Knowledge Protection and Modularity of Innovation Activities in Firms: Evidence from U.S. Trade Secrecy Law

ABSTRACT

Strategy scholars have theoretically explored the relationship between knowledge protection and modularity of innovation activities in firms, but this relationship has yet to be empirically tested in the literature. Leveraging state-level staggered changes in U.S. trade secrecy law and using a network modularity measure, this paper examines how trade secret protection affects the modularity of inventor collaborations in firms. Analyzing intrafirm collaboration patterns in U.S. patent data from 1,022 high-tech firms between 1976 and 2017, we find that increased trade secret protection is negatively associated with the modularity of inventor collaborations within firms. This effect is more pronounced for firms with superior technologies and those geographically collocated with competitors—factors that enhance firms' knowledge-spillover concerns—and less pronounced for firms in industries where alternative appropriability mechanisms are highly effective. Moreover, our findings suggest that the increased betweenness centrality of new hires (skilled and junior) serves as an important underlying mechanism for the treatment effect. These results contribute to the literature by illuminating how firms strategize their internal innovation activities for knowledge protection and by underscoring its underlying mechanism.

Keywords: innovation, modularity, inventor collaboration, knowledge protection, trade secrecy law, human capital, difference-in-differences

INTRODUCTION

Strategy and organization scholars have long recognized the relationship between knowledge protection and modularity of innovation activities in firms (Baldwin & Henkel, 2015; Liebeskind, 1997; Rønde, 2001). Protecting a firm's proprietary knowledge can be extremely challenging if employees have unrestricted access to it. Accordingly, firms may be incentivized to increase organizational separation among employees so that individual employees possess only a limited fraction of the firm's knowledge (Liebeskind, 1997; Seo & Somaya, 2022; Rønde, 2001). Modularity—a design approach that creates a high degree of independence between the components of a system (Sanchez & Mahoney, 1996)—can serve as an effective organizational mechanism for this purpose. According to this perspective, therefore, firms may intentionally modularize their innovation activities within the organization, particularly when their proprietary knowledge is weakly protected by law (Rønde, 2001).

Although the significant role of modularity in knowledge protection has been explored theoretically, it has yet to be empirically tested. A critical question, therefore, remains: *Do firms reduce the modularity of their innovation activities when legal protections for their proprietary knowledge are strengthened?* Answering this question is not straightforward because modularity also provides technical and organizational benefits to firms. Modularity enables firms to leverage the division of labor, reduce coordination costs, and enhance strategic flexibility and adaptability (Baldwin & Clark, 2000; Chandler, 1962; Helfat & Eisenhardt, 2004). Given the 'power of modularity' in value creation, it is *not* theoretically clear whether stronger legal knowledge protections would result in reduced modularity of innovation activities within firms. It is entirely possible that firms may continue to maintain high modularity even under stronger legal knowledge protections if the reduced benefits of modularity in knowledge protection do not outweigh its advantages in knowledge production, which indicates that firms' knowledge production and protection processes are largely independent. On the other hand, if stronger knowledge protections significantly reduce the modularity of innovation activities in firms, it would have significant implications for the literature, suggesting that a potential trade-off could exist between knowledge production and protection mechanisms in firms.

To fill this gap in the literature, this paper empirically examines the relationship between knowledge protection and the modularity of innovation activities in firms. However, conducting this empirical examination presents significant challenges. First, empirically analyzing knowledge protection of firms is difficult (Contigiani et al., 2018; Png, 2017). Although patent citations are often used as a proxy for knowledge spillovers, they also reflect the technological quality of inventions, thus making it challenging to disentangle the effects of knowledge protection from those of knowledge production when using patent citation measures. Furthermore, quantifying the modularity of a firm's innovation activities is also challenging (Hoetker, 2006; Worren et al., 2002). It requires assessing the degree of interactions both within and across internal innovation communities in firms, which is often hard to achieve using secondary, observable data.

In this paper, we employ several empirical strategies to address these challenges. First, we exploit the legal changes in trade secret protection in the United States—a significant legal safeguard for firms' proprietary knowledge. Trade secret protection has changed significantly across the states at different times, largely due to the enactment of legislation based on the Uniform Trade Secrets Act (UTSA). These staggered state-level changes provide quasi-exogenous variations in knowledge protections of U.S. firms. Utilizing these variations, we empirically investigate how the innovation activities of firms are affected by their ability to protect their proprietary knowledge. To implement this analysis, we construct a state-level trade secrecy index updated through 2017, extending the prior work of Png (2017).

Second, to empirically assess the structural properties of innovation activities in firms, we utilize a network modularity measure developed in statistical physics (Clauset et al., 2004). This method is designed to identify and quantify the community structure—"the division of network nodes into groups where connections are dense within the groups but sparse between them" (Clauset et al., 2004, p. 69)—of large-scale networks, such as scientist collaborations, using a greedy optimization algorithm. Employing this approach, we quantify the degree of modularity in inventor collaborations within firms and examine the impact of trade secret protection on this structural property.

Specifically, we analyze inventor collaboration patterns in U.S. patent data from 1,022 high-tech firms between 1976 and 2017. Our regression analyses demonstrate that stronger trade secret protection significantly reduces the modularity of inventor collaborations within firms. Further corroborating the role of modularity for knowledge protection, this treatment effect is more pronounced for firms with superior technology and those geographically collocated with competitors—factors that enhance knowledge protection risks—and less pronounced for firms in industries where alternative appropriability mechanisms are highly effective. Moreover, we find that higher trade secret protection increases the betweenness centrality of skilled hires and junior hires, who are generally less socialized and thus do not typically take a central position connecting internal innovation communities. These results provide valuable insights into the underlying mechanism connecting knowledge protection and the modularity of innovation activities in firms.

Our findings make important contributions to the strategy and organization literature. Specifically, by highlighting the impact of knowledge protection on how firms organize innovation activities within the organization, our research provides novel insights into the origin of firms' capabilities to integrate diverse knowledge inputs within the organization for innovation (Carnabuci & Operti, 2013; Grant, 1996; Henderson & Clark, 1990; Kogut & Zander, 1992).

THEORETICAL BACKGROUND

Building on Simon's (1962) concept of *a nearly decomposable system*, modularity refers to a special form of design which intentionally creates a high degree of independence or 'loose coupling' between components (or divisions) of the system (Sanchez & Mahoney, 1996). This approach provides many technical and organizational benefits for value creation in firms. As Sanchez and Mahoney (1996) point out, for example, modularity can improve the productivity of new product development processes of firms. In tightly integrated, less modularized systems, changes to one component necessitate significant adjustments in many others, which require extensive managerial coordination efforts. In contrast, modularization enables firms to streamline their new product development processes and enhance overall efficiency by reducing coordination costs within the system (Baldwin & Clark, 2000).

Moreover, a loosely coupled system tends to be more flexible and adaptable to environmental changes (Chandler, 1962; Helfat & Eisenhardt, 2004). Because modifications to one component do not necessarily require changes in others, firms can change their components more quickly and frequently, incurring lower organizational costs when the system is more modularized. Therefore, in a turbulent environment marked by rapid changes in markets, technologies, or regulations, modularized new product development processes likely outperform tightly integrated ones. These technical and organizational benefits can encourage firms to modularize their innovation activities by partitioning them into *internal innovation communities*, each of which is largely independent and loosely interacts with the others to support the whole innovation system.

However, modularized innovation systems are not without downsides for value creation. A critical drawback of this structural decomposition is that it may undermine firms' innovation capabilities by hindering knowledge integration within organizations (Grant, 1996). Viewing innovation as a process of knowledge recombination, prior research emphasizes that impactful innovations are generated by integrating diverse knowledge inputs across different technological domains (Fleming, 2001; Rosenkopf & Nerkar, 2001). From this perspective, firms may lose innovation opportunities when their innovation activities are highly decomposed, thus constraining intensive interactions and information exchange across internal innovation communities. Accordingly, the modularization of firms' innovation activities is likely to be achieved only to the extent that the benefits and costs are balanced to enhance overall innovation performance.

In addition to its roles in value creation (or knowledge production), strategy and organization scholars have also theoretically explored the significant role of modularity for value appropriation (or knowledge protection) for firms (Baldwin & Henkel, 2015; Liebeskind, 1997; Rønde, 2001). A significant component of a firm's proprietary knowledge consists of tacit information or knowhow in innovation processes; as a result, interfirm knowledge spillovers tend to occur through social interactions across firm boundaries (Saxenian, 1996; Sorenson et al., 2006). Hiring knowledge workers (e.g., scientists, engineers) is thus arguably one of the most effective channels for a firm to acquire knowledge from other firms

(Song et al., 2003; Singh & Agrawal, 2011). Research also suggests that interfirm collaborative interactions, such as joint product development alliances, can be a critical source of interfirm knowledge spillovers (Hernández et al., 2015; Mowery et al., 1996; Rosenkopf & Almeida, 2003).

When a firm faces significant threats of interfirm knowledge spillovers, it may be a reasonable strategy to restrict employees' access to the firm's proprietary knowledge (Baldwin & Henkel, 2015; Liebeskind, 1997; Rønde, 2001; Seo & Somaya, 2022).[1] If employees hold only a partial fraction of the firm-level knowledge, interfirm knowledge spillovers may be less severe, even when employees interact across firm boundaries. Firms can achieve this goal by modularizing their innovation activities within the organization. For instance, scientists in an R&D division may be effectively prevented from interacting with employees in other divisions simply because the organizational structure does not facilitate such interactions across divisions (Liebeskind, 1997). From this perspective, firms' innovation activities may be *more* modularized within the organization when their proprietary knowledge is weakly protected by law (Rønde, 2001).

A key anecdotal example is the Manhattan Project during World War II. To prevent the enemy from learning the overall picture of the project during the development of nuclear weapons, military officers enforced strict compartmentalization, severely limiting interaction across development units. In his memoir, General Leslie M. Groves (1983), the military director who oversaw all aspects of the Manhattan Project, stated that "this system of compartmentalization had two principal advantages. The most obvious of these was that it simplified the maintenance of security" (p. 454). As a result, scientists often had no idea what their colleagues down the hall were working on, which led to significant coordination challenges. Accustomed to the free exchange of ideas, many scientists criticized this policy.

[1] In the innovation context of this paper, we focus on knowledge that can generate economic value in a firm's R&D process, such as information about product specifications and technical details of product development processes. Other types of firm secrets, with which R&D employees have limited knowledge or interaction (e.g., customer lists, input costs), are excluded from this discussion. This is consistent with our empirical measurement of modularity based on inventor collaborations documented in U.S. patents.

For example, J. Robert Oppenheimer, the Director of the Los Alamos Laboratory, insisted that weekly scientific colloquia and other forms of open communication were essential to solving complex problems. Due to security concerns, however, such openness was restricted to the top echelon of scientists at Las Alamos, and the compartmentalization policy was rigorously enforced throughout the project (Atomic Heritage Foundation, 2014).

However, the theoretical relationship between modularity and knowledge protection still remains ambiguous. Even if strengthened legal protection mechanisms reduce the need for modularization for the purpose of knowledge protection, as theoretically explored above, firms may still maintain high modularity under strengthened knowledge protection laws due to the technical and organizational benefits of modularity (e.g., reduced coordination costs). In other words, it is entirely possible that firms may modularize their innovation activities for the purpose of knowledge protection only to the extent they do not exceed the optimal level for value creation. If their modularization level is not currently suboptimal for value creation, increased legal knowledge protection may not necessarily reduce the modularity of innovation activities in firms.

Furthermore, from the perspective of complexity as a barrier to imitation by competitors, modularity may pose a risk to knowledge protection rather than serve as a protective mechanism. To replicate a highly integrated system—where divisions are highly interdependent—imitators must acquire knowledge of the entire system; partial knowledge is insufficient for successful imitation (Ganco, 2013; Rivkin, 2000). In contrast, for a highly modularized system—where divisions operate independently and are only loosely connected—acquiring knowledge of a modularized division may be enough to replicate value-adding work (Ethiraj et al., 2008; Pil & Cohen, 2006). Moreover, in a highly modularized system, architectural knowledge that connects and coordinates different divisions within the organization is often concentrated among a few employees, thus making it more vulnerable to *keystone risk*; that is, the loss of key personnel can significantly disrupt critical organizational assets (Briscoe & Rogan, 2016). From this perspective, firms' innovation activities may be *less* modularized within the organization when their proprietary knowledge is weakly protected by law. If this is the case, stronger legal protection of knowledge would actually encourage greater modularity in firms' innovation activities, rather than reduce it.

Despite the significant strategic implications of modularity for knowledge protection, the current literature lacks empirical investigation into this relationship. Arguably, this is largely due to challenges in measuring and quantifying these variables. Addressing these empirical challenges, this paper seeks to examine this open question empirically. Specifically, we investigate how trade secret protection—a critical safeguard for firms' proprietary knowledge—affects the structural patterns of innovation activities in firms. If modularity is significantly employed as a knowledge protection mechanism—particularly at the expense of knowledge integration benefits—we predict that stronger trade secret protection will reduce the modularity of innovation activities in firms.

EMPIRICAL CONTEXT: U.S. TRADE SECRECY LAW

We turn to a discussion of the specific aspects of trade secret law that have changed in the United States over time, which serves as the empirical context for this paper. From a historical standpoint, modern U.S. trade secret law dates from the middle of the 19th century (Denicola, 2011). As the master-apprentice relationship eroded with the arrival of the Industrial Revolution, courts developed a new set of rules to replace the shared responsibilities to guard secret knowledge in the workplace (Fisk, 2001). Known as the "common law," courts established this set of legal rules on a case-by-case basis across the states. In 1939, a group of legal experts collected the general principles of trade secret law under the common law into a treatise, called the Restatement (First) of Torts. Under the Restatement, a trade secret "consist[s] of any formula, pattern, device or compilation of information which is used in one's business, and which gives him an opportunity to obtain an advantage over competitors who do not know or use it."[2] Although the Restatement set forth the general principles of trade secret law under the common law, this treatise was not binding on courts, and the common-law process of judicial decision-making resulted in significant variation across the states in their levels of trade secret protections. As a result, in 1979, the

[2] Section 757, cmt. b (1939).

National Commission on Uniform State Laws promulgated model legislation called the Uniform Trade Secrets Act (UTSA) and issued an amended version of the UTSA in 1985. Since that time, legislatures in every state except New York have now enacted the UTSA into their state statutory law (Menell et al., 2025)—either exactly as written or with some modifications.[3]

Overall, the UTSA provides stronger trade secret protections over the common law set forth in the Restatement in at least three important ways. First, the UTSA abandoned the requirement of continuous use of a trade secret in one's business. 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] Stated differently, a "trade secret" under the UTSA consists of any information (1) that is "secret," (2) that has "independent economic value" that results from its secrecy, and (3) that is subject to "reasonable efforts" to keep it secret (Rowe & Sandeen, 2015). While trade secret protection can be lost through independent development, reverse engineering, or public disclosure, the UTSA now has a broader scope of protection than the Restatement in its definition of a "trade secret." In addition to protecting more traditional forms of trade secrets like technical information, processes, and methods, the UTSA's expanded definition of a "trade secret" encompasses "negative information" about what works or does not work well. Thus, unlike the Restatement, the results of failed R&D projects are protected under the UTSA. Second, the types of prohibited action, known as "misappropriation," are expanded under the UTSA. While the Restatement prohibited wrongful use or disclosure of a trade secret, the UTSA expands the types of misappropriation to explicitly include mere wrongful *acquisition*. Thus, simply acquiring a trade secret through means like theft, bribery, espionage, or inducement of a breach of a duty to maintain

[3] Some states' adoption of the UTSA with modifications helps to explain why there is some variation across the states in their post-UTSA scores for our main independent variable below.

[4] Unif. Trade Secrets Act § 1(4) (Unif. L. Comm'n 1985).

secrecy is prohibited under the UTSA. Lastly, the UTSA retains remedies that were historically available under the common law, such as monetary damages to compensate a trade secret owner for misappropriation and court orders, known as "injunctions," that prohibit the use or disclosure of a misappropriated trade secret. However, the UTSA also specifically includes the availability of punitive monetary damages in the amount of twice the amount of compensatory monetary damages. These punitive damages are additional damages that a court can award to the trade secret owner in cases where there is willful and malicious misappropriation (Sandeen & Rowe, 2018).

Figure 1 present the enactment of the UTSA across the states through 2017. Leveraging these staggered state-level changes in U.S. trade secret law, we empirically examine how strengthened legal knowledge protection affects inventor collaboration patterns within firms.

[Insert Figure 1 about here]

METHODS

Data and Sample

Following prior research (e.g., Guler & Nerkar, 2012; Paruchuri, 2010), we empirically investigate the structural patterns of innovation activities in firms by analyzing intrafirm inventor collaboration observed in U.S. patent data. Since U.S. patent law mandates that all individuals who contributed to an invention be listed as inventors on the patent application, we can objectively measure and evaluate how individual inventors collaborate within firms by examining patent documents. Recent advancements in name disambiguation algorithms have further improved the precision of identifying inventors listed in patent documents.

It is important to note that this patent-based measure of inventor collaboration may not effectively capture collaborative activities in unpatented inventions. Although increased trade secret protection may decrease firms' incentives to patent their inventions (Png, 2017), this possibility would not introduce significant bias into our estimations, given that changes in collaboration patterns for unpatented inventions, influenced by changes in trade secrecy law, may not systematically differ from those in collaboration patterns for patented inventions. Nevertheless, to isolate the effect of trade secret protection on innovation activities in firms, we also control for potential confounding effects arising from decreased patenting incentives by conditioning on the number of patents and inventors of firms.

Furthermore, prior research documents that patents and secrecy can function as complements, often combined to protect a single invention (Arundel, 2001; Hall et al., 2014). As Arora (1997) points out, firms' innovation outputs tend to include both tacit and explicit elements, with explicit components typically protected through patents and tacit components through secrecy. Graham (2004) demonstrates that patents and secrecy can be used to protect the same invention at different stages, allowing firms to delay the revelation of information by keeping the codified part of an invention secret while preserving the option to use patent protection later. Corroborating the results of a 2018 survey conducted by the U.S. Census Bureau and the National Center for Science and Engineering Statistics that found that U.S. companies that perform or fund R&D ranked trade secrets as more important than any other type of intellectual property, legal cases demonstrate that firms indeed utilize trade secret law to protect information developed in the R&D process. Moreover, court opinions show that firms use trade secret law to protect information that serves as a complement to inventions for which they apply for patents. Consistent with these arguments, our sample data show that firms' patenting behavior did not significantly decrease following the enactment of trade secret. Given that patent data offer valuable and otherwise inaccessible information into the nature of innovative intrafirm collaboration across multiple firms and industries over time, we leverage patent data to analyze inventor collaboration patterns within firms.

Our regression sample was constructed by combining several databases. First, data from original utility patents were collected from the PatentView database, which provides unique identifiers of individual inventors and assignees based on name disambiguation algorithms, as well as detailed technical information on granted patents (e.g., application/issue date, patent class, citations). We then collected information on publicly traded high-tech firms in the United States from the COMPUSTAT database, which contains detailed information on firms' locations and financials.[5] These two datasets were matched based on the GVKEY code provided by the Global Corporate Patent Dataset (GCPD). Given that the GCPD provides data on patents granted through 2017, our sample period was constructed between 1976 and 2017. During the period, 3,453 U.S. firms in high-tech industries were matched to 2,082,645 utility patents. Furthermore, to minimize random noise in quantifying the structural patterns of inventor collaboration within firms, we excluded cases with too few inventors or patents. Specifically, we dropped observations for firms that had fewer than 10 unique inventors or fewer than 10 unique patents in our regression sample. Consequently, the final sample used in our regression analyses contains 10,335 firm-year observations from 1,022 firms between 1976 and 2017.

Dependent Variable: Modularity

To measure the modularity of inventor collaboration in firms, we use a network modularity measure developed by Clauset et al. (2004). We first create an inventor collaboration network of each firm at the focal year, in which vertices (i.e., inventors) are connected by undirected edges (i.e., co-patenting ties). Then, in each collaboration network, we identify 'internal innovation communities' using a greedy optimization process. This process begins with each vertex being the sole member of a community, and the two communities whose amalgamation produces the largest increase in the modularity of the network are repeatedly combined until every vertex belongs to a community.[6] The modularity score (Q) is defined as follows:

$$Q = \frac{1}{2m}\sum_{vw}\left[A_{vw} - \frac{k_v k_w}{2m}\right]\delta(c_v, c_w)$$

[5] Following Hecker's (2005) classification, our high-tech industries are defined at the four-digit NAICS level, based on employment rates of technology-oriented workers (e.g., scientists, engineers) from U.S. Bureau of Labor Statistics data. This sample still accounts for a substantial portion of the dataset—70% by firm count (1,022 of 1,546) and 80% by observation count (10,335 of 16,123). We focus on high-tech industries, because they are both innovation-intensive and patent-intensive compared to other industries. However, we also conduct robustness checks including all industries (see the Robustness Checks section).

[6] This algorithm produces good approximations of the global maximum modularity with high computational efficiency, which performs well in both contrived test cases and real-world situations (Clauset et al., 2004). The R package '*igraph*' was used to implement this process.

where m refers to the number of edges (i.e., collaboration ties) in the network, A_{vw} equals 1 if vertices (i.e., inventors) v and w are connected and 0 otherwise, k_v is the degree (i.e., the number of direct ties) of vertex v, and $\delta(c_v, c_w)$ equals 1 if vertices v and w belong to the same internal innovation community and 0 otherwise. Ranging from 0 to 1, this score increases with greater divisions in the network, indicating greater within-community edges compared to between-community edges. Because this measure is calculated as the difference between the fraction of edges that fall within communities and its expected value in the case of a randomized network, its nonzero values represent deviations from randomness. Thus, this modularity score can be interpreted as the probability that two randomly selected inventors are located within the same internal innovation community in the firm.

Our dependent variable, *Modularity*, is operationalized as this modularity score of the firm's inventor collaboration network in the focal year. The average modularity score in our sample is 0.747 (SD=0.190). That said, a one–standard deviation decrease in our dependent variable corresponds to a 19–percentage point reduction in the probability that two randomly selected inventors are located within the same internal innovation community in the firm—an economically substantial effect.

Figure 2 illustrates two examples of inventor collaboration patterns within firms. Panel A depicts the collaboration pattern of inventors at Altera Corporation (1998–2000), while Panel B shows that of inventors at Analog Devices (1998–2000). Although both firms were semiconductor companies operating in similar technological environments, their inventor collaboration patterns differ substantially. Altera Corporation's inventor collaboration was more integrated and less modularized (modularity score = 0.584), whereas Analog Devices' collaboration was less integrated and more modularized (modularity score = 0.867). Notably, Altera Corporation was based in Silicon Valley, California, where trade secret protection is stronger than in Massachusetts, where Analog Devices was located. Although it is just a single-case comparison, we could posit that Altera Corporation may have adopted a less modularized approach due to a stronger legal framework for knowledge protection. We examine this hypothesis more rigorously in our regression analyses.

[Insert Figure 2 about here]

Independent Variable: Trade Secrecy Index

To operationalize the strength of legal protection of trade secrets, we construct our main independent variable, *Trade Secrecy Index*, by extending Png's (2017) work. The sources we used to update the index include recent versions of the main treatise that Png (2017) utilized in creating the original index (Malsberger et al., 2019), as well as court cases, state statutes, and law-related articles. Our *Trade Secrecy Index* spans from 1976–2017, which is the concluding year of the patent data mentioned above. Following Png's (2017) index, *Trade Secrecy Index* is constructed as a simple average of six measures for each state during each year:

1. Whether information must be in actual or intended business use to be protected as a trade secret (= 0 if information must be in actual or intended use, = 1 otherwise);
2. Whether information must be used or disclosed for it to be deemed to have been misappropriated (= 0 if information must be used or disclosed, = 1 if it includes mere improper acquisition or no requirement);
3. Multiple of actual damages available in punitive damages;
4. Whether reasonable efforts are required to maintain secrecy (= 0 if reasonable efforts required, = 1 otherwise);
5. The limitation on the time for the owner to take legal action for misappropriation (known as the "statute of limitations") in number of years; and
6. Whether the length of an injunction is limited to eliminating the advantage from misappropriation (= 0 if yes, = 1 otherwise).

The overall index score is operationalized as the average of the six measures, with each item normalized by its minimum and maximum values to produce a continuous scale ranging from 0 to 1.[7] A higher score therefore represents stronger trade secret protection. Greater scores in the first three measures included in this variable correspond with increases in trade secret protection due to the passage of the UTSA for the reasons explained above. For the latter three measures, these are generally areas in which a particular state might modify the UTSA to provide more or less protection than the UTSA when the state enacts the UTSA into its statutory law, so these three measures capture variation in the state UTSA statutes as enacted. For example, regarding the fourth measure, while most states follow the

[7] For some states, the statute took effect in later months, such as October or November. To account for this issue, for statutes that became effective in July or later, we incorporate the legal changes starting from the following year in constructing the index. Our results remain consistent without this adjustment (not reported due to space constraints).

UTSA's requirement of including "reasonable" efforts in the definition of a "trade secret," Colorado's UTSA statute refers only to "measures" rather than "reasonable measures." Therefore, the language of this statute is arguably more protective of trade secrets because measures that fall below a threshold of "reasonableness" could still be deemed sufficient by a court for information to meet the definition of a "trade secret." Regarding the fifth measure, the UTSA includes a statute of limitations of three years, but Georgia's USTA statute is more protective of trade secrets because its statute of limitations is five years, thus allowing more time for a trade secret owner to file a claim in court for trade secret misappropriation. Relatedly, Alabama's UTSA statute is less protective than the UTSA because it includes a statute of limitations of two years. Finally, the UTSA includes a requirement that the length of an injunction be limited to eliminating the advantage from misappropriation. However, some states, such as Alabama, have been more protective of trade secrets by not including this requirement in the UTSA statute and more broadly simply allowing "[s]uch injunctive . . . relief as may be appropriate," which therefore could allow for perpetual injunctions. As such, our *Trade Secrecy Index* captures nuanced differences across the states in terms of the strength of trade secret protection.

Legal cases demonstrate that firms indeed draw upon the strengthened trade secret laws that our updated *Trade Secrecy Index* measure captures. In line with the more expansive UTSA protections that were not permitted under the common law, companies have relied on trade secret protection for allegations of improper acquisition (rather than simply improper disclosure or use) as well as to protect the results of "negative information" (i.e., failed research attempts). Moreover, as a deterrent to willful and malicious misappropriation, courts in post-UTSA cases have issued large punitive damages awards that would not have been permitted under pre-UTSA law.

Following prior research (e.g., Andreicovici et al., 2025; Seo & Somaya, 2022), we construct our time-varying, state-level index based on the location of corporate headquarters. Empirical evidence suggests that courts most often apply the UTSA law of the headquarters state in trade secret litigation disputes. Andreicovici et al. (2025) analyze published trade secret litigation cases of public firms from 1999 to 2009 and find that in 90% of the cases under state jurisdiction and 80% of the cases under federal jurisdiction, the state UTSA law of the claimant's headquarters was applied. Thus, it is reasonable to posit that in developing their organizational strategy, firms are most likely to take into account the UTSA enactment in their headquarters state. Nonetheless, we also triangulate by constructing average index scores based on R&D locations (proxied by assignee locations in patent documents) and inventors' residences (proxied by inventor locations in patent documents), weighted by the number of patents at each location.

Control Variables

Our regression models include various time-varying control variables at the firm level. Specifically, we include the number of patents as well as the number of inventors in our regression models. As discussed earlier, increased trade secret protection may decrease firms' incentives to patent their inventions (Png, 2017), which could subsequently reduce the number of unique inventors identified in patent documents. Conditioning on these variables helps us isolate the effect of trade secret protection on the structure of inventor collaboration within firms. Additionally, prior research suggests that the geographic scope of invention activities can serve as an effective organizational mechanism for knowledge protection (Alcácer & Zhao, 2012; Kim, 2016). To account for this effect, we include the average value of geographic dispersion of inventors' state/country-level residence in the patents of firms as a control (Seo et al., 2020).[8] *R&D Intensity* (i.e., R&D expenditures scaled by total assets) is included as another firm-level control to rule out potential confounding effects arising from changes in firms' overall innovation efforts. Furthermore, our regression models include *Total Assets* (i.e., the book value of total assets in $100 million USD) to account for the overall firm size effect and *Return on Assets* (i.e., net income or loss scaled by total assets) to control for the effect of firms' profitability. Lastly, we include firm-fixed effects in regression models to account for any time-constant unobserved firm heterogeneities

[8] Geographic dispersion of inventors in patents is measured as follows: $\text{GeographicDispersion}_i = 1 - \sum_l p_{il}^2$, where p_{il} is the proportion of inventors on patent i in state/country-level residence l.

and industry-year-fixed effects to eliminate any industry-sector trends, such as technological uncertainty and industry and product lifecycle, as well as any year-specific shocks in the error term.

Empirical Model

To estimate the effect of trade secret protection on modularity of inventor collaboration in firms, we use ordinary least square regression models with fixed effects, specified as follows:

$$y_{it} = \alpha + \beta\ Index_{st} + \gamma\ \mathbf{X}_{it} + \mu_i + \tau_{jt} + \varepsilon_{it}$$

where i, t, s and j index a firm, year, state, and industry sector (two-digit NAICS), respectively; y_{it} is the dependent variable (*Modularity*), $Index_{st}$ refers to the main independent variable (*Trade Secrecy Index*), $\mathbf{X}_{it}$ is a vector of firm-level control variables, μ_i represents firm-fixed effects, τ_{jt} is industry-year-fixed effects, and ε_{it} is an error term. Notably, including industry-year-fixed effects allows us to compare only firms within the same industry sector and the same year, thereby providing more valid counterfactuals compared to using only year-fixed effects. That is, given a state-level change in trade secret law, our regression models compare firms within the affected state to those in the same industry sector in other states without that change. Thus, in this specification, β effectively captures the main treatment effect of this study (i.e., the impact of trade secret protection on modularity). In all regression models, standard errors are clustered at the state level, addressing potential heteroskedasticity and serial correlations of observations within the same state (Cameron et al., 2011).

RESULTS

Main Regression Results

Table 1 reports the descriptive statistics and correlations of our regression variables. Notably, after the UTSA enactment, the average value of our dependent variable, *Modularity*, declined from 0.772 to 0.734 in our sample, indicating a 5% decrease. The UTSA enactment also more than doubled the sample average of our main independent variable, *Trade Secrecy Index*, increasing it from 0.171 to 0.474.

[Insert Table 1 about here]

Table 2 shows the results of the main regression analyses. In Column 1, the coefficient for *Trade Secrecy Index* is negative and statistically significant (β = -0.074; *p-value* = 0.008). Given that the enactment of the UTSA increased the *Trade Secrecy Index* by 0.430 at the state level in our sample states, this estimate indicates that the legal changes reduced, on average, the probability that two randomly selected inventors within a firm belong to the same internal innovation community by 3.2 percentage points, representing a 4.3% decrease relative to the sample mean of modularity (0.747). Although the estimated effect (i.e., a 3.2 percentage-point change) may seem small at first glance, considering the fact that modularity varies little within firms, it represents a substantial organizational impact. Specifically, given that the within-firm standard deviation of modularity is 0.087, the influence of strengthened trade secret laws accounts for 37% of this within-firm variation, indicating that enhanced trade secret protection significantly adjusts the structure of inventor collaboration that would otherwise change very little.

[Insert Table 2 about here]

As shown in Column 2, the result is consistent with the inclusion of firm-level controls (*p-value* = 0.010). Furthermore, the results are largely consistent when assignee locations or inventor locations are used for the construction of the trade secrecy index (Columns 3 to 6). Corroborating the significant role of modularity for knowledge protection, these results indicate that increased legal knowledge protection can reduce the modularity of innovation activities in firms. As discussed earlier, these findings imply that firms may be incentivized to modularize their innovation activities for the purpose of knowledge protection, even beyond the optimal level for value creation, particularly with respect to the potential for generating high-quality inventions. Consistent results are obtained when modularity is constructed in using a three-year window.

To specifically focus on the effect of the UTSA enactment, we also conducted difference-in-differences (DID) analyses, in which *UTSA Enactment* is a dummy indicator that equals 1 when the state of a firm's headquarters has enacted the UTSA by or in the current year and 0 otherwise. As shown in Table 3, the coefficients for *UTSA Enactment* are negative and statistically significant, with (*p-value* = 0.002) or without controls (*p-value* = 0.003). The estimates indicate that the enactment of the UTSA resulted in a 4.7% decrease relative to the sample mean (0.747). Figure 3 presents event-time plots that illustrate the impact of the UTSA enactment on inventor collaboration patterns within firms. As shown in the plot, prior to the UTSA enactment, both treatment and control group firms followed a common trend in modularity, and there are no statistically significant differences between the groups in the pretreatment years. Additionally, the slopes of the linear year trends between the two groups in the prior 10 years (or 5 years) before enactment do not differ significantly. Following enactment, however, modularity in treatment group firms (with the UTSA) significantly decreased compared to control group firms (without the UTSA). These findings corroborate the claim that firms may be more willing to reduce the modularity of their innovation activities when legal protections of their proprietary information are strengthened. Notably, as shown in the figure, the treatment effect becomes statistically significant (at the 95% confidence level) starting in the second year after the UTSA enactment. This delayed effect is understandable, as firms often require substantial time to adjust their organizational structures and implement changes in response to the law (Burnes, 2000).

[Insert Table 3 and Figure 3 about here]

To check the possibility that our DID results are generated by chance, we performed a set of placebo tests by randomizing the treatment indicator. Specifically, we performed 1,000 randomized treatment analyses without control variables and another 1,000 analyses with the variables included. In our main regression sample, the UTSA was enacted in 40 out of 42 states between 1981 and 2014.[9] For each analysis, therefore, we randomly selected 39 states and independently assigned each a treatment year between 1981 and 2014. Using the corresponding treatment indicator, we re-estimated the DID regression models. The resulting placebo DID coefficients were, on average, close to zero and statistically insignificant (average *t*-statistic = 0.081 without controls and 0.082 with controls). Notably, in each set of 1,000 simulations, no estimate was smaller than our main DID coefficient (-0.035). These results indicate

[9] It is worth noting that nine states were excluded from our regression analyses due to having no observations: Arkansas, Hawaii, Mississippi, North Dakota, New Mexico, South Dakota, Tennessee, Vermont, and Wyoming.

that our primary findings are unlikely to be driven by spurious or arbitrary patterns from data construction or estimation procedures.

In addition, recent research has shown that traditional staggered difference-in-differences analyses with two-way fixed effects (TWFE) may produce misleading estimates, particularly when groups that have already received the treatment are included in the control group (e.g., Callaway & Sant'Anna, 2021). Addressing this issue, we followed Callaway and Sant'Anna's (2021) method in which a regression exclusively uses states that 'never' or have 'not yet' enacted the statute as the comparison group. Consistent with our main findings, the average treatment effect of *UTSA Enactment* was negative and statistically significant (β = -0.040; *p-value* = 0.003).[10]

Robustness Checks

To examine the robustness of our main findings, we performed a number of additional analyses. First, we replicated our regression analyses including observations with smaller networks, specifically those with at least five inventors and five patents. Our findings remained robust with this expanded sample. Second, we performed our regression analyses including non-high-tech industries. The results were robust even with the inclusion of firms that are less innovation-intensive or patent-intensive. Third, we reconstructed our *Trade Secrecy Index* by excluding observations in which there were no identified previous legal cases involving trade secrets for any of the six component measures of the index. Using this alternative measurement, we found consistent results. Lastly, we replicated our analyses using fractional logit regression models. Consistent results were observed with this alternative model specification.

Supplementary Analysis

Several supplementary analyses were performed to examine the impact of trade secret protection on other firm-level technological outcomes. We first examined its influence on the average team size in

[10] This analysis was implemented by using a Stata command, *csdid*. The estimate was calculated using a simple aggregation method. The result remains robust when restricting the comparison group to only the 'never' enacted group (β = -0.036; *p-value* = 0.008).

innovation activities, an important aspect of collaborative innovation in firms (Seo & Somaya, 2022; Toh & Polidoro, 2013). Trade secret protection is not significantly associated with *Invention Team Size* (measured by the number of inventors per patent) (*p-value* = 0.964). This result indicates that our main findings are primarily driven by changes in *who* collaborates *with whom* within firms, not just by changes in project size. That is, increased trade secret protection is likely to foster collaboration between inventors *across* different innovation communities within the organization.

Furthermore, several analyses were performed to examine whether our findings might simply reflect structural changes *outside* of innovation activities caused by the legal change. One plausible scenario is the consolidation of business portfolios. Enhanced trade secret protection might have encouraged firms to concentrate on fewer business or geographic segments to better exploit certain trade secrets. In this case, the reduced modularity of innovation activities might simply be a byproduct of these broader organizational changes. To empirically assess this possibility, we collected data from Compustat Historical Segments and measured the sales proportion of the largest business or geographic segment in each year. The trade secrecy index is not significantly associated with *Largest Business Segment Ratio* (*p-value* = 0.821) or *Largest Geographic Segment Ratio* (*p-value* = 0.489). These results help us rule out the possibility that the reduced modularity of innovation activities in our sample firms is simply a byproduct of business portfolio consolidation following strengthened trade secret protection.

We also examined whether sample firms experienced overall structural centralization after the legal changes. Specifically, we tested the effect of trade secret protection on firms' nonproduction overhead expenses, which are expected to decline when firms become more centralized by eliminating duplicated business activities (Anderson et al., 2003). *Overhead Efficiency*—measured as selling, general, and administrative expenses scaled by total sales—is not significantly associated with the trade secrecy index (*p-value* = 0.297). These additional analyses therefore mitigate concerns about overall structural centralization as an alternative explanation for our main results.

It is also possible that, following enhanced trade secret protection, firms might have added new business activities that are inherently more centralized. To address this issue, we examined whether enhanced trade secret protection increased firms' capital expenditures, which represent investments in long-term assets such as property, plant, equipment, or technology and thus are likely to reflect expansion of business activities. *Capital Expenditure*—measured as capital expenditures scaled by total assets—did not change significantly after legal knowledge protection was strengthened (*p-value* = 0.949). Therefore, the addition of new business activities (particularly those associated with capital expenditures) is unlikely to be a primary driver of our findings.

Lastly, we investigated whether our findings primarily stem from overall knowledge protection per se or from restrictions on interfirm employee mobility related to trade secret protection. Prior research suggests that employer-friendly trade secret protections, such as the adoption of the inevitable disclosure doctrine (IDD), may affect individual inventors' incentives to use patents to signal to the external labor market (Contigiani et al., 2018). To assess this issue, we examined the relationship between IDD adoption and our modularity variable. We find no significant correlation between IDD adoption and modularity (*p-value* = 0.516), suggesting that our findings are driven by overall trade secret protection rather than employee-mobility restrictions.

Heterogeneous Treatment Effects

To further empirically corroborate the perspective of modularity as a knowledge protection mechanism, we examined how our treatment effect differs across firms depending on the factors that enhance firms' knowledge-spillover concerns. Specifically, building upon prior research, we analyzed the moderating effects of two firm-level risk factors: (1) technological superiority and (2) competitor collocations. Firms with particularly superior technologies relative to industry competitors may be more concerned about outward knowledge spillovers than those with weaker technological positions (Barney, 1991; Reed & DeFillippi, 1990). Furthermore, given the localized nature of interfirm knowledge spillovers (Alcácer & Zhao, 2012; Jaffe et al., 1993; Sorenson et al., 2004), firms more closely collocated with competitors are likely to be more concerned about knowledge spillovers than geographically isolated firms.

The first firm-level moderator, *Technological Superiority*, was measured by the number of forward citations the focal firm received from other firms in the focal year, scaled by its average number in its three-digit NAICS code. The second firm-level moderator, *Competitor Collocations*, was calculated as the number of three-digit NAICS competitors conducting R&D with patents within a 50-mile radius of the focal firm's R&D locations. In this measure, R&D activities and locations were determined based on the latitude and longitude coordinates of patent assignee locations of firms. To reduce the impact of extreme outliers, these variables were winsorized at the top 1 percent.

The effect of trade secret protection is significantly moderated by these firm-level risk factors. As illustrated in Panel A of Figure 4, the negative impact of trade secret protection on modularity becomes more pronounced as a firm's technological superiority increases. The point estimate of the treatment effect is -0.055 (*p-value* = 0.047), which is 26% smaller than the main average treatment effect reported in Table 2 (-0.074) when *Technological Superiority* is at its minimum value of zero. In contrast, when *Technological Superiority* is one standard deviation above its sample mean (5.688), the treatment effect is estimated to be -0.093 (*p-value* < 0.001), which is 26% larger than the main average treatment effect. Similarly, as illustrated in Panel B of Figure 4, the estimated treatment effect is not statistically different from zero when *Competitor Collocations* is zero (β = -0.039; *p-value* = 0.243). When *Competitor Collocations* is one standard deviation above its sample mean (1.982), however, it is -0.103 (*p-value* < 0.001), which is 39% larger than the main average treatment effect. Notably, these risk factors are positively correlated with firm modularity individually, supporting the theory that firms with greater knowledge-spillover concerns tend to adopt a more modular structure.

[Insert Figure 4 about here]

Furthermore, we explored industry-level heterogeneity of the treatment effect. Firms can use various appropriability mechanisms—such as patents, complementary assets, and lead-time advantages—to capture economic value from their knowledge assets, and the effectiveness of these mechanisms differs substantially across industries (Cohen et al., 2000; James et al., 2013). Accordingly, firms in industries where such alternative appropriability mechanisms are highly effective are likely to be less concerned about knowledge spillovers than those without them, even when trade secret protection is weak. Therefore, if our main finding is primarily driven by reduced concerns over outward knowledge spillovers stemming from stronger trade secret protection, the effect may be relatively marginal for firms in industries where alternative mechanisms provide effective knowledge protection.

To assess this heterogeneity, *Alternative Appropriability* was constructed as an industry-level binary moderator that is equal to 1 for firms in industries with alternative appropriability scores (excluding trade secrecy) above the sample median, based on the survey by Cohen et al. (2000). Consistent with our prediction, the effect of trade secret protection is weaker for firms in industries where alternative appropriability mechanisms are strong. Specifically, the estimated effect of trade secret protection on modularity is -0.106 (*p-value* = 0.002), which is 45% greater than the average treatment effect when *Alternative Appropriability* equals 0 (i.e., alternative appropriability mechanisms are weakly effective). However, the effect is not statistically different from zero for firms in industries where alternative appropriability mechanisms are strongly effective (β = -0.017; *p-value* = 0.610), as illustrated in Panel C of Figure 4. Given that firms in industries with other highly effective appropriability mechanisms can serve as additional counterfactuals for estimating the treatment effect of increased trade secret protection, these results provide further empirical evidence that reduced knowledge-spillover concerns lead to less modularization of innovation activities in firms.

Mechanism Analysis

Lastly, to explore the underlying mechanism for our treatment effect, we conducted additional analyses focused on changes in the network characteristics of inventors within firms. Our main findings demonstrate that firms' innovation activities become less modularized when legal knowledge protection is strengthened. This decrease in modularity reflects greater collaboration among inventors *across* internal innovation communities within firms. Accordingly, it is important to understand which types of inventors are likely to play this brokerage role following stronger trade secret protection. To address this, we examined how trade secret protection influences the betweenness centrality of inventors within the firm's collaboration network.

In network analysis, betweenness centrality is defined as the number of shortest paths between pairs of other vertices that pass through a given vertex, normalized by the total number of vertex pairs in the network, thus capturing the extent to which a vertex (or an actor) serves as a bridge between different communities within the network (Girvan & Newman, 2002; Wasserman & Faust, 1994). In the context of an intrafirm collaboration network, inventors with higher betweenness centrality are those who play a pivotal role in linking and coordinating across internal innovation communities. By analyzing changes in inventors' betweenness centrality, therefore, we can identify *who* drives the integration of innovation activities within firms, contributing to the observed reduction in modularity, after the legal changes.

Drawing on research on strategic human capital and employee mobility (Mawdsley & Somaya, 2016), we examined the role of new hires. New hires are critical for providing new skills and knowledge necessary for innovation activities in firms (Song et al., 2003; Rosenkopf & Almeida, 2003; Wang & Zatzick, 2019). Paradoxically, however, these new hires might not take a central role in bridging multiple innovation communities within organizations because they are less socialized and thus typically less trusted compared to incumbent inventors (Allen, 2006). If a legal knowledge protection mechanism alleviates this trust issue for new hires, we can reasonably predict that the betweenness centrality of those who recently joined the firm will be strengthened following the increased knowledge protection, relative to that of incumbent inventors.

First, consistent with the prediction, our data indicate that new hires—whether skilled or junior—tend to exhibit lower betweenness centrality as compared with incumbent inventors.[11] The average betweenness centralities for skilled hires, junior hires, and incumbent inventors are 0.356, 0.231 and

[11] Following prior research (e.g., Ganco, 2013; Song et al., 2003), inventors' interfirm mobility events were identified by changes in their GVKEY codes, matched with assignee names in the patent records. We defined 'new hires' as inventors who filed a patent within three years of their first patent with the firm. To account for the time required for socialization (e.g., Bidwell, 2011; Groysberg et al., 2008), we measured these new hires over the three years following their initial patenting year at the new firm. The results remain robust when using a one-year window. Then, 'skilled hires' are those who had previously patented at another company before joining the focal firm, while 'junior hires' are those without any prior patenting experience. 'Incumbent inventors' are those who are neither skilled nor junior hires in the focal firm. To account for changes in hiring strategies, we control for the number of new hires in the regression analyses.

0.954, respectively. That is, within firms, the betweenness centralities of skilled and junior hires are, on average, 63% and 73% lower than those of incumbent inventors. Then, we performed regression analyses using these betweenness centrality variables as dependent variables. The results show that trade secret protection is *positively* related to the betweenness centrality of *skilled* (β = 0.314; *p-value* = 0.004) and *junior hires* (β = 0.196; *p-value* = 0.001), who are typically less trusted and thus do not hold central positions that bridge internal communities. These findings suggest that increased knowledge protection may reduce a firm's modularity by deploying new hires in more central positions that connect and coordinate across internal innovation communities within the organization.

Notably, trade secret protection is *not* significantly related to the betweenness centrality of *incumbent* inventors (β = 0.040; *p-value* = 0.812), which is consistent with our prediction. Incumbent inventors are generally more socialized and trusted, making them central figures in innovation activities. Because these inventors *already* occupy central positions, they are relatively less affected by such institutional changes in knowledge protection. Moreover, prior studies have highlighted substantial adjustment costs associated with redeploying existing human capital within organizations (Argyres et al., 2019; Boyacıoğlu et al., 2024). Considering these costs, it may be relatively challenging for firms to change the positions of incumbent hires rather than assigning hired inventors to new roles.

Therefore, these results corroborate our theoretical mechanism and offer valuable insights into the underlying mechanism: legal knowledge protection can influence the modularization of firms' innovation activities by shaping the deployment of new hires in intrafirm collaboration networks. Specifically, the findings suggest that legal knowledge protection can alleviate trust issues that often hinder effective integration within organizations. When trade secret protection is strengthened, firms may feel less constrained by socialization and trust concerns regarding new hires, leading them to be more confident in assigning skilled hires to central brokerage positions to facilitate knowledge integration within the organization.

DISCUSSION AND CONCLUSION

This paper examined how knowledge protection affects the structural pattern of innovation activities within firms. Exploiting state-level changes in U.S. trade secrecy law and using a network modularity measure developed in statistical physics, our regression analyses demonstrated that increased knowledge protection reduces the modularity of inventor collaborations in firms. Corroborating prior theoretical exploration of the role of modularity for knowledge protection, these findings suggest that firms may modularize their innovation activities even beyond the optimal level for value creation. In further support of this claim, the treatment effect was shown to be greater for firms with superior technologies and those collocated with competitors, which increases their concerns about outward knowledge spillovers, and weaker for firms in industries where alternative appropriability mechanisms are highly effective. Finally, we found that increased trade secret protection enhances the betweenness centrality of new inventors, both skilled and junior hires, as an important mechanism in integrating innovation communities in firms.

The findings of this paper make important contributions to the strategy and organization literature. First, this research provides novel insights into the origin of firms' integration capabilities. Prior research emphasizes the importance of firms' ability to integrate diverse knowledge inputs within the organization (Grant, 1996; Henderson & Clark, 1990; Kogut & Zander, 1992). Given the strategic importance of these integration capabilities, a key research question has been why firms differ in these capabilities and how they originate (e.g., Carnabuci & Operti, 2013). This study provides empirical evidence that firms' ability to protect proprietary knowledge—including through legal protection mechanisms—can significantly influence their capacity to integrate diverse knowledge inputs for innovation. Prior research suggests that human capital acquisition provided by new hires plays a critical role in enhancing firm performance (Mawdsley & Somaya, 2016; Song et al., 2003; Wang & Zatzick, 2019). Notably, our data indicate that new hires tend to be less integrated than incumbents. According to our findings, when firms can better protect their knowledge assets, they become more willing to integrate skilled or junior hires into innovation activities.

Our findings also contribute significantly to understanding a central question in the innovation literature: how does appropriability affect firm innovation? It is well-established that strong appropriability can incentivize firms to invest in innovation (e.g., Arrow, 1962; Teece, 1986). Firms are more likely to invest when they can capture the economic value of their outputs. However, research also shows that strong appropriability may constrain firms' innovation activities by reducing knowledge spillovers across firms—an essential source of innovation inputs (Laursen & Salter, 2006). As such, the current literature views appropriability as a factor that enhances firms' incentives to innovate but restricts their innovation capabilities. This research, however, raises the possibility that stronger appropriability can enhance firms' overall innovation capabilities. Specifically, under weak appropriability regimes, firms may be encouraged to constrain and compartmentalize collaborative interactions within the organization for the purpose of knowledge production, which could ultimately undermine their ability to generate impactful innovations by integrating diverse knowledge inputs (Grant, 1996; Liebeskind, 1997; Rønde, 2001). According to this paper, therefore, the relationship between appropriability and innovation capabilities of firms may be more complex than previously recognized. Future research could fruitfully examine the conditions under which appropriability enhances or limits firms' innovation capabilities.

Although this paper offers important implications, it is important to discuss the generalizability of our findings to different contexts. To enhance the internal validity of our regression analysis, we focus on a specific type of knowledge-protection mechanism (i.e., trade secret protection), which provides a quasi-exogenous source of variation. Consequently, the impacts of non-legal knowledge-protection mechanisms (e.g., lead-time advantages, firm-specific investments) remain an open question. Additionally, our patent-based methods only capture the collaboration patterns in invention activities that actually resulted in patents. Our estimates could be biased if collaboration patterns for patented and non-patented inventions are systematically different. As discussed earlier, this possibility may not pose a serious problem in our research, given that patenting behavior did not significantly decrease in our sample firms after the enactment of the trade secret statutes. Nevertheless, it still remains uncertain whether our findings can be generalized to other innovation-intensive contexts with lower patenting intensity.

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TABLE 1. Descriptive Statistics and Correlations of Variables

Variable	Obs	Mean	SD	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Modularity	10,335	0.747	0.190							
Trade Secrecy Index	10,335	0.367	0.170	-0.109						
Number of Patents	10,335	150.69	505.57	0.229	-0.014					
Number of Inventors	10,335	233.87	726.05	0.252	-0.015	0.982				
Geographic Dispersion	10,335	0.091	0.077	-0.156	0.099	-0.044	-0.020			
R&D Intensity	10,335	0.143	0.495	-0.101	0.024	-0.033	-0.033	0.047		
Total Assets	10,335	6.204	20.668	0.202	-0.007	0.417	0.464	0.096	-0.055	
Return on Assets	10,335	-0.064	5.503	0.018	-0.002	0.005	0.005	-0.003	0.246	0.007

TABLE 2. Effect of Trade Secret Protection on Modularity

DV: *Modularity*	(1)	(2)	(3)	(4)	(5)	(6)
	Headquarters Location		Assignee Locations		Inventor Locations	
Trade Secrecy Index	-0.074** (0.027) [0.008]	-0.073* (0.027) [0.010]	-0.049* (0.023) [0.040]	-0.051* (0.023) [0.030]	-0.058* (0.026) [0.032]	-0.059* (0.027) [0.032]
Controls	No	Yes	No	Yes	No	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2 (within)	0.040	0.044	0.037	0.042	0.036	0.041
# Firms	1,022	1,022	1,000	1,000	1,003	1,003
# Observations	10,335	10,335	10,199	10,199	10,258	10,258

Standard errors are clustered by states; $^{**}p<0.01$, $^{*}p<0.05$, $^{\dagger}p<0.10$.

TABLE 3. Difference-in-Differences Analysis

DV: *Modularity*	(1)	(2)
UTSA Enactment	-0.035** (0.011) [0.002]	-0.035** (0.011) [0.003]
Controls	No	Yes
Firm FE	Yes	Yes
Industry-Year FE	Yes	Yes
R^2 (within)	0.040	0.045
# Firms	1,022	1,022
# Observations	10,335	10,335

Standard errors are clustered by states; $^{**}p<0.01$, $^{*}p<0.05$, $^{\dagger}p<0.10$.

FIGURE 1. Timeline of Uniform Trade Secrets Act Enactment

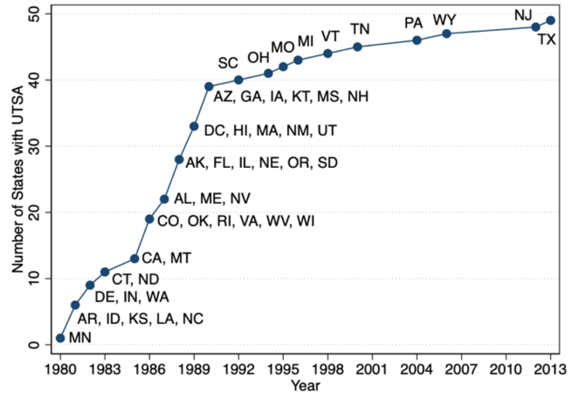
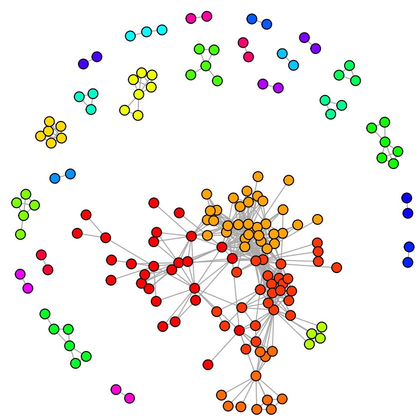


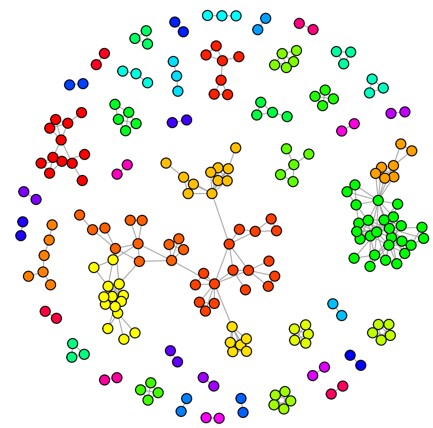
FIGURE 2. Modularity of Inventor Collaboration in Firms

Panel A: Altera Corporation



Modularity Score (Q) = 0.584
Trade Secrecy Index = 0.442

Panel B: Analog Devices



Modularity Score (Q) = 0.867
Trade Secrecy Index = 0.241

FIGURE 3. Event Study Estimates (with 95% Confidence Intervals)

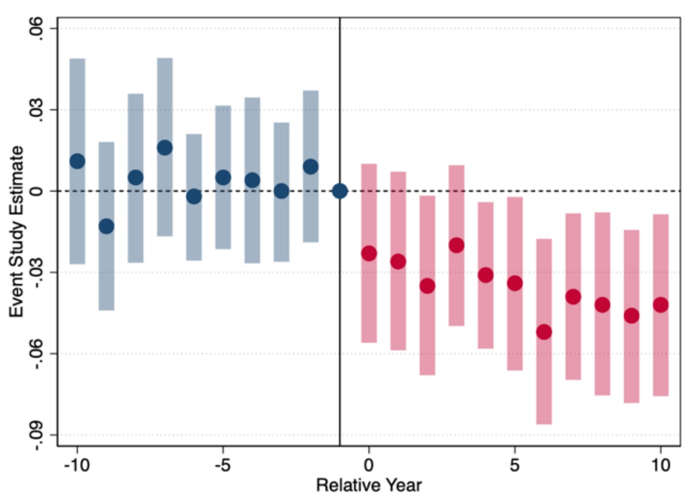
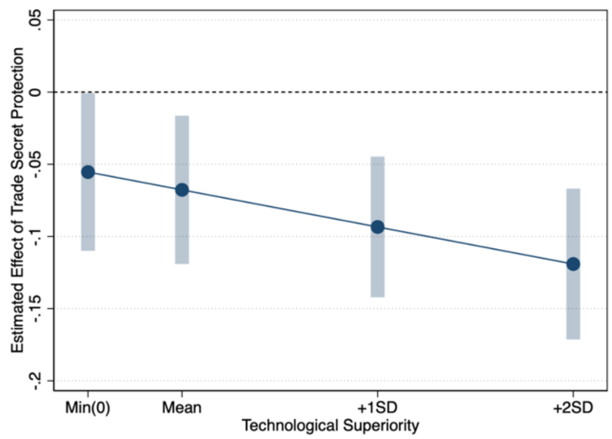
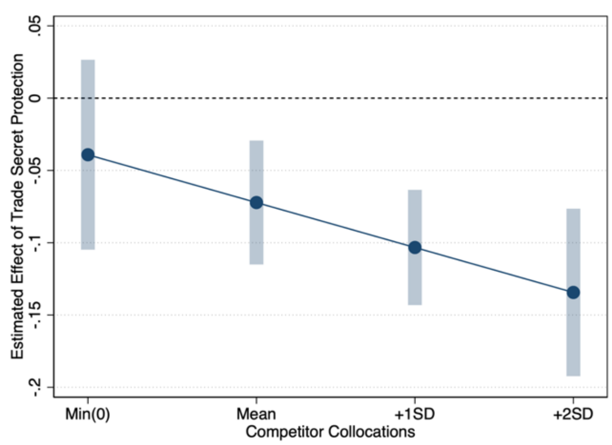


FIGURE 4. Moderation of Firm-level Knowledge-Spillover Risk
(with 95% Confidence Intervals)

Panel A: Technological Superiority



Panel B: Competitor Collocations



Panel C: Alternative Appropriability