Compustat and the Center for Research in Security Prices (CRSP) databases between 1980 and 2017. The patent-related data come from the European Patent Office (EPO) Worldwide Patent Statistical Database (PATSTAT, 2018 edition), which provides detailed and comprehensive information on both U.S. and non-U.S. patents. American depositary receipts, closed-end funds, non-U.S. firms, and real estate investment trusts are removed from the sample. Because of data availability, I remove firms that do not have patent information that is required in estimating the pool of technology spillovers. The final sample consists of 27,613 firm-years involving 4,156 firms.

3.2 Methods

I calculate the *spillover pool* in the spirit of Jaffe (1986), Bloom, Schankerman, and Van Reenen (2013) and Tseng (2022), which is equal to $\sum_{j \neq i} w_{ij} CRD_j$. w_{ij} is technological proximity as an uncentered correlation coefficient of innovation activities of firm i and its peer firm j:

$$S_i S_j' / (S_i S_i')^{0.5} (S_j S_j')^{0.5}. \tag{1}$$

$S_i = (S_{i,1}, \ldots, S_{i,p})$ is a vector of innovation activity in technology classification p for firm i. p refers to the 3-digit International Patent Classification (IPC) code, and innovation activity refers to the number of patents that a firm has applied for at the USPTO. Namely, $S_{i,p}$ is the number of patents that firm i applied (eventually granted) in IPC code p in a given year. *CRD* is firm R&D capital measured as in Chan, Lakonishok, and Sougiannis (2001), which is equal to $CRD_{it} = R\&D_{it} + 0.8R\&D_{it-1} + 0.6R\&D_{it-2} + 0.4R\&D_{it-3} + 0.2R\&D_{it-4}$. This equation assumes that the productivity of each dollar of R&D spending declines linearly by 20 percent per year. Namely, I estimate spillover pool as the weighted sum of other firms' R&D, where weights are proportional to these firms' proximities in technology space. When firm *i* is more correlated to other firms in technology space and its peer firm *j* has more R&D capital, the spillover pool is larger for firm *i*. The spillover pool is in millions of US dollars.

Based on the pool of technology spillovers, I further decompose it into *spillover pool from UTSA states* and *spillover pool from non-UTSA states*. *Spillover pool from UTSA states* is the spillover pool related to firms located in states that adopt the UTSA, which is equal to $\sum_{j\neq i, j\in UTSA} w_{ij} CRD_j$, where w_{ij} is technological proximity of firm *i* and its peer firm *j* located in states that adopt the UTSA. *Spillover pool from non-UTSA states* is the spillover pool related to firms located in states that do not adopt the UTSA, which is equal to $\sum_{j\neq i, j\in non-UTSA} w_{ij} CRD_j$, where w_{ij} is technological proximity of firm *i* and its peer firm *j* located in states that do not adopt the UTSA. In particular, I use location information of firms from Augmented 10-X Header Data but not location information from Compustat because Compustat does not keep the historical headquarters information.[10]

I use the example of Questcor Pharmaceuticals, Inc. to illustrate how I calculate the spillover pool in Figure 1. Questcor Pharmaceuticals is a biopharmaceutical company located in California, which focuses on the treatment of patients with serious, difficult to treat autoimmune and inflammatory disorders.[11] In 1999, this company has 47 peers (i.e., the senders of spillovers) which have positive R&D investments as well as positive proximities against Questcor

[10] Augmented 10-X Header Data could be downloaded at https://sraf.nd.edu/data/augmented-10-x-header-data/, which include historical location data since 1994. Before 1994, exact location information is unavailable in Augmented 10-X Header Data because the EDGAR was not available online (Chang, Hsiao, Ljungqvist, and Tseng, 2020). For those firm-years before 1994, I use data from Compact Disclosure database and manually check the location information of these firm-years. For the firm-years that are not covered in Compact Disclosure database, I use location information in 1994 to compute the spillover pool for the firm-years before year 1994. I acknowledge Professor Sheng-Syan Chen for offering use of the Compact Disclosure database.

[11] See https://www.forbes.com/companies/questcor-pharmaceuticals/#666a183ba0e1

Pharmaceuticals. 17 peers are located in California, 8 peers are located in Massachusetts, 5 peers are located in New Jersey, 4 peers are located in New York, and other peers are located in Colorado, Connecticut, Delaware, Illinois, Maryland, Maine, North Carolina, Oklahoma, Pennsylvania, or Washington. Among these states, New Jersey, New York, Maryland and Pennsylvania had not adopted the UTSA in 1999. The spillover pool from the non-UTSA states is then the sum of the products of R&D capital and the proximity of peers that are located in New Jersey, New York, Maryland, and Pennsylvania. The spillover pool from the UTSA states is measured in a similar fashion, where I also illustrate how it is computed in Appendix Table A3.

Insert Figure 1 around here

To estimate the spillover effect, I follow Jaffe (1986) and Bloom, Schankerman, and Van Reenen (2013) and estimate the regressions of the number of patents, R&D intensity, profit and Tobin's Q on the spillover pool from states adopting the UTSA and the spillover pool from states not adopting the UTSA. Specifically, I estimate following regression models:

$$y_{ikt} = b_0 + b_1 S_{ikt}^{UTSA} + b_2 S_{ikt}^{non\text{-}UTSA} + \boldsymbol{X}_{ikt}\boldsymbol{\gamma} + \eta_{kt} + \varepsilon_{ikt}. \quad (2)$$

The dependent variable y_{ikt} is the logarithm of *the number of patents*, *R&D-to-PPE ratio, profit*, or *Tobin's Q* for patent equation, R&D equation, profit equation, or Tobin's Q equation of firm *i* in industry *k* at year *t*. S^{UTSA} ($S^{non\text{-}UTSA}$) indicates the logarithm of *spillover pool from UTSA states* (*spillover pool from non-UTSA states*) that is previously defined. $\boldsymbol{X}$ is a set of control variables. η_{kt} is the industry-year joint fixed effects upon 2-digit Standard Industrial Classification (SIC) codes. I incorporate industry-year joint fixed effects into the regression to control for time-varying industry related latent variables, which include the time-varying product market competition conditions. Coefficient estimate of b_1 (b_2) stands for the estimate of technology spillovers from peers located in states adopting the UTSA (from peers located in states not adopting the UTSA).

3.3 Summary Statistics

Table 1 presents summary statistics in Panel A and industry distribution upon 2-digit SIC codes in Panel B of the sample firms between 1980 and 2015. I stop the sample in 2015 because the DTSA was enacted in 2016, and including data from after 2015 in the analysis of the USTA could be confounded by the federal trade secrets law. Variable definitions are described in Appendix Table A2. The means of *spillover pool*, *spillover pool from UTSA states*, and *spillover pool from non-UTSA states* are 8,998, 5,688, and 3,309 million dollars, respectively. Apparently, more spillovers come from the states adopting the UTSA, a finding likely caused by most states having adopted the UTSA after 2000. Panel B shows that the majority of the sample comes from manufacturing industries.

Insert Table 1 around here

4. Empirical Results

Before I perform the regression analysis, I study where potential technology spillovers may come from by identifying the location of peers that can spill over knowledge. In Table 2, I focus on peers that have proximity (between focal firms and peers) greater than zero (Panel A), greater than 5% (Panel B), 10% (Panel C) or 25% (Panel D), and the sample size is smaller when I impose a more restrictive proximity to identify peers. I then group my sample by whether or not the state adopts the UTSA and whether or not the peer is located in the state in which the focal firm is headquartered. I find that no matter which way I define peer firms, around 16% of peers are from the state in which the focal firm is located, partly supporting the notion that R&D spillovers are related to geographical clustering of innovative firms (Audretsch and Feldman, 1996). The other 49 states account for the majority of incoming spillovers. About 70% (30%) of peers come from states adopting the UTSA (not adopting the UTSA).

<u>Insert Table 2 around here</u>

4.1 Regression Analysis of Patents and R&D intensity

To investigate the effect of the UTSA on technology spillovers, I perform regression analyses of the number of patents. Table 3 presents the results, where I perform regression analysis of the number of patents in Models 1 and 2. The coefficient of log(*spillover pool*) is positive and significant at the 1% confidence level, confirming the existence of technology spillovers (Jaffe, 1986, Bloom, Schankerman, and Reenen, 2013). In particular, as presented in Model 2, the effect of spillover pools on patent counts is 27% (=1 − 0.0465/0.0632) lower for the firms whose peers are located in states with the UTSA than the firms whose peers are located in states without the UTSA, suggesting that technology spillovers (outflowing from peers to the focal firm) decrease 27% due to trade secrets laws.[12]

Moreover, Png (2017a) argues that stronger trade secrets laws may have conflicting effects

[12] Some states govern trade secrets by common law before they pass trade secrets laws, thus I use the state-level index of common law protection on trade secrets of Png (2017a) to correct trade secrets protections for those states that do not pass UTSA. For example, California passed UTSA in 1985, but its common law index was positive before 1985 (equal to 0.22). In this case, I set California as the state under trade secrets protections for whole sample period, and recalculate the two spillover pools. Unreported results show that the conclusion remains valid. Moreover, I replace industry-year joint fixed effect with firm and year fixed effects, and results are generally consistent in the patent equation. Yet, I fail to find significant result in following regression analyses of profit and Tobin's Q.

on R&D investments. First, stronger trade secrets protection raises R&D appropriability, giving firms greater incentive to engage in R&D activity. Yet, stronger protection reduces know-how from spillover senders, which may increase or decrease the R&D investment of firms depending on whether in-house R&D and spillover pools are substitutes or complements. By focusing on the trade secrets laws status which focal firms are subjected to, Png (2017a) finds that the UTSA encourages R&D investments.

I follow Png (2017a) but instead focus on the status of trade secrets laws that peer firms are subjected to and examine how it may affect the focal firm's R&D investments. It is plausible a free rider effect exists, where a firm may free ride on the R&D of other innovators and reduce its own R&D (Arrow, 1962). In Models 3 and 4 of Table 3, I estimate an R&D equation by regressing R&D intensity (*R&D-to-PPE ratio*) on spillover pools. In general, coefficients of log(*spillover pool*) are positive and significant at the 1% level, consistent with the complementary effect between the focal firm's R&D and spillovers. Moreover, coefficients of log(*spillover pool from UTSA states*) are lower than coefficients of log(*spillover pool from non-UTSA states*).[13] The effect of spillover pools on patent counts is 51% (=1 − 0.0029/0.0059) lower for the firms whose peers are located in states with the UTSA than the firms whose peers are located in states without the UTSA. In a robustness check, I regress R&D amount (*R&D expenditures*) on spillover pools, and unreported results are consistent. Thus, the adoption of the UTSA alleviates the spillovers effect in the setting of the R&D equation.

For robustness, I perform regression analyses of profit and Tobin's Q.[14] I present regression

[13] I also compute R&D intensity by R&D expenditures scaled by book assets or scaled by the number of employees, and results are similar. The results are weak when I scale R&D expenditures by sales, probably because sales are very volatile.

[14] Results are quantitatively similar to the results of the profit equation if I estimate the sales equation, where I regress the logarithm of sales on the logarithm of spillover pools and the logarithms of input factors such as R&D expenditure, the number of employees, and property, plant, and equipment.

analysis of profit in Models 3 and 4, and regression analysis of Tobin's Q in Models 5 and 6, respectively.[15] I also find that technology spillovers decrease 66% (=1 − 0.0060/0.0174) and 75% (=1 − 0.0061/0.0242) when the firm's peers are located in non-UTSA states based on the profit and Tobin's Q equations.[16] These results are presented in the Appendix Table A4.

One potential concern of the measure of spillover pool is that it is calculated from patent information, and the mechanism by which trade secrets laws affect spillovers could be that stronger trade secrets laws induce firms to reduce patenting (e.g., Png, 2017b), in turn reducing the potential spillover pool. Therefore, I use the aggregate R&D capital of all three-digit SIC industrial peers to measure spillover pool as a robustness check (e.g., Bernstein and Nadiri, 1989; Feinberg and Majumdar, 2001).[17] In unreported results, I find that coefficients of log(*spillover pool from UTSA states*) are insignificant, where log(*spillover pool from non-UTSA states*) are positive and significant at the 5% confidence level or better. Therefore, the results are quantitatively similar to my baseline models. Furthermore, technology spillovers are heavily related to geographical distance (Audretsch and Feldman, 1996; Fosfuri and Rønde, 2004). To control for geographical distance, I estimate spillover pool as $\sum_{j\neq i} w_{ij} d_{ij} CRD_j$, where w_{ij} is technological proximity as an

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[15] Control variables include log(*R&D expenditures*), log(*sales*), and *R&D-to-PPE ratio* in the patent equation. Control variables include log(*R&D expenditures*), *R&D-to-PPE ratio*, log(*PPE*), log(*employees*), log(*SG&A expenditures*) and log(*Cost of goods sold*) in the profit equation. I use a battery of control variables at the level of inputs in the patent and profit equations in the spirit of a production function structure (Jaffe, 1986; Bloom, Schankerman, and Van Reenen, 2013). In the Tobin's Q equation, I control for log(*R&D expenditures*), log(*sales*), *R&D-to-PPE ratio*, log(*PPE*) and log(*employees*).

[16] I perform a number of robustness checks and obtain consistent results, including (1) using the dependent variable in year *t*+1; (2) removing firms located in California; (3) replacing the number of patents with patent citations; (4) estimating the patent equation upon Poisson model; and (5) replacing profit by gross profit. I find consistent results (except for the patent equation) when I replace the industry-year joint fixed effects with state-year joint fixed effects. I also follow Jaffe (1986) and examine the interaction between R&D expenditures and spillover pools, yet I find no evidence that the UTSA affects the interaction.

[17] According to Bernstein and Nadiri (1989), the output of a given firm is determined by a production function with inputs of physical capital factor, variable factor, R&D capital factor and R&D spillover pool. In the estimation of the production function, the slope of R&D spillover pool captures to what extent R&D capital is appropriable. If the slope is equal to zero, then R&D capital is completely appropriable and there are no spillovers. If the slope is equal to 1, then R&D capital is completely inappropriable.

uncentered correlation coefficient of innovation activities of focal firm i and peer firm j, and d_{ij} is geographical distance between focal firm i and peer firm j; d_{ij} is standardized by scaling maximum distance of the sample firms (i.e., the distance is ranged between 0 and 1). The unreported results show that the results are quantitatively unchanged.

Finally, I control for location choice following Chen, Chen, Liang, and Wang (2020), who perform a Heckman two-stage regression to control for the location choice. In stage 1, a firm's location choice is estimated by a conditional multinomial logit regression with the dependent variable of a dummy that is equal to one if the firm's headquarters is located in a specific state and zero otherwise. Chen, Chen, Liang, and Wang (2020) incorporate independent variables including public R&D expense-to-GDP ratio, labor income growth rate, GDP growth rate, unemployment rate, and firm characteristics (firm size, book-to-market, operating profitability, asset growth, prior returns, R&D intensity, patent citations, citations per R&D dollar, Kaplan and Zingales index, idiosyncratic volatility, and illiquidity) as well as an exogenous variable of founder university, which is a dummy equal to one if a founder or co-founders of the firm has been enrolled in a university (for bachelor, masters, or PhD degree) in the state.[18] I then perform regression analysis by additionally including 'control functions' obtained from stage 1 to correct for the location choice. Unreported results show that the results are quantitatively similar after addressing location choice problem.

These results suggest the following policy implications. Trade secrets laws encourage firms to engage in innovation activity because trade secrets protections maintain R&D appropriability. Yet, extensive reduction in knowledge spillovers can hurt economic growth (Griliches, 1991;

[18] Founder generally prefers the location where she went to college and start her company (Chen, Chen, Liang, and Wang, 2020), because she is more familiar with the living style and environment of the location. Moreover, the location of the founder's university is unlikely to be correlated with firm performance and investments, which satisfies the exclusion restriction.

Agarwal, Audretsch, Sarkar, 2007). To link my results to economic growth, I use the profit equation (result presented in the Appendix Table A4), which is closely related to the economic growth, to interpret the policy implications. The profit equation shows that technology spillovers decrease 66% when peers are located in states adopting the UTSA. Given the non-significant estimate of the coefficient of log(*spillover pool from UTSA states*), the UTSA eliminates the effect of spillover pools on a firm's profit. Therefore, it seems that the UTSA impedes spillover driven economic growth. To justify such a strong trade secret protection in the US, policymakers should consider and gauge not only R&D appropriability but also other benefits (legal legitimacy, global competition, and antitrust) of such laws to balance their potential damage to economic growth due.

<u>Insert Table 3 around here</u>

4.2 Endogeneity

The relationship between the UTSA and technology spillovers could suffer endogeneity challenge. For example, if peer firms migrate towards UTSA states and focal firms grow their innovative activity over time, the correlation in time could induce a spurious correlation. However, if firms located in the states with the UTSA, and it is merely that these firms grow their innovation activity over time, then the control for time fixed effect should preempt the relationship proposed in the paper. In this paper, I find that the results remain held after controlling for the year fixed effect, or more precisely, the industry and year joint fixed effect, which subsumes the year fixed effect.

Furthermore, I address potential endogeneity issue because R&D investment is usually endogenously determined, and accordingly the R&D capitals of peer firms should be instrumented to alleviate the endogeneity concern. I follow Cohen, Coval, and Malloy (2011) and use influential congressional committee chairmanships as an exogenous variable. When a congressional member initially becomes an influential committee chairman, the chairman in power of the committee tends to allocate federal funds (for example, the earmarks) to their own state by increasing public real investments and public R&D, where the latter could crowd out R&D investment by the private sector. Because the congressional committee chairmanship is determined largely by seniority, the congressional committee chairmanship is exogenous to the economic environment and firm decisions (Cohen, Coval, and Malloy, 2011). For each calendar year, I perform a regression analysis of the R&D expenditures with industry fixed effect and employ explanatory variables of logarithm of size, book-to-market ratio, cash-to-asset ratio and an instrumental variable of influential congressional chairman dummy, which is equal to one if a firm is located in the state with a congressman initially serving as the chairman of the influential committee. The spillover pool is then equal to $\sum_{j \neq i} w_{ij} \widehat{CRD_j}$, where $\widehat{CRD_j}$ is the fitted R&D capital from abovementioned regression model, and where w_{ij} is technological proximity. Results in Table 4 show that the results are unchanged after addressing endogeneity concern.[19]

Insert Table 4 around here

4.2 Migrating Inventors and Technology Spillovers

Moreover, I examine how the UTSA may affect the inventor migration that is related to technology spillovers. Previous articles suggest that the migration of inventors contributes to

[19] The F-value of weak IV test is 8.25, satisfying the threshold, which is 8, and verifying the relevance restriction. I also follow Bloom, Schankerman, and Reenen (2013) and use tax policy changes as instruments; results are similar but slightly weaker. As Bloom, Schankerman, and Reenen (2013) also indicate that tax policy changes may be endogenous to shocks to the economic environment, congressional committee chairmanship could be a better instrumental variable in the test.

knowledge externality and technology spillovers (Møen, 2005; Agarwal, Ganco, and Ziedonis, 2009). The trade secrets laws, which increase the cost of departure of inventors moving to new companies, could prevent migrant inventors from being hired by firms that plan to enjoy the technology spillover benefits. I perform a regression analysis of migrant inventors using the Harvard Business School (HBS) patent and inventor database.[20] The dependent variable is the number of inventors migrating from peers to the focal firm in a given year. In Table 5, I estimate the effect of spillover pool on the migration of inventors by using a linear regression model in Models 1 and 2 and using a Poisson model in Models 3 and 4. I find that all other things being equal, the coefficients of log(*spillover pool from UTSA states*) are negative and significant at the 1% level, whereas the coefficients of log(*spillover pool from non-UTSA states*) are positive. These results suggest that there are fewer migrant inventors to the focal firms if their spillover senders are located in states adopting the UTSA.[21]

Insert Table 5 around here

4.3 The Trade Secrets Laws in States of Focal Firms

In this section, I analyze whether or not the focal firm's state adopting the UTSA may affect technology spillovers. As mentioned above, the UTSA of the focal firm is also relevant because by legal practices, the infringed firm can sue for trade secret theft in the state in which the plaintiff is located or in the state in which the defendant is located. Therefore, in Table 6, I divide the sample

[20] https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/5F1RRI. As noted by Li et al. (2014), the data correct inconsistent reports of individual inventors as well as the cases with duplication of names of inventors. Because of the database limitations, the sample period of this test ends in 2010.
[21] In unreported results, I examine the number of departing inventors (i.e., the inventors who migrate to other firms) of firms and the effect of trade secrets laws, and find that the UTSA adoption is negatively related to the departing inventors of firms.

into a subsample with focal firms in states adopting the UTSA and a subsample with focal firms in states not adopting the UTSA. I then regress *the number of patents* on *spillover pool*. Results in Table 6 show that the spillover effect (i.e., the coefficient of *spillover pool*) is stronger when the focal firm is located in a state not adopting the UTSA, though the economic impact is moderate.

Insert Table 6 around here

As discussed above, the infringed firm can sue for trade secrets theft in the state court with jurisdiction, in the state court in which the plaintiff is located, or where the defendant is located, or both (Almeling, Snyder, Sapoznikow, and McCollum, 2010; Effron, 2016). Therefore, the UTSA of the focal firm is also relevant in affecting the spillover effect from spillover senders to receivers. In Models 3 and 4 of Table 6, I divide the sample into a subsample with focal firms that are located in a state adopting the UTSA and a subsample with focal firms that are located in a state not adopting the UTSA, and then estimate the patent equation. I find that the impact of the UTSA (upon peers' side) on technology spillovers is quite similar for the state in which the focal firm is located not adopting the UTSA and for the state in which the focal firm is located adopting the UTSA.

5. Discussion

This paper examines whether and to what extent the trade secret legal protection may affect technology spillovers, where I focus on the UTSA as the means to protect the firm's trade secrets. The empirical results show that technology spillovers from peers located in states adopting the UTSA are 27% to 51% lower than technology spillovers from peers located in states not adopting the UTSA.

This paper contributes to the literature in three ways. First, this paper is the first study that directly estimates the relationship between trade secrets protection and technology spillovers. While many papers have mentioned the idea that trade secrets laws prevent spillovers (e.g., Hall, Helmers, Rogers, and Sena, 2014; Yeganegi, Laplume, Dass, and Huynh, 2016; Png, 2017), existing papers do not empirically test this effect and its magnitude. My paper addresses this gap in the innovation literature. Second, this paper echoes the reward theory in the law and economic literature (e.g., Liebhafsky, 1963; Kitch, 1977; Friedman, et al., 1991; Sichelman, 2010; Anderson, 2011). Under the regime of trade secrets protection, the innovators do not earn legal monopoly rent of the technologies but retain the know-how as a secret. Because innovators are not responsible for disclosing their technology secrets under the reward theory, the technologies do not spread out to the public sector, accordingly reducing technology spillovers. Third, the effect of the trade secret protection on technology spillovers is consistent with the institutional theory, which suggests that organizations should obey the rules and belief systems that prevail in an environment (Meyer and Rowan, 1977; DiMaggio and Powell, 1983). In particular, corporate policy (e.g., philanthropic donations) could be driven by peer pressures (Marquis and Tilcsik, 2016). That is, the innovation activity of a focal firm could be affected by its peers' R&D activities through spillover channels. Fourth, this article enriches our understanding on the real effect of the UTSA in the literature (e.g., Png, 2017, Glaeser, 2018; Sakaki and Thapar, 2018) by analyzing the technology spillovers. Thus, my paper further extends our knowledge to the finance and accounting literature.

This paper draws several policy implications based on the study of UTSA. While trade secret laws strengthen R&D exclusivity and encourage firms to engage in innovative activities, broadly reducing knowledge spillovers can harm economic growth (Griliches, 1991; Agarwal, Audretsch, and Sarkar, 2007). Understanding the magnitude of this economic impact is therefore critical for policymakers. I have found that technology spillover is greatly reduced when peers are located in states that have adopted the UTSA. Thus, UTSA may impede spillover-driven economic growth. To justify such strong trade secret protections in the United States, policymakers should consider the other benefits offered by trade secret laws (legal legitimacy, global competition, and antitrust) against their potential harm to economic growth. Furthermore, it is plausible that the states are adopting a kind of 'beggar thy neighbor' strategy, where the neighbor states are draining New York and Massachusetts especially after 2010, when most of states have passed the UTSA. However, the finding of this paper only explains the cross-sectional dynamic because all regression models control for the industry and year joint fixed effect. If New York and Massachusetts would both adopt the UTSA, then the cross-sectional variation stemming from the state-level trade secret law would disappear in my paper. In such case, whole spillover dynamic may or may not decline, depending on many other country level variables (e.g., federal government R&D funding, new innovation breakthrough, pandemics and so on). This is also why the industry and year joint fixed effects are controlled for in this paper.

6. Conclusion

Trade secret protections are usually considered to reinforce the technology advantage of innovative companies in the competitive product market, and trade secrets protections not only increase the appropriability of R&D but also reduce outgoing technology spillovers. In this article, I explore the economic impact of the trade secrets protections on the technology spillovers of firms by focusing on trade secrets laws in the United States.

I first focus on the staggered passage of the Uniform Trade Secrets Act (UTSA) to explore the effect of trade secrets laws on technology spillovers. In particular, I separate the pool of technology spillovers into the spillover pools from peers located in states adopting the UTSA and the spillover pools from peers located in states not adopting the UTSA. Using US listed firms between 1980 and 2015, I find that the effect of spillover pools on patent counts is 27% lower for the firms whose peers are located in states with the UTSA than for firms whose peers are located in states without the UTSA, suggesting that technology spillovers decrease 27% because of trade secrets laws. I also find that technology spillovers decrease 51% when a firm's peers are located in states adopting the UTSA using the R&D equations. These results show that trade secrets laws reduce technology spillovers and have a significant economic effect. Further, fewer migrant inventors move to the focal firms if their spillover senders are located in states adopting the UTSA. All my results are consistent with the reward theory in the law and economic literature.

This article derives several policy implications based on its study of the UTSA. Although trade secrets laws reinforce R&D appropriability and encourage firms to engage in innovation activity, extensive reduction in knowledge spillovers may hurt economic growth. I find that technology spillovers decrease strongly when peers are located in states adopting the UTSA. Hence, it is plausible that the UTSA impedes spillover driven economic growth. To justify such a strong trade secrets protection in US, policymakers should consider other benefits (legal legitimacy, global competition, and antitrust) provided by trade secrets laws to balance their potential harm to economic growth.

Finally, this paper can uncover potential venues for future research several mediation analyses. First, the focal firm may have R&D centers outside its headquarters location, so that technology spillovers may be influenced by the contamination effect in the R&D centers' states. Second, covenants not to compete (CNCs) could shape the effect of the UTSA on spillovers. Although employee movement serves as a major channel of technology spillovers, firms may avoid hiring their peers because of CNCs, which are related to state laws status and are heterogeneous among states (Marx, Singh, and Fleming, 2015). Third, the impact of peers' patents could be vital, in particular Glaeser (2018) suggest that trade secrets laws that in part substitute for filing patents to increase the degree of R&D appropriability lead to lower patenting rates of firms. All these future research plans enable us to learn more about the impact of the trade secret legal protection on the technology spillovers and its heterogeneous effects.

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Appendix Table A1.

Uniform Trade Secrets Act of Each State and Enactment Years

State	Year	State	Year
Alabama	1987	New Jersey	2012
Alaska	1988	New Mexico	1989
Arizona	1990	North Carolina	1981
Arkansas	1981	North Dakota	1983
California	1985	Ohio	1994
Colorado	1986	Oklahoma	1986
Connecticut	1983	Oregon	1988
Delaware	1982	Pennsylvania	2004
Florida	1988	Rhode Island	1986
Georgia	1990	South Carolina	1992
Hawaii	1989	South Dakota	1988
Idaho	1981	Tennessee	2000
Illinois	1988	Texas	2013
Indiana	1982	Utah	1989
Iowa	1990	Vermont	1996
Kansas	1981	Virginia	1986
Kentucky	1990	Washington	1982
Louisiana	1981	Washington D.C.	1989
Maine	1987	West Virginia	1986
Maryland	1989	Wisconsin	1986
Michigan	1998	Wyoming	2006
Minnesota	1980		
Mississippi	1990		
Missouri	1995		
Montana	1985		
Nebraska	1988		
Nevada	1987		
New Hampshire	1990		

Appendix Table A2.
Variable Definitions

Variable	Definition
The number of patents	The number of patents that a firm applied for at the U.S. Patent and Trademark Office.
R&D-to-PPE ratio	The ratio of R&D expenditures (*R&D*) divided by PPE.
Spillover pool	The spillover pool of Jaffe (1986), which is equal to $\sum_{j\neq i} w_{ij} CRD_j$, where w_{ij} is technological proximity as an uncentered correlation coefficient of innovation activities of focal firm *i* and peer firm *j*: $$S_i S_j' / (S_i S_i')^{0.5} (S_j S_j')^{0.5}.$$ $S_i = (S_{i,1}, \ldots, S_{i,p})$ is a vector of innovation activity in technology classification *p* for firm *i*. *p* refers to 3-digit International Patent Classification (IPC) code, and innovation activity refers to the number of patents that a firm applied for at the USPTO. Namely, $S_{i,p}$ is the number of patents that firm *i* applied (eventually granted) in IPC code *p* in a given year. *CRD* is firm R&D capital measured as in Chan, Lakonishok and Sougiannis (2001), which is equal to $$CRD_{it} = R\&D_{it} + 0.8R\&D_{it-1} + 0.6R\&D_{it-2} + 0.4R\&D_{it-3} + 0.2R\&D_{it-4}.$$ This equation assumes that the productivity of each dollar of R&D spending declines linearly by 20 percent per year. The spillover pool is in million dollars.
Spillover pool from UTSA states	The spillover pool related to firms located in states that adopt the UTSA, which is equal to $\sum_{j\neq i, j\in UTSA} w_{ij} CRD_j$, where w_{ij} is technological proximity as an uncentered correlation coefficient of innovation activities of two firms, focal firm *i* and peer firm *j*, where firm *j* is located in states that adopt the UTSA. *CRD* is firm R&D capital measured following Chan, Lakonishok, and Sougiannis (2001). The spillover pool from UTSA states is in millions of dollars.
Spillover pool from non-UTSA states	The spillover pool related to firms located in states that do not adopt the UTSA, which is equal to $\sum_{j\neq i, j\in non-UTSA} w_{ij} CRD_j$, where w_{ij} is technological proximity as an uncentered correlation coefficient of innovation activities of two firms, focal firm *i* and peer firm *j*, where firm *j* is located in states that do not adopt the UTSA. *CRD* is firm R&D capital measured following Chan, Lakonishok, and Sougiannis (2001). The spillover pool from non-UTSA states is in millions of dollars.
UTSA dummy	A dummy variable, which is equal to one for focal firms located in states that adopt the UTSA; zero otherwise.
R&D expenditures	Research and development expenditures, in million dollars.
Sales	Sales and revenues, in million dollars.
Employees	The number of employees, in thousand dollars.
PPE	Property, plant and equipment (net value), in million dollars.
SG&A expenditures	Selling, general and administrative expenditures, in million dollars.
Cost of goods sold	Cost of goods sold, in million dollars.
Capital-to-employee ratio	The ratio of PPE divided by employees
Bid-ask spread	Bid-ask spread is measured as $2 \times \left\lvert \text{price} - \frac{\text{bid+ask}}{2} \right\rvert / (\text{price in last December end})$, where the bid and the ask are bid and ask quotes from the CRSP database.
Inventors	The number of inventors who have ever filed patents.
Profit	The earnings before interest, taxes, depreciation, and amortization (EBITDA) in million dollars.
Tobin's Q	Measured as the market value of common equity plus short-term and long-term debts, divided by book assets.

Appendix Table A3.

Example of Questcor Pharmaceuticals, Inc. in Constructing Spillover Pool from UTSA States

Permanent number of the peer *j*	Proximity against Questcor Pharmaceuticals (w_{ij})	State of the peer *j*	R&D capital of the peer *j* (CRD_j)	$w_{ij}CRD_j$	Spillover pool from UTSA states of Questcor Pharmaceuticals $\sum_{j\neq i, j\in UTSA} w_{ij}CRD_j$.
78051	1.0000	CA	0.548	0.548	
79703	1.0000	CA	1.397	1.397	
79794	0.9487	CA	65.504	62.143	
60090	0.7071	CA	60.427	42.728	
76716	0.7071	CA	36.563	25.854	
83756	0.7071	CA	:	:	
85187	0.1400	CO	17.042	2.386	
76000	0.7675	CT	24.042	18.453	
79906	0.3015	DE	:	:	
:	:	:	:	:	
					0.548 + 1.397 + 62.143 + … = 16797.51

Appendix Table A4.

Regression Analysis of Patents, Profit, and Tobin's Q

Indep. var.	Model 1 Dep. var.: Log(number of patents)	Model 2 Dep. var.: Log(number of patents)	Model 3 Dep. var.: Log(profit)	Model 4 Dep. var.: Log(profit)	Model 5 Dep. var.: Log(Tobin's Q)	Model 6 Dep. var.: Log(Tobin's Q)
Log(spillover pool)	0.0876		0.0148		0.0202	
	(0.0048)		(0.0043)		(0.0051)	
Log(spillover pool from UTSA states)		0.0465		0.0060		0.0061
--- (A)		(0.0061)		(0.0053)		(0.0065)
Log(spillover pool from non-UTSA states)		0.0632		0.0174		0.0242
--- (B)		(0.0056)		(0.0048)		(0.0060)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Year and industry joint fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
R-sq	0.5225	0.5246	0.9076	0.9077	0.6141	0.6144
N	27,613	27,613	27,613	27,613	27,613	27,613
Coefficients differences between (A) and (B)		-0.0168		-0.0114		-0.0182
F-statistics of testing coefficients differences		33.9095		45.4005		91.2154
P-value		[0.0000]		[0.0000]		[0.0000]

Note: This table presents regression analysis for the number of patents, profit and Tobin's Q. The dependent variable in Models 1 and 2 is the logarithm of *the number of patents*. The dependent variable in Models 3 and 4 is the logarithm of *profit*. The dependent variable in Models 5 and 6 is the logarithm of *Tobin's Q*. Variable definitions are described in the Appendix Table A2. Year and industry (upon 2-digit SIC codes) joint fixed effects are included but not presented. Coefficient differences between *log(spillover pool from UTSA states)* and *log(spillover pool from non-UTSA states)* and corresponding F-statistics are presented at the bottom of the table. Numbers in the parentheses are robust standard errors clustered at firm level. Numbers in brackets are the *p*-values of the F-statistics.

Table 1.

Summary Statistics

Panel A: Summary statistics

	Mean	STD	P5	P10	P25	Median	P75	P90	P95
Number of patents	21.74	96.11	1.00	1.00	1.00	3.00	11.00	39.00	81.00
Profit	494	2,701	-29	-13	1	22	152	741	1,878
Tobin's Q	45.88	484.41	1.36	1.86	3.39	8.20	23.84	66.32	124.69
Spillover pool	8,998	21,113	0	0	0	100	5,200	31,073	60,370
Spillover pool from UTSA states	5,688	14175	0	0	0	11	2823	19,157	37,045
spillover pool from non-UTSA states	3,309	10,813	0	0	0	6	1,163	7,525	13,813
UTSA dummy	0.60	0.49	0.00	0.00	0.00	1.00	1.00	1.00	1.00
R&D expenditures	104	508	0	0	1	9	41	154	365
Sales	2,795	13,548	8	16	52	216	1,128	5,089	11,545
Employees	11	54	0	0	0	1	6	24	48
PPE	917	4,875	1	2	8	39	248	1,302	3,201
R&D-to-PPE ratio	2.33	27.87	0.00	0.00	0.04	0.23	1.11	3.34	6.16
Capital-to-employee ratio (‰)	79.52	499.35	6.93	9.98	17.13	30.39	59.61	123.88	212.06
Bid-ask spread	0.10	0.41	0.00	0.01	0.03	0.07	0.14	0.25	0.36

Panel B: Industry distribution

Subperiods \ Two-digit SIC codes	28	35	36	38	73	Others	All
1980s	650	1,078	1,135	630	191	2,796	6,480
	(2.4%)	(3.9%)	(4.1%)	(2.3%)	(0.7%)	(10.1%)	(23.5%)
1990s	1,281	1,271	1,621	1,152	748	3,229	9,302
	(4.6%)	(4.6%)	(5.9%)	(4.2%)	(2.7%)	(11.7%)	(33.7%)
2000s	1,299	949	1,557	1,162	1,045	2,535	8,547
	(4.7%)	(3.4%)	(5.6%)	(4.2%)	(3.8%)	(9.2%)	(31.0%)
2010s (up to 2015)	376	358	537	399	363	1,251	3,284
	(1.4%)	(1.3%)	(1.9%)	(1.4%)	(1.3%)	(4.5%)	(11.9%)
All	3,606	3,656	4,850	3,343	2,347	9,811	27,613
	(13.1%)	(13.2%)	(17.6%)	(12.1%)	(8.5%)	(35.5%)	(100.0%)

Note: This table presents summary statistics (Panel A) and industry distribution upon 2-digit SIC codes (Panel B) of the sample firms between 1980 and 2015. Variable definitions are described in the Appendix Table A2. SIC code 28 includes Chemicals and Allied Products; SIC code 35 includes Industrial and Commercial Machinery and Computer Equipment; SIC code 36 includes Electronic and Other Electrical Equipment and Components, Except Computer Equipment; SIC code 38 includes Measuring, Analyzing, and Controlling Instruments, Photographic, Medical and Optical Goods, Watches and Clocks; SIC code 73 includes Business Services.

Table 2.

Peers Distribution Sorted by Location of Peers

Panel A: Peers with proximity > 0

	Source of spillover	
	UTSA state	non-UTSA state
Focal state of receiving firm	0.1489	0.0165
	[138,899]	[15,399]
Other states	0.5597	0.2749
	[522,125]	[256,448]

Panel B: Peers with proximity ≥ 0.05

	Source of spillover	
	UTSA state	non-UTSA state
Focal state of receiving firm	0.1486	0.0166
	[134,408]	[15,026]
Other states	0.5603	0.2745
	[506,912]	[248,334]

Panel C: Peers with proximity ≥ 0.1

	Source of spillover	
	UTSA state	non-UTSA state
Focal state of receiving firm	0.1483	0.0167
	[129,003]	[14,547]
Other states	0.5613	0.2737
	[488,267]	[238,038]

Panel D: Peers with proximity ≥ 0.25

	Source of spillover	
	UTSA state	non-UTSA state
Focal state of receiving firm	0.1667	0.0188
	[129,003]	[14,547]
Other states	0.6309	0.3076
	[488,267]	[238,038]

Note: This table presents where spillover may come from by identifying the location of peers. Panel A presents the percentage of peers located in focal firm's state or in other states, and located in states adopting the UTSA or in states not adopting the UTSA, where peers are included when their proximities are greater than zero. Panel B presents percentage of peers located in the focal firm's state or in other states, and located in states adopting the UTSA or in states not adopting the UTSA, where peers are included when their proximities are greater than or equal to 0.05. Panel C presents the percentage of peers located in the focal firm's state or in other states, and located in states adopting the UTSA or in states not adopting the UTSA, where peers are included when their proximities are greater than or equal to 0.1. Panel D presents the percentage of peers located in focal firm's state or in other states, and located in states adopting the UTSA or in states not adopting the UTSA, where peers are included when their proximities are greater than or equal to 0.25. Numbers in the brackets are firm-year observations of peers.

Table 3.

Regression Analysis of Patents and R&D Intensity

Indep. var.	Model 1 Dep. var.: Log(number of patents)	Model 2 Dep. var.: Log(number of patents)	Model 3 Dep. var.: R&D-to-PPE ratio	Model 4 Dep. var.: R&D-to-PPE ratio
Intercept	0.3737	0.3889	0.1774	0.1798
	(0.9994)	(0.9973)	(0.1607)	(0.1606)
Log(spillover pool)	0.0876		0.0067	
	(0.0048)		(0.0008)	
Log(spillover pool from UTSA states)		0.0465		0.0029
--- (A)		(0.0061)		(0.0010)
Log(spillover pool from non-UTSA states)		0.0632		0.0059
--- (B)		(0.0056)		(0.0009)
Log(R&D expenditures)	0.2946	0.2898		
	(0.0068)	(0.0068)		
Log(sales)	0.1613	0.1614	-0.0214	-0.0217
	(0.0061)	(0.0061)	(0.0007)	(0.0007)
R&D-to-PPE ratio	-0.0003	-0.0004		
	(0.0003)	(0.0003)		
Capital-to-employee ratio ($\times 10^{-4}$)			-0.1969	-0.1975
			(0.0562)	(0.0561)
Bid-ask spread			0.0136	0.0133
			(0.0034)	(0.0034)
Year and industry joint fixed effects	Yes	Yes	Yes	Yes
R-sq	0.5225	0.5246	0.9076	0.9077
N	27,613	27,613	27,613	27,613
Coefficients differences between (A) and (B)		-0.0168		-0.0031
F-statistics of testing coefficients differences		33.9095		64.6268
P-value		[0.0000]		[0.0000]

Note: This table presents regression analysis for the number of patents and R&D intensity. The dependent variable in Models 1 and 2 is the logarithm of *the number of patents*. The dependent variable in Models 3 and 4 is the *R&D-to-PPE ratio*. Variable definitions are described in the Appendix Table A2. Year and industry (upon 2-digit SIC codes) joint fixed effects are included but not presented. Coefficient differences between *log(spillover pool from UTSA states)* and *log(spillover pool from non-UTSA states)* and corresponding F-statistics are presented at the bottom of the table. Numbers in the parentheses are robust standard errors clustered at firm level. Numbers in brackets are the *p*-values of the F-statistics.

Table 4.
Regression Analysis of Patents and R&D Intensity- Instrumental Variable Approach

Indep. var.	Model 1 Dep. var.: Log(number of patents)	Model 2 Dep. var.: Log(number of patents)	Model 3 Dep. var.: R&D-to-PPE ratio	Model 4 Dep. var.: R&D-to-PPE ratio
Log(spillover pool)	0.0876		0.0067	
	(0.0048)		(0.0008)	
Log(spillover pool from UTSA states) --- (A)		0.0225		0.0038
		(0.0103)		(0.0017)
Log(spillover pool from non-UTSA states) --- (B)		0.0690		0.0045
		(0.0083)		(0.0014)
Control variables	Yes	Yes	Yes	Yes
Year and industry joint fixed effects	Yes	Yes	Yes	Yes
R-sq	0.5225	0.5296	0.3424	0.3434
N	27,613	27,613	27,613	27,613
Coefficients differences between (A) and (B)		-0.0465		-0.0008
F-statistics of testing coefficients differences		7.5473		3.4596
P-value		[0.0060]		[0.0629]

Note: This table presents the second-stage results of two-stage least squared regression analysis for the number of patents and R&D intensity. The dependent variable in Models 1 and 2 is the logarithm of *the number of patents*. The dependent variable in Models 3 and 4 is the *R&D-to-PPE ratio*. In the first-stage regression, I estimate spillover pool as $\sum_{j \neq i} w_{ij} \widehat{CRD_j}$, where $\widehat{CRD_j}$ is the fitted R&D capital from regression R&D expenditures on size, book-to-market ratio, cash ratio and an instrumental variable of influential congressional chairmanship dummy. Variable definitions are described in the Appendix Table A2. Year and industry (upon 2-digit SIC codes) joint fixed effects are included but not presented. Coefficient differences between *log(spillover pool from UTSA states)* and *log(spillover pool from non-UTSA states)* and corresponding F-statistics are presented at the bottom of the table. Numbers in the parentheses are robust standard errors clustered at firm level. Numbers in brackets are the *p*-values of the F-statistics.

Table 5.
Regression Analysis for Migrated Inventors

Indep. var.	Model 1 Estimated by linear model	Model 2 Estimated by linear model	Model 3 Estimated by Poisson model	Model 4 Estimated by Poisson model
Intercept	-0.5093	-0.4876	-18.3388	-18.7759
	(1.5315)	(1.0949)	(1390.5087)	(3445.9614)
Log(spillover pool from UTSA states) --- (A)	-0.0366	-0.0148	-0.0342	-0.0234
	(0.0085)	(0.0057)	(0.0068)	(0.0071)
Log(spillover pool from non-UTSA states) --- (B)	0.0140	-0.0078	0.0034	0.0206
	(0.0079)	(0.0057)	(0.0061)	(0.0063)
Log(inventors)	0.8223	0.8169	1.0283	1.0516
	(0.0124)	(0.0105)	(0.0127)	(0.0127)
R&D-to-PPE ratio	0.0010	0.0007	-0.0246	-0.0015
	(0.0006)	(0.0004)	(0.0083)	(0.0037)
Log(PPE)	0.0404	0.0185	0.0154	0.0658
	(0.0195)	(0.0124)	(0.0208)	(0.0167)
Log(employees)	0.0602	0.0527	-0.1339	-0.1440
	(0.0230)	(0.0149)	(0.0234)	(0.0203)
Year and industry joint fixed effects	Yes	No	Yes	No
Year and state joint fixed effects	No	Yes	No	Yes
R-sq	0.2545	0.2609		
-2log likelihood			4156.5476	4588.3388
N	27,613	27,613	27,613	27,613
Coefficients differences between (A) and (B)	-0.0505	-0.0070	-0.0376	-0.0440
F-statistics of testing coefficients differences	64.6268	98.4034	5.1093	436.9005
P-value	[0.0000]	[0.0000]	[0.0000]	[0.0000]

Note: This table presents regression analysis for migrated inventors. The dependent variable is the number of inventors migrating from peers to the focal firm in a given year. Variable definitions are described in the Appendix Table A2. Year and industry (upon 2-digit SIC codes) joint fixed effects, or year and state joint fixed effects are included but not presented. Models 1 and 2 use linear regression model. Models 3 and 4 use Poisson model. Coefficients differences between *log(spillover pool from UTSA states)* and *log(spillover pool from non-UTSA states)* and corresponding F-statistics are presented in the bottom of the table. Numbers in the parentheses are robust standard errors clustered at firm level. Numbers in the brackets are the *p*-values of the F-statistics.

Table 6.
Regression Analysis for Patents-Location of Focal Firms

Ind. var.	Model 1 Using focal firms in UTSA states	Model 2 Using focal firms in non-UTSA states	Model 3 Using focal firms in UTSA states	Model 4 Using focal firms in non-UTSA states
Intercept	-0.9464	0.6000	-0.8412	0.6117
	(1.0023)	(0.9415)	(1.0009)	(0.9373)
Log(spillover pool)	0.0787	0.0858		
	(0.0064)	(0.0078)		
Log(spillover pool from UTSA states)			0.0337	0.0435
			(0.0088)	(0.0107)
Log(spillover pool from non-UTSA states)			0.0610	0.0761
			(0.0085)	(0.0091)
Log(R&D expenditures)	0.3387	0.2338	0.3325	0.2319
	(0.0092)	(0.0113)	(0.0092)	(0.0113)
Log(sales)	0.1738	0.1582	0.1740	0.1575
	(0.0082)	(0.0101)	(0.0082)	(0.0101)
R&D-to-PPE ratio	-0.0007	-0.0001	-0.0008	-0.0001
	(0.0004)	(0.0003)	(0.0004)	(0.0003)
Year and industry joint fixed effects	Yes	Yes	Yes	Yes
R-sq	0.5514	0.6257	0.5530	0.6291
N	16,507	11,106	16507	11106

Note: This table presents regression analysis for the number of patents. The dependent variable is the logarithm of *the number of patents*. Variable definitions are described in the Appendix Table A2. Models 1 and 3 include the focal firms that are headquartered in states adopting the UTSA. Models 2 and 4 include the focal firms that are headquartered in states not adopting the UTSA. Year and industry (upon 2-digit SIC codes) joint fixed effects are included but not presented. Numbers in the parentheses are robust standard errors clustered at firm level.

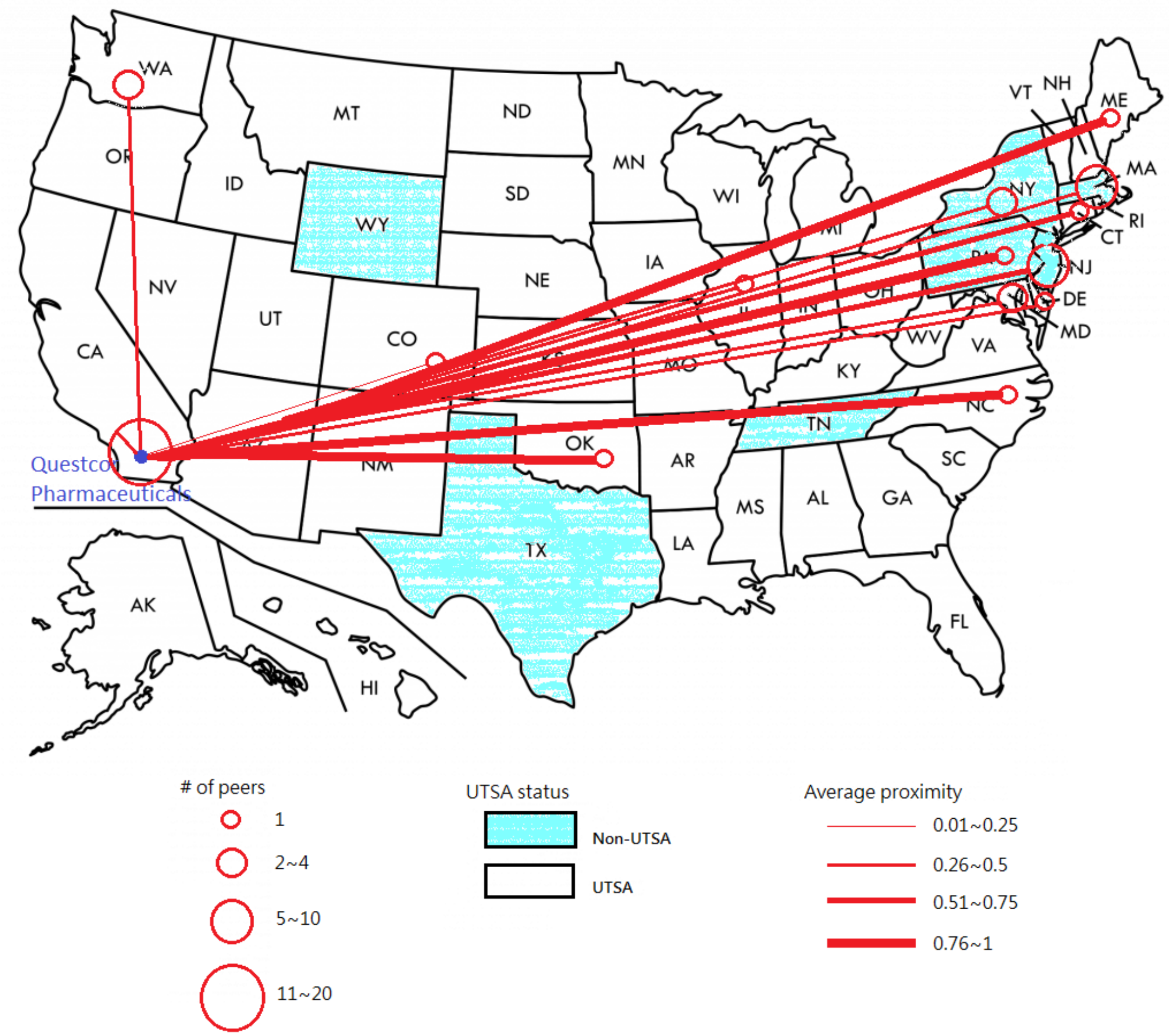

Figure 1.

Questor Pharmaceuticals and Locations of Its Peers with Positive Proximity

This figure presents the location of Questor Pharmaceuticals, Inc. and locations of its peers that had positive proximity against Questor Pharmaceuticals, Inc in 1999. The circle indicates the number of peers in each state. States *not* adopting the UTSA are highlighted with shadow. Red line represents the average of proximities of peers in each state, different fineness of lines corresponds to different level of average proximity.