Trade Secrets and Innovation: Evidence from the "Inevitable Disclosure" Doctrine

Andrea Contigiani
Wharton School,
Univ. of Pennsylvania
andcon@wharton.upenn.edu

Iwan Barankay
Wharton School,
Univ. of Pennsylvania
barankay@wharton.upenn.edu

David H. Hsu
Wharton School,
Univ. of Pennsylvania
dhsu@wharton.upenn.edu

October 2017

ABSTRACT

Does heightened employer-friendly trade secrecy protection help or hinder innovation? By examining U.S. state-level legal adoption of a doctrine allowing employers to curtail inventor mobility if the employee would "inevitably disclose" trade secrets, we investigate the impact of a shifting trade secrecy regime on individual-level patenting outcomes. Using a difference-in-differences design taking un-affected U.S. inventors as the comparison group, we find strengthening employer-friendly trade secrecy adversely affects innovation. We then investigate why. We do not find empirical support for diminished idea recombination from suppressed inventor mobility as the operative mechanism. While shifting intellectual property protection away from patenting into trade secrecy appears to be at work, our results are consistent with reduced individual-level incentives to signaling quality to the external labor market.

Keywords: innovation; trade secrets; knowledge workers; labor markets; inter-firm mobility.

Acknowledgements: We thank audience members at UC Berkeley, Boston University, Duke University, Emory University, University of Michigan, National University of Singapore, University of Florida, University of Hong Kong, University of Maryland, and University of Pennsylvania. We thank the Mack Institute for Innovation Management for generously funding this research.

Introduction

When surveyed about the most common modality for appropriating returns from both their product and process innovations, industrial managers most frequently respond that trade secrecy and the closely-related mechanism of lead time advantage are by far the most important channels (e.g., Cohen, et al., 2000). Despite the stated importance of the secrecy channel, the empirical social science literature has predominately focused on patents, which are rated as far less important in the surveys as a means of appropriating returns from innovation. The likely reason for this mismatch is observability, a prerequisite for empirical analysis: patent protection is granted in exchange for detailed disclosure, while managers have an economic incentive to keep trade secrets secret (discovering trade secrets via legal channels such as accidental disclosure, independent discovery, and backward engineering invalidates them).[1] The empirical literature on trade secrecy has therefore been understandably sparse, even while the theoretical literature suggests that the most important commercial business ideas are likely to be protected via trade secrets, especially in weak property rights regimes (Anton and Yao, 2004).[2]

A law and economics perspective of trade secrecy law suggests its evolution arising from the need to balance efforts to protect trade secrets (e.g., Friedman, Landes & Posner, 1991), and more specifically the interests of employers (in appropriating returns from their human capital investments) with those of employees (in self-determining career choice) (e.g., Fisk, 2001). This balance likely affects innovation processes and incentives. However, it is not theoretically clear how shifts in trade secrecy protection strength might impact innovation outcomes.

---

[1] Patent-based intellectual property protection is a useful contrast. To obtain a patent in the U.S., an invention should be novel (compared to the "prior art"), non-obvious, and useful. The quid pro quo of 20 years of patent protection of an invention is granted in exchange for detailed, codified invention disclosure. By comparison, trade secrets can apply beyond technical domains, and may include a broad spectrum of dimensions of business competitiveness (and so the scope of what could be protected by trade secrecy is much wider). Trade secrets protection against unlawful procurement can extend indefinitely and is adjudicated at the U.S. state level, as compared to patents, which are of fixed length and enforced at the federal level.

[2] See Moser (2012), Castellaneta, Conti & Kacperczyk (2017), and Png (2017) for recent exceptions.

On one hand, a more employer-friendly trade secrecy regime may incentivize employers to increase their investments in employee firm-specific human capital since the frictions to employee mobility are enhanced. This may boost innovation outcomes. On the other hand, the innovation literature has stressed the need for idea recombination for innovation outcomes (e.g., Fleming, 2001). To the extent that employer-friendly trade secrecy regimes place frictions on the circulation of individuals and ideas across technical, organizational and geographic boundaries, innovation outcomes may consequently be dampened (e.g., Hellmann and Perotti, 2011). Another set of theories, rooted in labor market dynamics, predicts a negative relation between a more employer-friendly trade secrecy regime and innovation outcomes. This is due to, among other things, muting employees' ability to use the external labor market to signal their quality (which could otherwise be useful in obtaining improved employment terms). Higher thresholds for labor market mobility stemming from an employer-friendly trade secrecy regime may therefore be associated with less employee innovation effort.

Because the theoretical relationship between trade secrecy regime and innovation outcomes is ambiguous (in large part because the production function of innovation is complex, multi-dimensional, uncertain, and hard to verify), we seek to empirically examine the relationship. We do so by exploiting a context afforded by shifting trade secrecy legal regimes (outside of contractual agreements) in a set of U.S. states to estimate the effect of trade secrecy environment on innovation outcomes. The "inevitable disclosure" doctrine (IDD) holds that courts may enjoin an employee from switching employers for a certain period of time if plaintiffs can show that it would not be possible for the employee to perform her job without *inevitably disclosing* the prior employer's trade secret (more on this in the next section). The prior literature on inventor human capital and organizations has tended to focus on contract law, either nondisclosure agreements or covenants not to compete, though that literature has not clearly established the effect on innovation outcomes. By contrast, we examine trade secrecy law in part because there are a range of circumstances tied to competitive situations in which contractual agreements are typically not struck between or among parties. This is due to, among other things, differences in corporates strategies and possible difficulties in governing such arrangements.

Using a difference-in-differences style empirical design, we find that the average effect of IDD on innovation quality, as measured by forward-citation-weighted patent counts, is negative, both at the inventor-year and U.S. state-year levels of analysis. We then explore the mechanisms that may be driving this effect. We first examine whether this negative effect is driven by a substitution away from the less effective appropriation channel (e.g., patenting) and into the strengthened channel (e.g., trade secrecy). We then analyze two theories predicting a negative relationship, mitigated inventor idea circulation resulting in lower idea recombination and muted inventor incentives arising from frictions to labor market mobility. By presenting empirical evidence on a sub-sample of data in which substitution between patenting and trade secrecy is unlikely, we conclude that our main results are consistent with the dampened labor market incentives mechanism. We also contextualize the other part of the sample which may be subject to intellectual property substitution in the face of altered trade secrecy business environments, arguing that at least part of the decline in patenting is linked to less innovation.

The remainder of the paper takes the following form. Section 2 discusses the institutional context: U.S. trade secrecy law and IDD. Section 3 summarizes the theoretical perspectives that may impact the relationship between IDD and innovation outcomes. Section 4 describes the dataset. Section 5 presents the main analyses and empirical tests of possible mechanisms. A final section concludes by discussing implications.

U.S. Trade Secrecy Law and the Inevitable Disclosure Doctrine

A critical period in the evolution of U.S. legal thought on trade secrecy law was in the 1890 to 1920 time-period. The norm in the antebellum U.S. was to presume that workers owned the rights to their ideas, unless there was an express contractual covenant to the contrary, under the thought that employer property was confined to physical manifestations of employer knowledge such as laboratory notebooks and physical equipment (Fisk, 2001). This sentiment started to change in the 1890s, and eventually shifted so that employer trade secrets expanded from discrete items to more inchoate employee know-how (Fisk, 2001).

The Uniform Trade Secrets Act (UTSA) of 1979 (and amended in 1985) was an attempt to bring some degree of national uniformity to the law of trade secrets (encompassing the definition of a trade secret, the requirements for protection, and the remedies for misappropriation) since the historical origins of the U.S. law arises from English common law – and so there was little uniformity across states in the definition and application of trade secrecy (National Conference of Commissioners on Uniform State Laws, 1985). According to the UTSA, which as of 2013 has been ratified by 47 state legislatures (albeit over a prolonged time span), a trade secret is a piece of information (including formulas, patterns, compilation, programs, devices, methods, techniques, or processes) that (1) derives economic value, actual or potential, from not being generally known to persons outside the organization and (2) is the subject of efforts that are reasonable under the circumstances to maintain its secrecy. While both parts of the definition are subject to interpretation, the second part is particularly so. For example, the standard for misappropriation is *not* whether a trade secret was discovered via illegal means.[3]

---

[3] One notable case, *DuPont v. Christopher* (431 F.2d 1012, 5th Circuit, 1970), involved a low-flying aircraft taking aerial pictures of an under-construction DuPont methanol manufacturing plant which was fenced-off on the ground.

An early expression of the legal theory of “inevitable disclosure” – the idea that a departing employee will “inevitably” disclose trade secrets, even without the intent of disclosing trade secrets (due to the inherent difficulty of compartmentalizing know-how), was a ruling by an early 20th century court: “equity has no power to compel a man who changes employers to wipe clean the slate of his memory.” (*Peerless Pattern Co. v. Pictorial Review Co.*, 132 N.Y.S. 37, 39 (App. Div. 1911) cited in Fisk, 2001: 494).

The key contemporary case applying the inevitable disclosure doctrine is *PepsiCo, Inc. v. Redmond*, 54 F.3d 1262 (7th Cir. 1995), which is widely-acknowledged as a legal turning point in the application of IDD. The *PepsiCo* case is interpreted as broadening the scope of the IDD doctrine beyond technical trade secrets, which was the traditional domain (e.g., Kahnke, Bundy & Liebman, 2008; Wiesner, 2012). In the case, William Redmond, a sports drink manager at PepsiCo in the early 1990s, accepted a job at a competing sports drink company, Quaker, in 1994. PepsiCo filed suit in the 7th District Court in Illinois, arguing that Redmond had access to its strategic and operating plans (trade secrets related to pricing, distribution, packaging, and marketing), and that he could not perform his new job at Quaker without inevitably disclosing PepsiCo’s trade secrets. In the words of the court: unless “Redmond possessed an uncanny ability to compartmentalize information, he would necessarily be making decisions about Gatorade and Snapple by relying on his knowledge of trade secrets.”[4] Redmond did not have a non-compete clause in place with PepsiCo (he was an employee at-will), and Redmond had an explicit confidentiality agreement in place with Quaker prohibiting him from disclosing others’ trade secrets. Despite these contractual agreements, in December 1994, the court enjoined Redmond from taking the new position through May 1995.

The court held that while not illegal to take aerial pictures, the defendant had wrongfully misappropriated DuPont’s trade secrets through their photographic industrial espionage.

[4] U.S. Court of Appeals for the Seventh Circuit - 54 F.3d 1262 (7th Cir. 1995).

Before describing our data and analysis on the impact of IDD on innovation, we first review the theories which may impact the relationship between an altered trade-secrecy regime and individual-level innovation.

Theoretical Background

The theoretical literature relating trade secrecy strength to innovation outcomes suggest opposing predictions. A positive relation may arise if employers are incentivized to enhance their investments in employee skill development and human capital as a result of the greater cost of employee departure under an employer-friendly trade secrecy regime. Firms may be differentially incentivized to invest in their employee's human capital development depending on the re-deployability of the resulting skills. On the one hand, if skills are largely *specific* to the focal organization (in that re-use of those skills in another organization is difficult or ineffective), employers may be willing to incur such investments in general (Becker, 1964; Gibbons and Waldman, 1999). Furthermore, this investment incentive might be bolstered when there are barriers to employee mobility in the labor market. On the other hand, employers may be hesitant to invest in more *general* employee human capital, skills which are interchangeable and equally applicable across organizations. Without labor market frictions, it may be difficult for firms to appropriate the returns from general human capital investment (Becker, 1964). However, the presence of labor market frictions, which raise the expected returns from these investments, may create organizational incentives to invest, even in the case of general human capital. Since these two forms of human capital investments may be critical inputs to the innovation process, and because employer-friendly trade secrecy regimes heighten frictions in the employee labor market, if this mechanism is salient, we would expect to observe a *positive* relation between an employer-friendly IDD regime and innovation outcomes. Consistent with this explanation, Png (2017), for example, finds that R&D expenditures for larger firms which are in more technology-intensive areas are positively related to state-level enactment of the Uniform Trade Secrets Act (UTSA) discussed above in our institutional background.

On the other hand, a more employer-friendly trade secrecy regime may dampen innovation through two channels: diminishing employees' incentives and reducing the potential of idea recombination. Individual-level innovation incentives stem in part from the competitive labor market, because employment terms are also driven by the employee's value, including innovation potential, in the labor market (e.g., Doeringer and Piore, 1971; Bulow and Summers, 1986). An employer-friendly trade secrecy environment may hamper the operation of that competitive external labor market, and so raises the possibility of dampened individual incentives for innovation. In Becker's (1964) framework, strengthened employer trade secrecy protection through legal doctrines such as IDD converts potentially general employees' skills into the firm-specific domain in function. As a consequence, employees may be less incentivized to acquire such skills in the first place, in part due to the diminished ability of employees to use the secondary labor market to bargain for better terms with the current employer. The net result is diminished inventor productivity. Acharya et al. (2013), for example, find that strengthened employee-friendly wrongful-discharge employment protection acts to spur innovation through reducing the potential of employer holdup.

To understand this mechanism more precisely, consider the behavior of inventors in the context of a signaling game (Spence, 1973) with incomplete information in which the workers differ in their productive ability, i.e. their ability to generate high-quality patents, and face a market of potential employers who set wages (Gibbons et al., 2005). Here, talented inventors have an incentive to produce patents of high quality that could not be generated by lower ability inventors (either for their lack of skill or because the investment would be inefficient). The empirical prediction of these signaling models is that firms of different types emerge, so inventors will move across firms and sort themselves into employment for high or low ability inventors, with a wage premium for high-skill inventors. However, with mobility frictions, as they exist under IDD, highly-skilled inventors no longer have an incentive to signal their talent to the market as they cannot sort themselves into employment and wages by skill level, and so invention quality consequently suffers.

An additional individual inventor response to an employer-friendly trade secrecy regime would be to shift the *nature* of her innovation efforts. Importantly, the preceding theory pertains only to the situation of employees wishing to continue working within the domain she has worked within under the original employer (consistent with the remedies available under IDD). If the employee were hired to conduct work in a different domain, the employer's argument for applying IDD to enjoin the employee would be considerably less compelling in court. Yet at the same time, it is likely that the new potential employer is interested in hiring the employee precisely because of her specialized knowledge and experience within a domain (for otherwise there would be a high degree of human capital substitution available – and likely without the potential legal encumbrances). We therefore posit that IDD incentivizes inventors to signal their skills and quality in other, non-competing markets and domains. An empirical prediction is that inventors under an employer friendly trade secrecy regime will be more likely to produce innovations which can be used across a wider spectrum of purposes (general-purpose technologies) relative to before exposure to such a regime.

Finally, the much-discussed mechanism of idea recombination as an important precursor to innovation may result not only because of the possible need to gather feedback about idea quality from diverse knowledge sources (e.g., Hellmann and Perotti, 2011), but also because idea recombination has been described as important to the innovation process itself (e.g., Fleming, 2001). Since an employer-friendly trade secrecy regime raises the employee costs of circulating in the labor market, thus diminishing the potential for idea recombination, innovation might be consequently hampered.

In summary, while the firm-specific investment channel predicts a positive effect of IDD on innovation, both the idea recombination and signaling theories predict a negative relation.

Data, Measures and Empirical Strategy

To empirically assess these theories, we follow the classification of IDD rulings published in Castellaneta et al. (2016), which in turn is based on a number of legal sources. These rulings are made at the U.S. state level, and are coded as rulings for and against the IDD (with one case being equivocal).[5] The 1995 Illinois *PepsiCo* case discussed above was a watershed case, and the first in the sequence of pro-IDD rulings.[6]

[5] The states ruling in favor of IDD are: Illinois (1995), New York (1997), Washington (1997), Utah (1998), Iowa (2002), Delaware (2006), and Pennsylvania (2010). The states ruling against IDD are: California (1944), Louisiana (1967), North Carolina (1976), New Jersey (1980), Minnesota (1992), Massachusetts (1995), Virginia (1999), Florida (2001), and Maryland (2004). New York (2003) is the equivocal case, which we do not utilize in our analyses. Figure 1 graphically illustrates the cumulative number of states with each type of ruling over time. The classification we follow interprets the IDD as a substitute for a noncompetition agreement, which accords with legal accounts of the doctrine, especially as exemplified in the *PepsiCo* case.

[6] Our original empirical strategy centered on comparing IDD adoption in Illinois in the aftermath of the *PepsiCo* case, as compared to other U.S. Midwestern states. The benefits of that design were that the legal environment shift in that context was important, swift, and arguably unanticipated. In addition, by focusing on a single case, differences in case facts (e.g., the importance of bad faith, the absence of a covenant not to compete, and pre-existing state-level ratification of the UTSA in applying the doctrine) to compare the necessary and sufficient requirements for IDD regime across jurisdictions become moot. On the other hand, questions of generalizability and of potentially unmeasured confounding events in a single state are the downsides. We thank the anonymous editorial team for the constructive suggestions on broadening our sample, though we note that results we report on the

[INSERT FIGURE 1 ABOUT HERE]

Patent data are sourced from the NBER (Hall et al., 2001) and Harvard IQSS Patent Network Dataverse (Li et al., 2014). These sources together allow us to construct firm and individual-level characteristics. We use utility patents and patent citations to develop measures of inventor-level innovation, inventor location, and inventor affiliation. The SIC-patent class concordance data is obtained from Silverman (1999), while state-level data come from the U.S. Bureau of Economic Analysis. The final sample includes 353,889 distinct inventors from all 50 U.S. states (and Washington, D.C.), observed up to 28 years (1976-2003), for a total of up to 2,772,278 inventor-year observations.[7]

Our main dependent variable is the count of eventually-granted patents weighted by forward citations (inspired by Trajtenberg, 1990 and follow-on work). As is common in the literature, we use the natural logarithm of these measures, calculated as log $(1+x)$, to diminish the impact of outliers. Because innovation is a long-term process, we include a temporal lag structure in our analysis to capture the possible delayed effect on innovation following the legal regime shift. The main independent variables are the post-IDD positive and negative regime dummies, which takes the value 1 for individual-year observations when a state had a legal precedent for IDD in place ("IDD positive"), or when a state court had ruled against IDD ("IDD negative"), and 0 otherwise. We use a parsimonious set of time-varying variables to control for other inputs to the innovation production function, including variables at the individual-level (log number of years since first patent and log patent stock during the previous four years),

broader sample are very consistent with our original empirical strategy, even after applying a synthetic state control method (Abadie, et al. 2010).

[7] We build our sample from the patent data. We retain patents for which both assignee and inventor information is available. We then build an inventor-year panel dataset where each inventor is present in the time window between her first patent and her last patent. We drop inventors who are present only in a single year in order to use inventor-level fixed effects in our empirical analyses.

organization-level (log age and log number of inventors), industry-level (log number of firms), and state-level (log population, and log total wage). Table 1 provides definitions and descriptive statistics of all variables used in the analysis.

[INSERT TABLE 1 ABOUT HERE]

Our main specification is a difference-in-differences design using ordinary least squares regressions on an individual-year panel dataset, in which the first difference is the IDD regime, and the second difference is the year of "treatment." In all specifications, we use standard errors clustered at the state level[8] to account for potential serial correlation of observations within the same state (Bertrand et al., 2004).

Empirical Results

Main results. Table 2 presents the temporal pattern of IDD (both positive and negative rulings) on innovation (panel A) and the main IDD effect on innovation (panel B). Panel A shows that the lead values of IDD (that is, IDD at *t+1* and *t+2*) are not statistically significant, suggesting no anticipation effects of legal regime changes. Furthermore, Panel A shows that only time lagged coefficient at the two and three year post-IDD positive rulings are economically and statistically significant, with an estimated five percent drop in citation-weighted patents in this within-inventor analysis.[9] For all time leads and lags, the IDD negative regime is not statistically

[8] This is the most conservative specification in this setting (using less conservative approaches such as individual-level clustered standard errors enhance the statistical significance of the estimated coefficients).

[9] Difference-in-differences analyses should not violate the parallel trend assumption, that the "control" and "treatment" groups are different from each other before the event. A regression of logged forward citation weighted patent counts on year dummies (the treatment year is the omitted reference year), inventor fixed effects, the IDD dummy (=1 for IDD positive or negative rulings, respectively in a given year for the focal inventor) and IDD * year effects yields yearly estimates of the IDD "treatment" effect. The results are presented in graphical form in Figure 2. They suggest that both the IDD positive and IDD negative effects do not follow any clear trend before the treatment year, and so our difference-in-differences specification is consistent with the parallel trend assumption.

significant. Because a negative ruling on IDD is essentially not changing the status quo trade secrecy environment, we are not surprised with this non-result.

[INSERT FIGURE 2 & TABLE 2 ABOUT HERE]

Panel B shows that an IDD positive regime is negatively associated with log citation-weighted patent counts at both the inventor-year level of analysis (specifications 2B-1 through 2B-4, which include individual and year fixed effects) and at the U.S. state-year level (columns 2B-5 and 2B-6, which include state and year fixed effects). In all specifications, state-clustered standard errors are presented in parentheses, and we show the results for both the two- and three-year treatment lag, based on the results of Panel A. The estimated effects are economically and statistically significant, with an estimated effect of about three to five percentage point drop in citation-weighted patents in the inventor analysis, depending on specification, and a twenty-three percentage point decline in the U.S. state level analysis for a discrete change into an IDD positive trade secrecy regime. The state level effects are higher since an important source of innovation is individual-level heterogeneity, which can only be captured with inventor fixed effects in the individual-level analysis.

Robustness checks. To verify the effect found in the main analysis, we conduct a variety of robustness checks in Table 3, spanning the domains of controls for potential confounding events and estimation methods (Panel A) and sample composition (Panel B).

[INSERT TABLE 3 ABOUT HERE]

We first examine whether differences in non-compete clause enforcement, as described in Garmaise (2011), matter. We employ Png's (2015; 2017) composite index, which incorporates both Garmaise's non-compete clause enforcement data as well as other elements of the state-level trade secrecy regime (with features such as variation in qualifications for trade secrecy protection, civil procedure regarding taking legal action, and remedies in case of violations), as a control variable in the first two columns of Table 3, Panel A. The negative impact of IDD previously reported remains essentially unchanged in magnitude and statistical significance. We next show result robustness to a time trend (specifications 3A-3 and 3A-4) and a state-specific time trend (specifications 3A-5 and 3A-6). Related to the latter robustness check, see also Figure 2 as a visual check of the parallel path assumption prior to treatment through an analysis of year-specific treatment effects. The next group of robustness checks, contained in Table 3, Panel B, varies the sample to examine whether the results are sensitive to the exclusion of inventors who change states (specifications 3B-1 through 3B-4) and the exclusion of inventors from the sample who change IDD regimes (columns 3B-5 through 3B-8). In both cases, the results are largely robust, though the statistical significance for the three-year lag with full control variables are noisier. Our conclusion on these last group of robustness checks is that possible violations of the stable treatment unit value are not driving the main results.

While Tables 2 and 3 document the negative relation between a two and three year lagged IDD positive regime and citation-weighted patent counts, the remainder of the empirical analyses investigate the potential explanations behind this effect. We do not consider the theoretical explanation centered on enhanced organizational human capital investments, which predicts a positive relation between IDD positive and innovation outcomes. We first examine whether a change in intellectual property rights (IPR) strategy substituting trade secrecy for patenting is driving the main results. We then examine the knowledge recombination and labor market signaling mechanisms in turn, as each theory is consistent with the negative main effect we find.

Mechanisms analysis. The first mechanism we explore is a shift away from patent protection in the face of a strengthened (from the employer's perspective) trade secrecy environment. This possible intellectual property rights (IPR) protection strategy shift could explain the diminished patenting-based innovation outcome if inventions which were formerly protected by patents are now protected via trade secrecy (Friedman et al., 1991; Png, 2015), with little or no change in actual innovation. In particular, the negative relation between strengthened trade secrecy and measured innovation (patent output) could result from reduced employee mobility due to employer-friendly trade secrecy environment. This may result in less potential for knowledge spillovers, which in turn may be manifested in less aggressive patenting (Kim and Marchke, 2005).

We exploit the heterogeneity of patent effectiveness across industries, as perceived and reported in surveys of industrial managers. Among manufacturing industries, Cohen et al. (2000) distinguish discrete from complex technologies. Discrete technologies are those typically composed of a relatively small number of components. Complex technologies are those that tend to be composed of a large number of components.[10] As Png (2015: 2) states: "For discrete technology products, the substitution between patents and secrecy will be relatively weak. So long as a product embeds at least one patent, it gets some of the advantages of a patent – the legal right to exclude, strategic purposes, publicity, underpinning licensing, and access to federal courts. Manufacturers of discrete technology products would be reluctant to switch the single invention from patent to secrecy and lose those advantages. By contrast, in complex technology

[10] To build these measures, we match inventor-year pairs to SIC codes since patents are not classified by industrial sectors. Using SIC-class concordance data (Silverman, 1999), we match each patent to its likely SIC code of application. We then aggregate this information to infer the likely SIC code for each inventor-year. Finally, we focus on manufacturing sectors and categorize each SIC as either discrete (SIC between 19 and 33: food, tobacco, textiles, apparel, lumber, furniture, paper, printing, chemicals, petroleum refining, rubber, leather, and varied material products) or complex (SIC between 34 and 39: fabricated metal, industrial machinery, computer and electronic components and equipment, transportation equipment, and measuring/optical/medical goods), as per Cohen et al. (2000). We conduct the analysis on these two subsamples separately, and present the results in Table 4.

products, there will be many patents to convey those advantages, even after substitution of some patents for secrecy. Hence, the substitution will be stronger among complex technology products."

[INSERT TABLE 4 ABOUT HERE]

Since the actor deciding on the possible IP form is the manager, and she is likely examining the invention rather than the inventor in determining the form of IP protection (patents versus trade secrets), we perform the analysis at the invention unit of analysis. Therefore, we regress innovation quality (log of forward citations for each given patent (mean=1.68 and standard deviation of 1.17)) on IDD regime at the time of patent application and individual and organization level controls. We first verify that for the sub-sample of discrete technologies, which comprises about a third of our overall sample, we find the negative relation between IDD ascension and innovation quality (compare the results of Table 4, Panel A, columns 3 and 4 as compared to the remaining columns of that panel). The same general pattern emerges at the inventor-year level of analysis, though the results are somewhat noisier (regression output available on request). It is interesting to note not only the negative relation for the "IDD positive" variable, but that the relationship flips for the "IDD negative" variable (the estimate is statistically and economically significant, with a discrete change from no IDD ruling to a negative ruling associated with a five to six percent increase in log patent citations for discrete technologies).[11]

Because the theoretical mechanisms explaining the main negative relation between an IDD positive regime and innovation outcomes take place at the inventor level, we now switch to

[11] While the heart of our mechanisms analysis examines the discrete technology sub-sample, we contextualize the complex technology sub-sample with respect to possible IP form substitution in the appendix.

that level in order to assess the mechanisms (Table 4, Panels B and C).[12] We start by examining the knowledge recombination mechanism. This view suggests that because circulating ideas for feedback and recombination may be instrumental for innovation, and because an IDD positive legal regime places frictions on inventor mobility across firms, we might believe that dampening knowledge recombination may be a leading mechanism for the negative innovation result. Since the concept of frictions to labor movement restraining mobility has been well-tested in the literature,[13] we do not dwell on it here.

Instead, we concentrate our efforts in directly exploring whether the IDD regime is associated with a validated measure of combinatorial novelty based on the work of Fleming and Sorenson (2001).[14] This measure captures the degree to which a focal invention has recombined elements which are relatively uncommon (a proxy of higher novelty) as compared to historical patents. We extend the measure to inventor-year patent portfolios, and use this as an outcome measure, with the main independent variable of interest the post-IDD positive regime indicator in a difference-in-differences type specification. If the knowledge recombination mechanism of explaining the adverse innovation impact of IDD is salient, we would expect that the IDD

---

[12] When we assess these mechanisms, we construct the inventor-year observations using the following procedure: 1) we classify each invention as discrete or complex (using SIC concordance via the Silverman (1999) method); 2) we classify each inventor-year as discrete or complex using a majority rule (the cases where an inventor has the same number of discrete and complex inventions in a year are very few, so the results are not sensitive to their inclusion or exclusion); and 3) we use an imputation approach to fill in inventor-year observations when there is no patenting, following a common practice in the literature (see for example Marx, Strumsky & Fleming (2009: 882)). The results reported in Table 4, panels B and C use the majority rule to classify inventors as discrete or complex (if more than 50% of the inventor-years of a given inventor classified as a given technology type), though the results are robust to alternate thresholds of above 75% and 100% (we report the lower threshold to maximize the number of usable observations).

[13] Several papers find that increased costs of inventor mobility dampen technical employee mobility (we also find the same empirical pattern in our sample). For example, Marx et al. (2009) report that an unanticipated shift in employee non-compete agreement enforcement in Michigan curtails such mobility.

[14] The combinatorial novelty measure is calculated as follows. We first compute recombination ease E_{st} for technology subclass s at time t as the ratio of number of subclasses combined with s and the number of patents in s. Combinatorial novelty C_p of patent p is the sum of recombination ease E_{st} for each subclass s associated to patent p. Finally, inventor-year combinatorial novelty C_t is the average of the combinatorial novelty C_p of all patents p applied for in year t.

variable would be negatively related to the combinatorial novelty variable. Across a range of empirical specifications, we do not find empirical support for this, for the sample as a whole, and for either the discrete- or complex-technology subsamples (Table 4, Panel B).

A different possible mechanism explaining the negative innovation effect of the IDD positive environment relates to the incentive structure of inventors. Inventors may be incentivized to innovate by generating more high quality patents in order to signal their quality to the competitive labor market so as to weaken potential hold-up problems inside a firm and obtain better employment terms. Under an employer-friendly trade secrecy regime such as IDD, which raises the cost of within-sector employee mobility, inventors' incentives to make use of the secondary labor market in their focal domain may be dampened. Inventors might instead be incentivized to vary the direction or nature of their innovation efforts in order to signal their skills and quality to organizations other than their direct competitors. We posit that IDD positive rulings incentivize inventors to signal their skills and quality in non-competing domains, and our empirical prediction is that more general-purpose innovations will be produced by inventors "treated" by IDD positive rulings. The mechanism suggests that if inventors' prospects for labor market bargaining as a result of their productive efforts in their focal technology area is curtailed, then they may be dis-incentivized in producing in the focal technology area. However, this diminished incentive does not hold in other technology domains, since IDD enforcement is specific to a given technology area.

We use the patent generality measure[15] (Hall et al., 2001) to proxy the *nature* of innovation produced, with the idea that while IDD may dampen inventors' within-sector incentives for innovation (for the reasons stated above), inventors may redirect their efforts to

[15] Patent generality is calculated as 1 minus the Herfindahl-Hirschman Index of patent classes in forward patent citations.

signaling their quality across sectors and technical application areas, where IDD does not apply. Lower values of this measure indicate little use of the focal patent in a broad range of patent classes within the set of forward citations to the focal patent.

We therefore analyze the effect of IDD on inventors' patent generality in using the same difference-in-differences style regression framework we have employed before (using mean patent generality at the inventor-year level of analysis). Note that this analysis does not try to directly link the higher inventor-level patent generality after IDD positive to the same regime shift post-IDD with respect to forward citation weighted patents. Instead, these analyses are complementary in describing possible inventor-level responses to the regime shift making trade secrets protection more employer friendly. The results are presented in Table 4, Panel C (columns 3-4 versus columns 5-6). The economically and statistically positive coefficient is confined to the part of the sample in which there is unlikely to be IP substitution: the discrete technology sub-sample. We interpret these results as consistent with a labor market signaling perspective in which inventors alter the direction of their inventive efforts to be more general-purpose, even if their incentives to produce "quality" patents/innovation in their focal domain (as measured by forward citation weighted patent counts) is dampened.

Our overall conclusions to our analysis of mechanisms are as follows: (1) our main evidence for the mechanisms is drawn for the "discrete" technologies, as they are unlikely to experience substitution, even in the face of differentially-altered IP regimes. This analysis is consistent with the labor market signaling mechanism and does not find support for the knowledge recombination mechanism. (2) some degree of substitution is likely to be taking place in the other part of our sample of the "complex" technologies. It is hard to quantify this effect, though comparisons of industry composition in light of the existing literature in markets for technology, patent propensity, and patent substitution with trade secrecy (contained in the Appendix) suggest that substitution is unlikely to account for the entire effect.

Discussion

Trade secrecy is an inherently difficult phenomenon to study empirically, and theoretical analyses, as we discussed, point to conflicting predictions on shifts in trade secrecy regime and innovation outcomes. Our empirical results, drawn from U.S. state-level trade secrecy environment shifts resulting from the Inevitable Disclosure Doctrine, suggest that shifting to an employer-friendly trade secrecy regime may hinder innovation as measured by forward-citation weighted patent grants. Further analysis suggests that this result is more consistent with an explanation rooted in dampened inventor incentives in signaling their quality to the external labor market as compared to the more common mechanism discussed in the management literature, placing frictions on idea recombination by individuals.

These findings suggest that the *non-patent* intellectual property legal environment (most prior work has focused on patenting) in which individuals and organizations operate can influence innovation outcomes. Paradoxically, our results suggest that what many firms and managers may lobby or wish for – a strengthened trade secrecy environment – may backfire with respect to inventor-level patent output.[16] The topic of appropriation of R&D-based activities is of course a long standing and important theme in the management of innovation/technology literature (e.g., Cohen, 2010). The literature has mainly followed variation in appropriation along

[16] In a working paper, Liu (2016) reports a positive relation between IDD and patent-based outcome measures for a sample of "high tech" industries. He defines such industries by categorizing their occupational make-up (via observed broad occupational titles contained in the Bureau of Labor Statistics data). An industry is classified as High Tech if the industry engineer employment percentage is double the average industry engineer employment for that year. In addition to a different focus of study, our samples differ by institutional environment categorization. As a result, we believe it is difficult to directly compare our papers.

industry lines – for example, the classic Yale and Carnegie Mellon industry surveys organize managerial perceptions of appropriation along industry lines. By contrast, not only do we consider non-patent based intellectual property, we also look beyond traditional industry boundaries in appropriability environments. This difference results in part from trade secrecy law adjudication at the U.S. state level. The managerial implication is that there can be differences in appropriability environment within industries, and so more active firm management of IP form (rather than mere consideration of industry membership) may be important.

Beyond the high-level recognition that the knowledge worker labor market environment and the associated incentives generated can impact innovation, our work on the associated mechanisms also hold a number of managerial implications. While one theory consistent with the main empirical pattern is that reduced idea recombination and cross-fertilization may be the operative mechanism, our results are not consistent with this mechanism. On the other hand, the labor market signaling view has not received as much attention in the strategic management literature. Managers should be aware that employee innovative effort, aside from intrinsic motivation, may also rely on expectations of employment terms and career advancement, as well as the ability to weaken potential hold-up problems inside a firm. Such advancement, in turn, may depend on both internal-to-the-firm and external career paths. If frictions are placed on the external path, that may have behavioral implications for technical staff within the focal organization. Our results suggest that this may be manifested in dampened incentives as a result of the threat of internal hold-up as well as a redirection in inventive effort (concentrating on more general-purpose inventions which would not be subject to the restrictions of the IDD).

More generally, since trade secrecy is a commonly used form of intellectual property protection by industrial managers, a deeper understanding of how and when it is used, together with how it operates, should be of managerial interest. Beyond managerial implications, our results also relate to the geography of innovation policy discussions and the debates in that literature regarding the role of regional culture versus legal infrastructure in innovation outcomes (e.g., Saxenian, 1994; Gilson, 1999). Our results do not speak to the role of regional culture, but do support the view that regionally-based legal infrastructure can alter innovation incentives and outcomes.

Despite the suggestive evidence associated with the mechanisms we analyze, we hope that this study is a beginning of further empirical research deepening our understanding of the relationship between trade secrecy law and innovation.

References

Abadie A, Diamond A, Hainmueller J (2010). "Synthetic control methods for comparative case studies: estimating the effect of California's tobacco control program." *Journal of the American Statistical Association*, 105: 493-505.

Acharya VV, Baghai RP, Subramanian KV (2013). "Wrongful discharge laws and innovation," *Review of Financial Studies* **27** (1): 301-346.

Anton JJ, Yao DA (2004). "Little patents and big secrets: Managing intellectual property," *RAND Journal of Economics* **35** (1): 1-22.

Arora A, Fosfuri A, Gambardella A (2001). *Markets for Technology: The Economics of Innovation and Corporate Strategy*. Cambridge: MIT Press.

Arundel, A. Kabla, I. (1998). "What percentage of innovations are patented? Empirical estimates for European Firms," *Research Policy*, 27: 127-141.

Becker, G (1964). *Human Capital*. Chicago: University of Chicago Press.

Bertrand M, Duflo E, Mullainathan S (2004). "How much should we trust differences-in-differences estimates?" *The Quarterly Journal of Economics*, 119: 249-275.

Bulow JI, Summers LH (1986). "A theory of dual labor markets with application to industrial policy, discrimination, and Keynesian unemployment," *Journal of Labor Economics*, 4: 376-414.

Castellaneta F, Conti R, Veloso FM, Kemeny CA. (2016). "The effect of trade secret legal protection on venture capital investments: Evidence from the inevitable disclosure doctrine," *Journal of Business Venturing*, 31: 524-541.

Castellaneta F, Conti R, Kacperczyk A. (2017). "Money secrets: how does trade secret legal protection affect firm market value? Evidence from the Uniform Trade Secret Act," *Strategic Management Journal*, 38: 834-853.

Cohen WM, Nelson RR, Walsh JP (2000). "Covering their intellectual assets: appropriability conditions and why U.S. manufacturing firms patent (or not)" NBER working paper 7552, National Bureau of Economic Research, Cambridge, MA. Available at: http://www.nber.org/papers/w7552.

Cohen WM (2010). "Chapter 4 - Fifty years of empirical studies of innovative activity and performance," *Handbook of the Economics of Innovation*.

Doeringer PB, Piore MJ (1971). *Internal Labor Markets and Manpower Analysis*. Lexington, MA: Heath.

Fisk, C (2001). "Working knowledge: Trade secrets, restrictive covenants in employment, and the rise of corporate intellectual property, 1800-1920," *Hastings Law Review* **52**: 441-535.

Fleming, L (2001). "Recombinant uncertainty in technological search," *Management Science* **47** (1):117-132.

Fleming L, Sorenson O (2001) Technology as a complex adaptive system: Evidence from patent data. *Research Policy* **30**:1019–1039.

Friedman DD, Landes WM, RA Posner (1991). "Some economics of trade secret law," *Journal of Economic Perspectives*, 5: 61-72.

Gans J, Hsu DH, Stern S (2008). "The impact of uncertain intellectual property rights on the market for ideas: evidence from patent grant delays," *Management Science*, 54: 982-997.

Garmaise MJ (2011). "Ties that truly bind: noncompetition agreements, executive compensation, and firm investment," *Journal of Law and Economics & Organization* 27: 376-425.

Gibbons R, Katz LF, Lemieux TH, Parent D. (2005) "Comparative advantage, learning, and sectoral wage determination," *Journal of Labor Economics* 23(4): 681-724.

Gibbons R, Waldman M. (1999). "A theory of wage and promotion dynamics inside firms," *Quarterly Journal of Economics,* 114: 1321-358.

Gilson, RJ (1999). "The legal infrastructure of high technology industrial districts: Silicon Valley, Route 128, and covenants not to compete, *New York University Law Review* 74: 575-629.

Hall B, Jaffe A, Trajtenberg M (2001). "The NBER patent citation data file: Lessons, insights, and methodological tools," NBER working paper 8498, National Bureau of Economic Research, Cambridge, MA. Available at: http://www.nber.org/papers/w8498.

Hellmann T, Perotti E (2011). "The circulation of ideas in firms and markets," *Management Science* 57 (10): 1813-1826.

Kahnke R, Bundy KL, Liebman KA (2008). "Doctrine of Inevitable Disclosure," Faegre & Benson LLP. Accessed at: www.faegrebd.com/webfiles/Inevitable%20Disclosure.pdf

Kim J, Marschke G (2005). "Labor mobility of scientists, technological diffusion, and the firm's patenting decision," *Rand Journal of Economics*, 36: 298-317.

Li GC, Lai R, D'Amour A, Doolin DM, Sun Y, Torvik VI, Yu AZ, Fleming L (2014). "Disambiguation and co-authorship networks of the U.S. patent inventor database (1975-2010)," *Research Policy* **43**: 941-955.

Liu Z (2016). "Intellectual Property Allocation and Firm Investments in Innovation", McCombs School of Business, University of Texas at Austin working paper.

Marx M, Strumsky D, Fleming L (2009). "Mobility, skills, and the Michigan non-compete experiment," *Management Science* **55** (6): 875-889.

Moser P (2012). "Innovation without patents: Evidence from world's fairs," *Journal of Law and Economics* **55** (1): 43-74.

National Conference of Commissioners on Uniform State Laws (1985). "Uniform Trade Secrets Act with 1985 Amendments," Available at: http://www.uniformlaws.org/shared/docs/trade%20secrets/utsa_final_85.pdf.

Png, IPL (2015). "Secrets and patents: Theory and evidence from the Uniform Trade Secrets Act," *working paper*, National University of Singapore.

Png, IPL (2017). "Law and innovation: Evidence from state trade secrets laws," *Review of Economics and Statistics*, 99: 167-179.

Saxenian, A (1994). *Regional Advantage*. Cambridge: Harvard University Press.

Silverman, BS. (1999). "Technological resources and the direction of corporate diversification: Toward an integration of the resource-based view and transaction cost economics," *Management Science* **45** (8): 1109-1124.

Spence M (1973). "Job market signaling." *Quarterly Journal of Economics* 87(3): 355-74.

M. Trajtenberg (1990). "A penny for your quotes: patent citations and the value of innovations," *Rand Journal of Economics*, 21: 172-187.

Wiesner, RM (2012). "A state-by-state analysis of inevitable disclosure: A need for uniformity and a workable standard," *Marquette Intellectual Property Law Review* **16**: 211-231.

Table 1
Variable definitions and descriptive statistics
(Individual-year unit of analysis)

VARIABLE	*DEFINITION (data source)*	*MEAN*	*STD. DEV.*
Dependent variables			
Log citation weighted patent count	Log of the number of eventually-granted patent applications weighted by number of forward citations within 4 years from grant (IQSS/NBER)	0.84	1.18
Log mean combinatorial novelty	Log of the mean of the combinatorial novelty of the eventually-granted patent applications. Combinatorial novelty measures the degree to which the individual inventions recombine infrequently combined technology areas (Fleming and Sorenson, 2001)	2.15	0.81
Mean patent generality	1-Herfindahl-Hirschman Index of primary patent classes in forward patent citations (IQSS/NBER)	0.44	0.26
Independent and control variables			
Trade secrecy regime			
IDD positive	Binary variable taking value 1 when a positive ruling for IDD is in place and 0 otherwise (Castellaneta et al., 2016)	0.06	0.23
IDD negative	Binary variable taking value 1 when a negative ruling for IDD is in place and 0 otherwise (Castellaneta et al., 2016)	0.29	0.45
Individual-level controls			
Log individual experience	Log number of years since the inventor appears in the dataset (IQSS/NBER)	1.80	0.70
Log 4-year Patent Stock	Log of number of patents in the prior four years (IQSS/NBER)	1.08	0.69
Organization- and industry-level controls			
Log organization age	Log number of years since organization appears in dataset (IQSS/NBER)	2.39	0.68
Log organization size	Log number of inventors belonging to the organization (IQSS/NBER)	4.02	2.42
Log industry size	Log number of inventors in 3-digit SIC (IQSS/NBER & Silverman, 1999)	5.27	1.84
State-level controls			
Log state population	Log of the state total population (Bureau of Economic Analysis website)	16.03	0.85
Log state total wage	Log of the state sum of wages and salaries in thousands of US dollars (Bureau of Economic Analysis website)	18.51	0.98

Table 2
Employer-friendly trade secrecy regime (IDD) and innovation: main analyses

Panel A: IDD effect over time

Dependent variable	*Log citation weighted patent count as of time t*					
	(2A-1)	**(2A-2)**	**(2A-3)**	**(2A-4)**	**(2A-5)**	**(2A-6)**
IDD positive t+2	-0.002 (0.012)					
IDD negative t+2	0.011 (0.016)					
IDD positive t+1		-0.005 (0.020)				
IDD negative t+1		0.0175 (0.016)				
IDD positive t			-0.022 (0.017)			
IDD negative t			0.020 (0.017)			
IDD positive t-1				-0.032 (0.018)		
IDD negative t-1				0.019 (0.036)		
IDD positive t-2					-0.050 (0.025)	
IDD negative t-2					0.009 (0.029)	
IDD positive t-3						-0.043 (0.036)
IDD negative t-3						-0.001 (0.016)
Ind.-, org.-, industry- & state-controls	Y	Y	Y	Y	Y	Y
Indiv. & year FE	Y	Y	Y	Y	Y	Y
N	2,067,187	2,420,276	2,772,278	2,419,698	2,066,356	1,762,862
Adj. R^2	0.40	0.38	0.35	0.34	0.35	0.35

Panel B: Main effect at the inventor-year and state-year levels of analysis

Dependent variable	*Log citation weighted patent count*					
Unit of analysis	**Inventor-year**				**U.S. state-year**	
Time window	*t+2*		*t+3*		*t+2*	*t+3*
	(2B-1)	**(2B-2)**	**(2B-3)**	**(2B-4)**	**(2B-5)**	**(2B-6)**
IDD positive	-0.045 (0.015)	-0.033 (0.018)	-0.049 (0.018)	-0.037 (0.015)	-0.231 (0.127)	-0.234 (0.107)
IDD negative	0.024 (0.023)	0.031 (0.021)	0.015 (0.021)	0.022 (0.021)	-0.177 (0.133)	-0.155 (0.131)
Ind.-, org.-, & industry-controls	N	Y	N	Y	N	N
State controls	N	Y	N	Y	Y	Y
Indiv. & year FE	Y	Y	Y	Y	N	N
State & year FE	N	N	N	N	Y	Y
N	2,067,187	2,067,187	1,763,496	1,763,496	1,326	1,275
Adj. R^2	0.25	0.26	0.26	0.27	0.96	0.97

Note: State-clustered standard errors in parentheses in both panels.

Table 3
Employer-friendly trade secrecy regime (IDD) and innovation: robustness checks

Panel A. Robustness to potential confounds: inventor-level of analysis

Dependent variable	*Log citation weighted patent count*						*Citation weighted patent count*	
Estimation method	*OLS*						*Poisson*	
Time window	*t+2*	*t+3*	*t+2*	*t+3*	*t+2*	*t+3*	*t+2*	*t+3*
	(3A-1)	**(3A-2)**	**(3A-3)**	**(3A-4)**	**(3A-5)**	**(3A-6)**	**(3A-7)**	**(3A-8)**
IDD positive	-0.032 (0.017)	-0.036 (0.014)	-0.082 (0.031)	-0.143 (0.041)	-0.096 (0.032)	-0.153 (0.044)	-0.064 (0.027)	-0.059 (0.031)
IDD negative	0.030 (0.027)	0.021 (0.002)	0.049 (0.036)	0.023 (0.039)	0.062 (0.064)	-0.030 (0.072)	0.044 (0.018)	0.0180 (0.022)
Trade secrecy index	-0.009 (0.023)	-0.014 (0.025)						
Ind.-, org.-, industry- & state-controls	Y	Y	Y	Y	Y	Y	Y	Y
Indiv. & year FE	Y	Y	Y	Y	Y	Y	Y	Y
Time trend	N	N	Y	Y	N	N	N	N
State-specific time trend	N	N	N	N	Y	Y	N	N
N	2,067,187	1,763,496	2,067,187	1,763,496	2,067,187	1,763,496	1,907,452	1,627,639
Adj. R^2	0.26	0.27	0.24	0.26	0.25	0.26	N/A	N/A

Panel B. Robustness to sample composition: inventor-level of analysis

Dependent variable	*Log citation weighted patent count*							
Sample	*Inventors who do not change state*				*Inventors who do not change IDD regimes*			
Time window	*t+2*		*t+3*		*t+2*		*t+3*	
	(3B-1)	**(3B-2)**	**(3B-3)**	**(3B-4)**	**(3B-5)**	**(3B-6)**	**(3B-7)**	**(3B-8)**
IDD positive	-0.050 (0.015)	-0.028 (0.002)	-0.044 (0.019)	-0.019 (0.018)	-0.050 (0.014)	-0.037 (0.018)	-0.046 (0.019)	-0.032 (0.014)
IDD negative	0.003 (0.046)	0.033 (0.046)	-0.003 (0.045)	0.027 (0.045)	0.013 (0.038)	0.027 (0.038)	0.007 (0.034)	0.020 (0.035)
Ind.-, org.-, industry- & state-controls	N	Y	N	Y	N	Y	N	Y
Indiv. & year FE	Y	Y	Y	Y	Y	Y	Y	Y
N	1,581,745	1,581,745	1,325,937	1,325,937	1,736,865	1,736,865	1,465,375	1,465,375
Adj. R^2	0.25	0.26	0.26	0.27	0.25	0.26	0.26	0.26

Table 4
Employer-friendly trade secrecy regime (IDD) and innovation: mechanisms

Panel A: Potential IP substitution analysis: "discrete" vs. "complex" inventions (invention level of analysis)

Dep. variable	*Log patent citations*					
Sample	full		"discrete" inventions		"complex" inventions	
	(4A-1)	**(4A-2)**	**(4A-3)**	**(4A-4)**	**(4A-5)**	**(4A-6)**
IDD positive	-0.021 (0.005)	-0.015 (0.005)	-0.058 (0.009)	-0.051 (0.009)	-0.005 (0.006)	-0.001 (0.006)
IDD negative	0.098 (0.002)	0.093 (0.002)	0.051 (0.004)	0.050 (0.004)	0.113 (0.003)	0.107 (0.003)
Ind., team, and org. controls	N	Y	N	Y	N	Y
SIC2 & year FE	Y	Y	Y	Y	Y	Y
N	792,804	792,804	238,281	238,281	554,523	554,523
Adj. R^2	0.17	0.18	0.10	0.11	0.17	0.18

Panel B: Knowledge recombination mechanism (inventor-year level analysis)

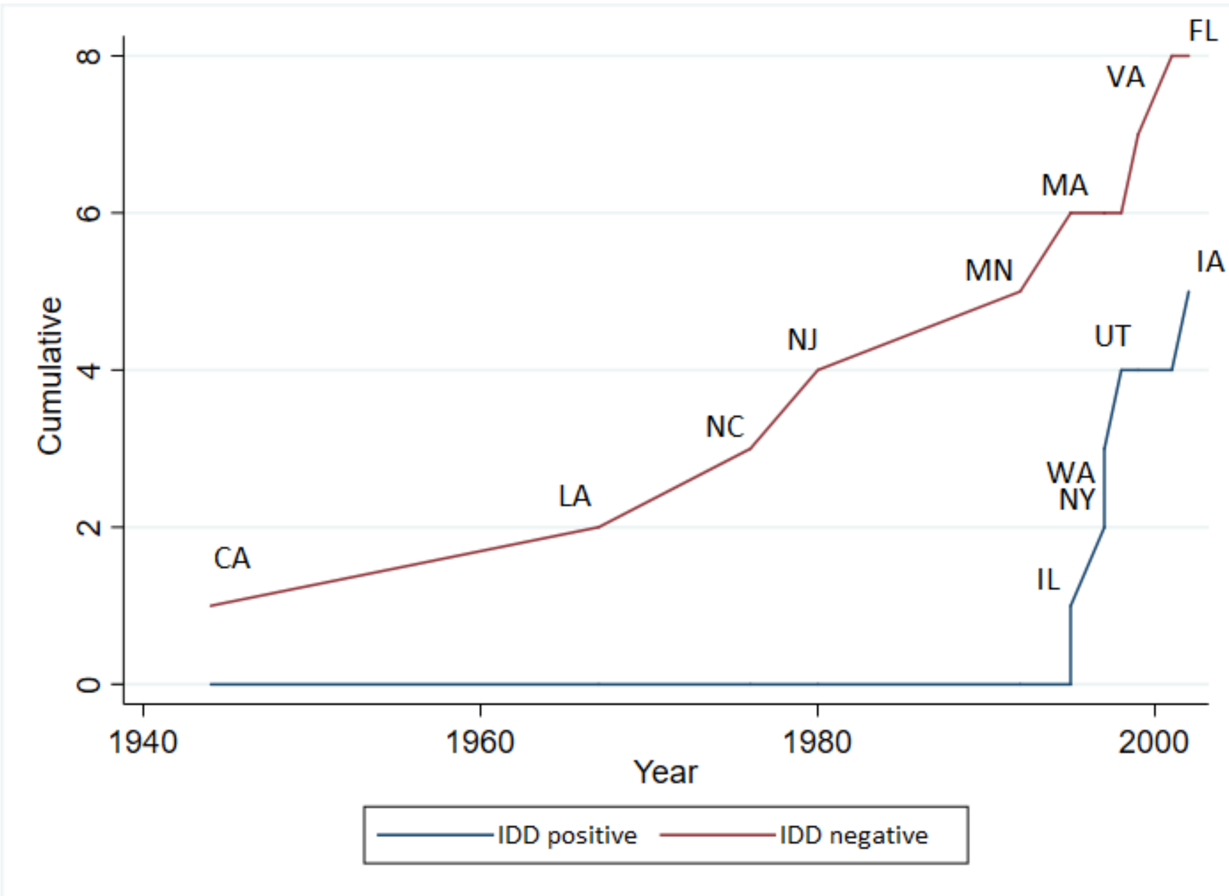
Dep. variable	*Log mean combinatorial novelty*					
Sample	full		"discrete" inventions		"complex" inventions	
Time widow	*t+2*	*t+3*	*t+2*	*t+3*	*t+2*	*t+3*
	(4B-1)	**(4B-2)**	**(4B-3)**	**(4B-4)**	**(4B-5)**	**(4B-6)**
IDD positive	-0.010 (0.017)	-0.007 (0.017)	-0.029 (0.036)	-0.020 (0.027)	0.016 (0.020)	0.016 (0.026)
IDD negative	-0.008 (0.011)	-0.006 (0.007)	-0.020 (0.013)	-0.016 (0.011)	0.016 (0.009)	0.011 (0.009)
Ind.-, org.-, industry- & state-controls	Y	Y	Y	Y	Y	Y
Ind. & year FE	Y	Y	Y	Y	Y	Y
N	897,582	758,575	202,644	172,706	431,906	363,382
Adj. R^2	0.46	0.47	0.34	0.34	0.34	0.34

Panel C: Labor market signaling mechanism: correlates of patent generality (inventor-year level analysis)

Dep. variable	*Mean patent generality*					
Sample	full		"discrete" inventions		"complex" inventions	
Time widow	*t+2*	*t+3*	*t+2*	*t+3*	*t+2*	*t+3*
	(4C-1)	**(4C-2)**	**(4C-3)**	**(4C-4)**	**(4C-5)**	**(4C-6)**
IDD positive	0.006 (0.004)	0.010 (0.004)	0.027 (0.005)	0.034 (0.005)	0.001 (0.004)	0.004 (0.005)
IDD negative	0.002 (0.004)	-0.001 (0.004)	-0.003 (0.004)	-0.006 (0.005)	0.010 (0.003)	0.003 (0.004)
Ind.-, org.-, industry- & state-controls	Y	Y	Y	Y	Y	Y
Ind. & year FE	Y	Y	Y	Y	Y	Y
N	819,229	691,408	181036	154,091	404,530	339,892
Adj. R^2	0.35	0.35	0.34	0.34	0.35	0.35

Note. To define "discrete" and "complex" technologies, we follow Cohen et al. (2000) by focusing on manufacturing sectors and categorize each SIC as either discrete (SIC between 19 and 33) or complex (SIC between 34 and 39). In panels B and C, inventors with more than 50% of her inventor years classified as a given technology "type" (discrete or complex) are categorized within each category. The reported results are robust to restricting the sample to a 100% criterion too. IDD positive and negative states are shown in Table 1, with all other U.S. states as controls. OLS coefficients are reported (state-clustered standard errors are in parentheses). Panel A is restricted to patents where all inventors are based in the same IDD regime in order to unambiguously assign IDD regime to each patent. In panel A control variables include: log inventor team size, log average inventor experience, log average inventor tenure, log average organizational age, and log average organizational size. In panels B and C individual-, organization-, industry-, and state-level controls are listed in Table 1.

Figure 1
Inevitable disclosure doctrine (IDD) rulings over time



Note: only graphed through 2003 since the analysis discontinues in that year. The y-axis is cumulative number of states. The x-axis is time. Source: Castellaneta et al. (2016).

Figure 2
Year-specific "treatment" effects of pro- and against-IDD rulings

Figure 2A: IDD positive rulings

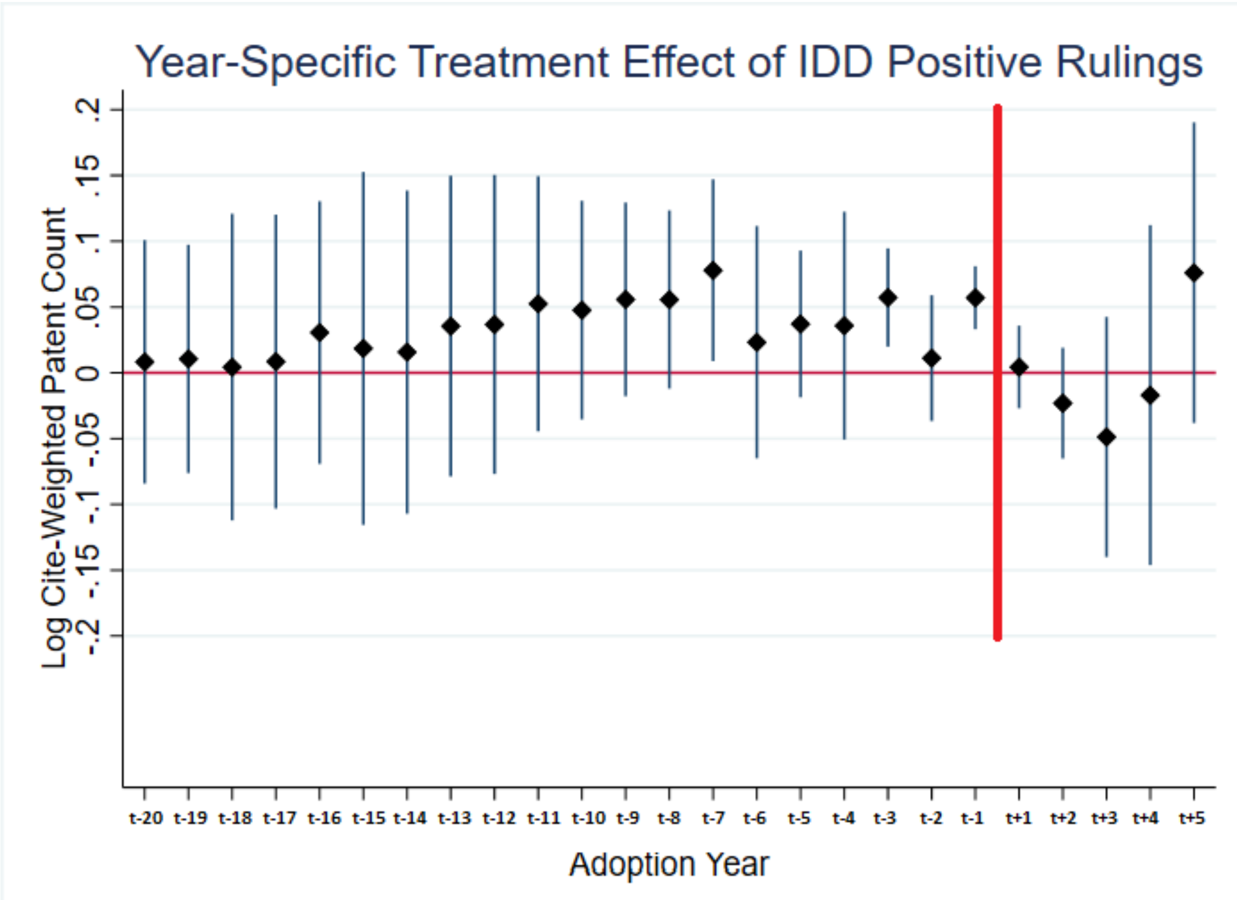
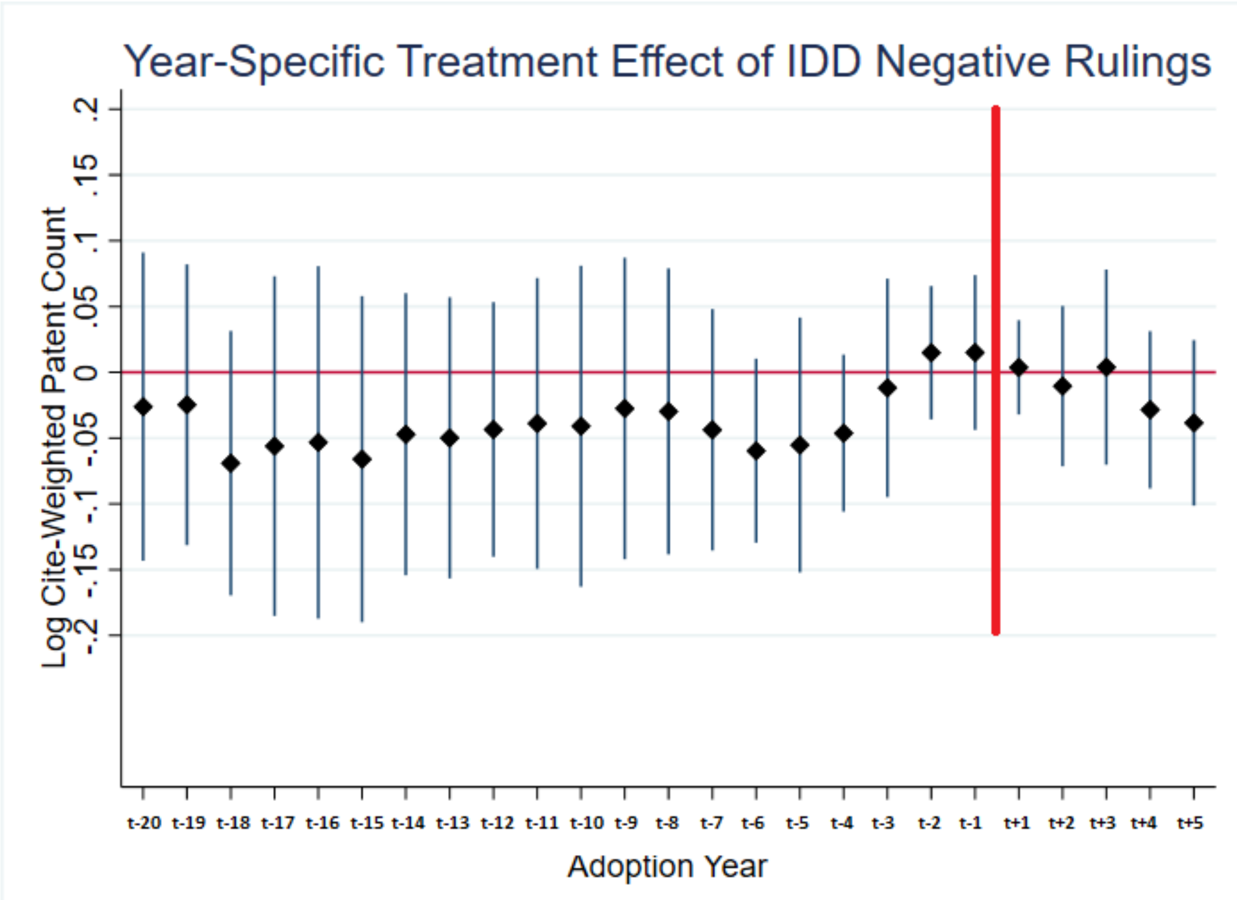


Figure 2B: IDD negative rulings



Note: the red line denotes the "treatment" year, and the omitted coefficient in the estimation is also the treatment year. Dots denote regression coefficient estimates (of log citation weighted patent count) on year-specific treatments, and vertical black bars denote the 95% confidence interval around the coefficient. The regressions include inventor and year fixed effects. The graphs show little or no pre-trend prior to the treatment year.

Appendix: Trade secrecy / patent substitution analysis in the complex technology sub-sample

This appendix further discusses the possibility of intellectual property form substitution (trade secrecy versus patenting) in the wake of differential strengthening of the employer-friendly trade secrecy regime. The main text concentrates on the case of "discrete" technologies, which are unlikely to face the substitution. For that reason, we rely on the discrete sub-sample to assess our mechanisms. This appendix discusses the possible substitution in the complex technology sub-sample, for the sake of contextual understanding rather than for direct evidence of mechanisms.

Substitution is more likely to hold in the context of complex technologies following trade secrecy regime shifts, and so the open question is how to understand and interpret the degree of substitution versus "real" effects of reduced innovation in this sub-sample. Even though we do not rely on this sub-sample for empirical assessment of our mechanisms, we wish to qualitatively understand the likely behavior of this sub-sample, especially since it comprises about two-thirds of our overall sample. Consider Appendix Table 1, which lists the two digit SIC codes of complex technologies appearing in our sample, in descending order of frequency.

Appendix Table 1: Comparison of our sub-sample of complex technologies, by industry

Two digit SIC code	*Industry description*	*Fraction of the complex sub-sample (within our data)*	*Serrano (2010) share of "traded" technologies* *[From Serrano's Table 2, Panel A, p. 693]*	*Arundel & Kabla (1998) sales-weighted patent propensity* *[From Arundel & Kabla's Table 1, p. 133. Baseline for all product innovations within their sample: 35.9%]*
36	Electronic and electrical equipment (except computers)	44.4%	13.8%	43.6% ("electronic equipment")
35	Industrial and communications machinery, and computers	28.6%	12.9%	52.4%-56.8% ("machinery and office equipment"); 46.6% ("communications equipment")
37	Transportation equipment	14.8%	12% ("mechanical")	
38	Measuring, controlling, and analyzing equipment	6.8%		56.4% ("precision instruments")
34	Fabricated metal products	4.8%		
39	Miscellaneous manufacturing	0.6%		

The first two columns list each of the two digit SIC sectors contained within the "complex" technology broad category. The third column describes the relative frequency (as a percentage of the complex technologies) of each sector, and is sorted in descending order of incidence within our sample. The final two columns provide comparisons to two papers related to sector-level activity in the markets for technology (Serrano, 2010) and patenting propensity (Arundel and Kabla, 1998). The table and page references in the header of these final two columns refer to those contained within the cited papers.

The markets for technology literature has identified patenting as important in transacting in the market for technology (Arora, Fosfuri & Gambardella, 2001; Gans, Hsu & Stern, 2008), and so we compare the industrial composition of our complex technology subsample to the findings in the literature describing the level of activity in the markets for technology along industry lines (Serrano, 2010) in the fourth column. There is a great deal of overlap between the complex industry sub-sectors in our sample and the Serrano (2010) sub-sectors with regard to market for technology activity. With the exception of the drugs/medical and chemical sectors, which experienced patent market transactions at a rate of 16% and 14.9%, respectively (note: these two sectors are *not* categorized as complex technologies), the sectors comprising the complex technology sectors listed in the above table were the most frequently transacted in the Serrano sample.

Likewise, as shown in column 5 above, using a survey of European industrial firms, Arundel and Kabla (1998) describe the sales-weighted patent propensity of sectors also contained within our sample of complex technologies. The patenting propensity in the Arundel and Kabla (1998) data was systematically higher in each of the sectors they studied (ranging from 43.6% to 56.8%) which are also present within our set of "complex" industries, as compared to their baseline patenting propensity for all product innovations in their sample (35.9%). This suggests that among our complex technologies, patent propensity may also be high.

One important caveat to these comparisons is that they are not in general made in the face of differential changes in one IP regime over another, as would be the case in IDD positive and negative rulings as compared to patent protection. Png (2015) examines such changes in the wake of state-level adoption of the Uniform Trade Secrets Act (UTSA). He finds (his Table 5) that in two sectors (electronic accessories (SIC3 code: 367) and general industrial machinery (SIC3: 356)), there is a negative and significant relation between UTSA and patent counts. These two 3 digit SIC industries seem to belong within our first and third 2 digit SIC industries (ranked by frequency of representation in our sample). It is notable that Png (2015) finds no significant effect when he analyses the computer and office equipment industry (SIC3: 357), which is our second most frequent "complex" technology by frequency.

Having examined the degree to which there might be substitution across forms of IP protection, we also verified that inventors were not switching from discrete to complex inventions/technologies (or vice-versa) in response to the altered trade secrecy regime. We confirm that this is not the case for both levels of each type of technology (discrete and complex), as well as the shares of each type (formal regression output available on request).