Intellectual Property Allocation and Firm Investments in Innovation

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Abstract

Successful innovations are achieved by combining employee ingenuity with firm resources. However, firms will suppress investment if employees can easily leave the firm and take these innovations with them. I provide new evidence on how changes to employee outside options impact innovation incentives using state court decisions to adopt the Inevitable Disclosure Doctrine (IDD), which strengthens firm trade secret protections by limiting employee mobility. I find that IDD adoption leads to an increase in innovation output and investment in high technology industries, where employee outside options are higher, but not in low technology industries. Furthermore, I find that these firms are able to hire talented employees. These results show that decreasing the ability of employees to leave the firm in high technology industries can be mutually beneficial.

JEL classification: D86, J62, K31, O31, O34

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1 Introduction

Economists have made important strides in understanding the factors that influence innovative activity within corporations. Innovation success has been linked to financial structure, competitive environment, and managerial compensation. However, the literature has largely treated the innovation process itself as a black box, abstracting away from the collaborative efforts of employees and firms that ultimately drive the development of new products, designs, and processes. This omission is significant, as it masks the potentially important role of incentives to invest time, effort, and financial resources in the innovation process.

New innovations are inherently difficult to describe ex ante and verify ex post. As a result, conventional solutions that provide incentives to innovate are difficult to achieve (Aghion and Tirole, 1994). Instead, a party's incentives to invest in innovation depend primarily on how successful innovation affects the value of its outside options, as in the standard incomplete contracting framework of Grossman and Hart (1986) and Hart and Moore (1990). This paper empirically investigates how incentives arising from outside options impact corporate innovation by exploiting a series of shocks to employees' outside options – state-level adoptions of the "Inevitable Disclosure Doctrine" (IDD). The doctrine increases trade secret protections by allowing firms to enforce restrictions on the ability of employees who know important trade secrets to leave and compete against the firm. This doctrine effectively constrains the outside options of employees involved in innovation by limiting their ability to depart with innovative knowledge.[1]

To provide a formal framework for understanding how these changes should affect innovation, I present a simple model of investment in innovation. In the model, a firm and employee contribute complementary innovative inputs, reflecting the idea that the most successful corporate innovations are achieved by combining employee ingenuity with firm resources. The employee acquires knowledge in the process of successful innovation that increases the value of her outside options, perhaps by making her more worthy to other employers or by improving her prospects as an entrepreneur. The departure of the employee and the resulting loss of her knowledge decreases the

[1] See Section 2 for a more detailed description of IDD.

value of the innovation to the firm to the point where it is willing to match the value of her outside option in order to retain her.[2]

The direct consequence of tightening constraints on the ability of the employee to depart with valuable knowledge is an increase in the firm's and a decrease in the employee's return from innovation and, as a result, a change in innovation incentives. Moreover, additional firm investment in innovation increases the returns to the employee's inputs because of investment complementaries, which strengthens the employee's incentives to innovate. The net effect of these changes in incentives results in an inverted U-shaped relationship between innovation activity and the ability of employees to leave with innovative knowledge. Additionally, because innovation inputs are complementary, more talented employees may match to firms with tougher protections against employee knowledge expropriation.

Motivated by these insights, I examine changes in patents and patent citations – measures of innovative output – after IDD adoption. Relying on IDD adoption as a shock to outside options is useful for three reasons. First, it allows me to circumvent the need to precisely measure the level of and changes to employee outside options. Second, even if outside options could be measured, concerns about omitted variables and reverse causality would make it difficult to make causal inferences about any observed relationship between innovative output and measures of outside options.[3] Focusing on shocks that are plausibly exogenous with respect to innovation allows me to make stronger inferences. Third, the use of staggered state-level shocks allows me to control for a number of potentially contaminating factors, including unobserved time-varying firm characteristics.

I implement my empirical analysis by examining patents and patent citations three years before and after adoption IDD adoptions. In particular, my empirical strategy focuses on comparing changes in innovative activity around these shocks between high technology firms, where employ-

[2]"Did you realize that approximately 42% of the average company's intellectual capital exists only within its employees' heads?" - Thomas Brailsford

[3]For example, more innovative firms may attract more intrinsically-motivated employees, and hence do not need to provide strong incentives like the ability transfer knowledge. Alternatively, as firms in an industry invest more in innovation, innovative employees become more mobile and their ability to transfer knowledge increases.

ees can take more valuable knowledge if they depart, and low technology firms, where they have less knowledge to take. The model's chief prediction implies that innovative activity should increase after IDD adoption in high technology firms relative to low technology firms. Consistent with this prediction, after IDD adoption, both patents and citations increase by 9 - 15% in high technology firm establishments in states affected by IDD adoption relative to low technology firm establishments.

One concern with this approach is that IDD adoption could be related to characteristics of firms in the adopting state. For example, a state court may be more inclined to adopt IDD when the state has more innovative companies that are likely to benefit from and push for these protections. However, this concern is partially mitigated by the fact that IDD adoption is the result of state court decisions rather than legislative actions, assuming that the latter are more likely to be influenced by lobbying efforts. In any case, to further address this concern, I exploit the fact that firms often innovate in different states, and I use these unaffected establishments to account for any unobserved firm-level difference in and changes to technology, financial constraints, or firm operations within each year. Specifically, I estimate triple-differences regressions comparing innovative output (1) across establishments in adopting and non-adopting states, (2) before and after IDD adoption years, and (3) between high and low technology firms. This approach allows me to filter out the effects of any time-varying firm-level variables that may be correlated with innovation outcomes that could complicate inference, such as firm-wide investment increases or changes in the incentives to patent innovation. Even after controlling for these time-varying firm-level factors, patents and citations increase by 9 - 21% after IDD adoption in high technology establishments relative to low technology establishments.

Next, I focus on firm investment in innovation. The model demonstrates that a firm can only achieve more innovation after a weakening of employee outside options if the firm increases investment in innovation. Consistent with this response, I find that high technology firms increase R&D investment spending after IDD adoption.[4] Furthermore, the ability to increase investment

[4]This result is similar to Png (2015), who finds that high technology firms increase R&D investment after passage of the UTSA.

also depends on the firm's financial strength. To this end, I proxy for the ease of increasing innovation investment by using ex ante firm leverage, the Kaplan and Zingales (1997) index, the Whited and Wu (2006) index, and the SA index (Hadlock and Pierce, 2010) and separately examine changes in innovation in firms that are more or less likely to be financially constrained using the same triple-differences set up. In firms that are less likely to be constrained, the effect of IDD adoption on high tech firms is positive and significant, while no such change is observed for firms that are more likely to be constrained.[5]

Finally, I examine how the ability of firms to attract and hire employees changes around IDD adoptions. One might expect that IDD protections would make it more difficult for a firm to attract talented employees because the firm keeps a greater share of the gains from innovation. However, I demonstrate in an extension of my model that talented employees may match to firms with stricter protections in equilibrium. Since talented employees are inherently more productive, they will provide more effort in response to increases in firm investment in innovation, and, thus, experience a greater benefit as a result. I measure the fraction of new inventors at an establishment and identify highly skilled employees as inventors who have previously published a highly cited patent.[6] I then examine changes in the fraction of total, skilled, and unskilled new hires in the triple-differences framework. Consistent with IDD adoption enhancing a firm's ability to hire more talented employees, high technology firms hire 2% more highly skilled inventors each year after IDD adoption.

The main identification strategy in this paper uses state-level shocks in a triple-differences setting. Even though this strategy controls for a multitude of factors, there could be other sources of endogenous variation that are unaccounted for. First, other state-level changes favorable to innovation might occur around IDD adoption. To address this concern, I form synthetic control groups using small, private firms in states affected by IDD, which should be affected by state innovation incentives but less affected by employee-employer frictions. I confirm that the results

[5]Changes to patent and trade secret protections can impact the pledgeability of intangible assets (Klasa et al. (2015) and Mann (2015)). However, IDD adoption is unlikely to influence innovation more in constrained firms.

[6]I identify firm new comers using the same methodology as Bernstein (2015).

hold when using these synthetic controls. Second, trade secret protections could shift incentives to patent innovations. Kim and Marschke (2005) argue that firms with high employee mobility prefer to use patents, not trade secrets, to better protect ideas from employee expropriation. Therefore, IDD should have a negative impact on patenting at high technology firms, where mobility is high, relative to low technology firms. Since I document that high technology firms increase patenting relative to low technology firms, the effect I identify on patented innovations is likely to be a lower bound for the effect of IDD on total innovation.

This paper builds on broad literature that studies labor laws, employee incentives, and innovation. Acharya et al. (2013, 2014) find that wrongful discharge laws reduce employer hold up. Griffith and Macartney (2014) link employment protections to more radical innovations. Also, Bradley et al. (2015) look at the impact of unions on employee protection and misaligned effort incentives. Both Klasa et al. (2015) and Png and Samila (2015) document that highly skilled and highly educated employees have an outsized reduction in mobility after states adopt IDD, which can impact corporate decisions like firm leverage. Also, Marx et al. (2009) and Garmaise (2009) provide links between non-compete, mobility, and investment. This paper adds to the literature by connecting changes in employee outside options to firm investment and provides evidence that decreasing employee outside options can improve innovation outcomes.

This paper also contributes to the literature on incomplete contracts and management of R&D. Grossman and Hart (1986) and Hart and Moore (1990) illustrate the insight that bilateral relationships suffer from hold up problems. In this spirit, Aghion and Tirole (1994) and Tirole (1999) study the integration decisions of R&D units, Almazan et al. (2007) study firm location decisions and the development of human capital, and Fulghieri and Sevilir (2011) study worker incentives and merger-spinoff decisions. My model builds on the intuition in these models and focuses on incentives problems caused by incomplete contract within the firm. Furthermore, my paper provides empirical support that incomplete contracting mechanisms have significant effects on firm dynamics.

This paper also contributes to the recent literature on corporate innovation. Several studies

have documented how different corporate decisions and characteristics can lead to changes in innovation such as IPOs (Bernstein, 2015), corporate conglomeration (Seru, 2014), hostile takeovers (Atanassov, 2013), mergers and acquisitions (Bena and Li, 2014), financial constraints (Almeida et al., 2013), and competition (Grieser and Liu, 2016). Also, other institutional factors like banking deregulation (Chava et al., 2013; Cornaggia et al., 2015), analyst coverage (He and Tian, 2013), stock liqudity (Fang et al., 2014), and corporate venture capital (Chemmanur et al., 2014) have been linked to innovation. In addition, innovation has been linked to CEO and board of directors factors like incentive pay (Ederer and Manso, 2013), tolerance for failure (Manso, 2011; Tian and Wang, 2014), and board independence (Balsmeier et al., 2015). My paper adds to this literature by directly studying the employee-employer relationship and considering how to provide incentives to both parties.

The rest of the paper is as follows. Section 2 provides institutional details about trade secrets and IDD. Section 3 presents a model of innovation using complementary employee and firm inputs. Section 4 outlines the data used. Section 5 provides the empirical results and tests of model prediction. Section 6 concludes.

2 Trade Secrets and Inevitable Disclosure Doctrine

For many firms, the human capital of their employees represents a large fraction of company value, but it is an input which the company does not fully own. To help protect human capital, research, and new technologies, firms often use trade secrets laws. For example, Intel and Broadcom settled a lawsuit in 2000 that challenged the ability of employees to change jobs at will. At the heart of the dispute was that Intel wanted to prevent employees from joining Broadcom merely because of the threat that they might violate Intel's trade secrets. This is the exact issue the Inevitable Disclosure Doctrine addresses.

The Inevitable Disclosure Doctrine (IDD) holds that in certain circumstances, if an employee holds critical information about firm trade secrets, she can be temporarily (or even permanently)

denied from working in a specific job, because doing so would inevitably lead to the disclosure of her former firm's trade secrets. While there are many definitions of trade secrets the main components that comprise a trade secret are (1) information (2) that is valuable because of its secrecy, and (3) whose owner reasonably tries to maintain that secrecy. The law protects trade secrets from two main forms of misappropriation: improper means and disclosure. Improper means usually ranges from an employee copying confidential records to industrial espionage. However, each state sets its own laws governing trade secrets, thus IDD is not uniformly accepted by all states.

In general, IDD allows courts to prevent an employee from working for his employer's competitors because of the threat of misappropriation. The firm needs to prove that the trade secret is valuable and that it has gone to adequate lengths to keep it secret. Also, the firm needs to show that to succeed in the employee's new role she will rely on the former employer's trade secrets. If these conditions are met, the court can rule to temporarily or permanently ban the employee from joining a competitor.

Table 6 provides a list of cases when IDD was first approved by a state supreme court (Kahnke et al., 2008). Figure 6 visually plots which states have adopted IDD. Panel A shows the relevant states where state courts adopted IDD between 1989 and 2000. Panel B shows the states which adopted IDD prior to 1989.

To better understand how IDD is applied, I summarize a court case in Utah.

2.1 Case: Norvell Inc. vs Timpanogos Research Group Inc.

Timpanogos Research Group (TRG), a company formed by a group of former Norvell Inc. employees, tried to sell intellectual property to Microsoft. However, Norvell sued TRG alleging that the intellectual property in question comprises Norvell trade secrets obtained by former employees Darren Major, Larry Angus, and Jeff Merkey. Norvell claimed that the ideas, designs, and templates shown to Microsoft were created at Norvell and, therefore, are trade secrets belonging to Norvell. In this case, the state court ruled in favor of Norvell and placed an injunction on Major, Angus, and Merkey from working in a related industry for at least 9 months, ending 1.5 years after

they left Norvell.

The defendants were long time employees of Norvell Inc. All of the defendants signed paperwork that prevents them from misappropriating trade secrets. Together they worked on Norvell's Wolf Mountain Project, which began in March 1995. During this time, Merkey told several Norvell coworkers that he had intentionally under documented his work so that it would be "in his head and not Norvell's."[7] In late 1996 and early 1997, Wolf Mountain was released internally to gather feedback from other Norvell computer engineers. Since the Wolf Mountain Project received harsh criticism from the core operating group at Norvell, the project's prospects at Norvell seemed dim. In March and April 1997, Major, Angus, and Merkey resigned from Norvell to start a new corporation, Timpanogos Research Group, which focused on exploring Wolf Mountain Project ideas outside of Norvell. In April 1997, Merkey approached Microsoft, a Norvell competitor, to gauge their interest in the Wolf Mountain Project.

In the end, the state court ruled in favor of Norvell. Since (1) Merkey, Angus, and Major took Novell trade secrets with them to TRG, (2) the threatened harm to Novell outweighted the potential damage to defendants and (3) the proposed injunction was not adverse to the public interest, the judge determined that an injunction was an appropriate remedy. The length of the injunction was determined by the estimated time it would take to roll out a completed product. For the defendants in this case, it was set to 9 months, ending approximately 1.5 years after they left Norvell. During this time, they were not allowed to use any of Norvell's trade secrets or confidential technical information and would have to explicitly tell future employers about this injunction.

[7] Some quote him as also saying that when he left Novell he would take with him "the crown jewels", which they interpret to be the most sensitive technologies developed in Wolf Mountain.

3 Theoretical Motivation

3.1 Set up

The model consists of a firm (F), an employee (E), and one joint innovation project. At $t = 0$, the firm hires an employee and invests I in the project. At $t = 1$, upon observing the firm's investment in the project, the employee chooses her level of effort, e, which is observable but not verifiable. Also, effort has a quadratic disutility cost, $c(e) = \frac{e^2}{2}$. Thus, the total returns to the project can be expressed as: $R = eI^{\alpha}$, where $\alpha < \frac{1}{2}$ is the output elasticity of the investment. At $t = 2$, after the output is realized, the firm pays the employee. The employee has no resources and is protected by limited liability. The firm and employee are also risk neutral.

3.2 Frictionless Benchmark

The frictionless benchmark for this model is a self-funded entrepreneur who decides how much capital to invest and how much effort to put into the project. The entrepreneur maximizes $eI^{\alpha} - \frac{e^2}{2} - I$. Taking first order conditions with respect to effort and investment and solving analytically yields the following solutions:[8]

$$I^{FB} = \alpha^{\frac{1}{1-2\alpha}}, e^{FB} = I^{FB\alpha} = \alpha^{\frac{\alpha}{1-2\alpha}}. \tag{1}$$

Furthermore, the total expected output in the scenario can be solved analytically.

$$R^{FB} = e^{FB} I^{FB} = \alpha^{\frac{2\alpha}{1-2\alpha}}. \tag{2}$$

[8] I take the second order conditions to verify that this solution is a local maximum.

3.3 Firm-Employee Model

If firm investment and employee effort are made by separate parties, the division of ex post surplus will be important to investment decisions. Again, the firm invests at $t = 0$ and the employee invests at $t = 1$.

At $t = 2$, project output is realized, but is not verifiable. Since the output is innovation, it is difficult to describe ex ante and not verifiable ex post in court. Furthermore, I assume that employee investment is unobservable. Thus, complete contracts are not avaliable. Also, unlike innovation contracts between firms, there are no productive assets in innovation. One potential protection is a patent, but patents only convey partial ownership of intellectual property. This is because there is other valuable information such as the designs that did not work, the future prospects, and potential improvements that are discovered in the innovation process. I will refer to the employee's knowledge of these ideas as her inalienable human capital that is developed during the innovation process.

The employee's outside option is δI^{α}, which represents her outside option – the ability to depart the firm with valuable knowledge about the firm's innovation. The firm must match the employee's outside option which leaves leaves $(1-\delta)I^{\alpha}$ for the firm.[9] Thus, the payoffs are $\delta e I^{\alpha}$ and $(1-\delta)eI^{\alpha}$ for the employee and the firm, respectively. The employee and firm maximization functions are given below.

$$\begin{aligned} U_E &= \max_{e}\{\delta \times e \times I^{\alpha} - \frac{e^2}{2}\}, \\ U_F &= \max_{I}\{(1-\delta) \times e \times I^{\alpha} - I\}. \end{aligned} \tag{3}$$

I solve this model backwards by starting from the employee's effort decision. At $t = 1$, the employee can observe the firm's investment. The employee trades off increased likelihood of success with the quadratic cost of effort. The optimal effort of the employee is

[9] This assumes that there is no deadweight loss if the employee leaves. If one adds deadweight loss and assumes the firm and the employee will share it according to their bargaining power, the model conclusions will be not be affected.

$$e^*(I) = \delta I^\alpha. \tag{4}$$

Next, I can solve for the firm's investment, I, as the firm tries to maximize the NPV of the investment. I assume the firm is unconstrained and can finance investment at zero marginal cost. Since investment has decreasing marginal returns, it will be bounded. Taking the employee's effort as a function of firm investment, I can analytically solve for the optimal investment level of the firm. [10]

$$I^* = (2\alpha(1-\delta)\delta)^{\frac{1}{1-2\alpha}}. \tag{5}$$

Furthermore, I can plug optimal investment into the employee's optimal effort and derive the analytic solution for employee effort and expected returns.

$$e^*(I^*) = \delta I^* = \delta(2\alpha(1-\delta)\delta)^{\frac{\alpha}{1-2\alpha}}. \tag{6}$$

$$R^* = e^* I^{*\alpha} = \delta(2\alpha(1-\delta)\delta)^{\frac{\alpha+1}{1-2\alpha}}. \tag{7}$$

Comparing these values to Equation 1, firm's investment and employee's effort are lower than first best. Since the surplus created is split by two parties, each party will underinvest. This follows from the intuition of Hart and Moore (1990) who show that complementary assets should be owned together.

3.4 Results

Proposition 1. *The relationship between employee outside options and expected project returns is not monotonic:*

$$\frac{dR^*}{d\delta} < 0,\ if\ \delta > \overline{\delta}\ \ and\ \ \frac{dR^*}{d\delta} > 0,\ if\ \delta < \overline{\delta} \tag{8}$$

[10] Note that $I^* < 1$ because $2\alpha < 1$, $(1-\delta) * \delta) < 1$, and $\frac{1}{1-2\alpha} > 0$. This will also imply that $e^* < 1$.

Appendix A.1 provides the proof and the equation that determines $\overline{\delta}$. The returns of the project are determined by the complementary investments of the employee and the firm. When employee outside options are large, the firm is not investing as much and has a higher marginal impact on total innovation. Therefore, total innovation will increase if innovation allocation shifts from the employee to the firm.

This model also provides other implications related to firm investment when employee allocation decreases. If total innovation increases when innovation allocation shifts from the employee to the firm, then the firm must be investing more in the project. Clearly, when employee allocation decreases and the firm does not change investment, the employee has weaker investment incentives. Thus, gains in innovation must be due to firm investment which increases project returns and catalyzes employee effort. These ideas can be captured by the following corollaries.

Corollary 1. *Firm investment must increase if a decline in employee outside options leads to increases in expected project returns.*

$$\frac{dI^*}{d(-\delta)} < 0, \; if \; \delta > \overline{\delta}. \tag{9}$$

Corollary 2. *If firm investment is fixed, decreasing employee outside options leads to a decrease in expected project returns.*

$$\frac{dR(e^*(I), I)}{d(-\delta)}|_{I=\bar{I}} < 0. \tag{10}$$

Appendix A.2 provides the proofs for these corollaries.

3.5 Employee Matching

So far the model has assumed that there is a representative employee the firm can hire. However, a more realistic assumption is that employees differ in ability or skill. One way to model their

differences is to vary the disutility of effort by employee skill, where the highest skilled employees would have the lowest disutility of effort.

Proposition 2. *If employee outside options are high, there will be a negative assortative match between skill and outside options.*

$$\frac{\partial^2 U_{emp}(c,\delta)}{\partial c\, \partial(\delta)} < 0 \text{ if } \delta > \hat{\delta}. \tag{11}$$

Appendix A.3 provides the proof that shows that employee utility is supermodular in disutility of effort and employee outside options. When employee outside options are high, there will be a negative assortative match between employee outside options and skill (or positive assortative match between employee outside options and disutility of effort). Intuitively, when employee outside options are high, the firm is reluctant to invest and relatively lower employee outside options are associated with more investment. Thus, the skilled employee, who is more willing to increase effort, would match with the firms that provide more investment. This is similar to the intuition of Sattinger (1980) and Gabaix and Landier (2008) where worker skill and capital investment are complements.

3.6 Discussion

One key assumption of my model is the lack of complete contracts. Since innovation is often a scenario of *indescribable contingencies*, the two parties cannot commit to a contract that would not be renegotiated after project success is observed (Tirole, 1999). Specifically, when success is not verifiable and one party can renegotiate a better outcome, the ex ante contract payoffs will be the same as the renegotiation proof payoffs.

Another key assumption of my model is the exogeneity of employee outside options. In the literature, several papers have documented how firms strategically choose their location, debt level, or patenting propensity to limit the options of their employees (Almazan et al., 2007; Matsa, 2010; Kim and Marschke, 2005). However, the previous arguments are not as strong in the context

of innovation, which requires high human capital employees working on specific projects. First, mobility is higher for high human capital employees overall. Hence, firm location will only weakly affect bargaining power. Second, each innovative project typically represents a small fraction of overall firm value. Therefore, the threat of bankruptcy is not credible because it is unlikely that the firm's success relies on the particular project. The third point about patent propensity is a relevant concern that I will attempt to address by looking within and across firms.

The most interesting results from the model are when employees can easily depart with valuable knowledge. However, if it is easy for employees to give up these rights, then the assumption of exogeneity is invalid. One might think that employees can sign non-competes with their employer to try to achieve this. In reality, the enforcement of non-competes is set by the state courts and the employee and employer treat this as a exogenous parameter. There is very little ability to tailor employee contracts that differ in their treatment of employee mobility. Thus, to identify how mobility and knowledge of employees affect innovation and investment, I study how shocks to the ease of departing the firm and compare there effects across firms with heterogeneous knowledge.

4 Data and Summary Statistics

4.1 Patent data

I use patent data from the National Bureau of Economic Research (NBER) patent data project, the Harvard Patent Database (Li et al., 2014), and the patent data from Kogan et al. (2012) (henceforth KPSS). In a joint effort, the United States Patent and Trademark Office (USPTO) and Hall et al. (2001) (henceforth HJT) have collected data on over 3 million patents and 16 million citations. The project has recently been updated to include all patents granted from 1976-2006. For each patent, I observe the patent's technological category, application date, grant date, the list of cited patents, and information about the patent's assignees (i.e. owners). I use the Harvard Patent Database and the KPSS patent data to supplement the NBER data. It is well-documented that patenting (citing) propensities exhibit tremendous heterogeneity across patent technology classes

and through time HJT developed a structural approach and a reduced-form approach to adjust patent and citation counts. In this paper, I follow related finance literature and employ the reduced-form approach, adjusting for patent class propensities as suggested by Seru (2014) and Lerner and Seru (2015). The procedure involves sorting patents into 6 major technological classes. Citations are adjusted by dividing by the average number of citations in each class - grant year. These adjusted patents (citations) are then aggregated at the firm-year or firm-state year level, creating a weighted sum of each firm's patents.

Following the literature, I use the patent application year as the year of record for a patent. HJT points out that there is, on average, a 2-year delay between when a patent is applied for and when it is granted. To mitigate concerns regarding truncation bias, I use the Harvard Patent Database, which contains detailed information about patents granted through 2010. The last patent application year of interest in our sample is 2006. This allows for four additional years for patents to receive grant status and citations.

It is also difficult to precisely measure patent citations, which are also subject to truncation bias (Lerner and Seru, 2015). Patent citations can arrive up to 100 years in the future. HJT and Dass et al. (2015) claim that having three to four years of additional data can drastically mitigate issues with citation truncation. In line with this, I use the KPSS data, which has patent citations that have been updated through 2012. This gives even the last patents granted in our sample, those granted in 2010, at least three years to accumulate citations. To further account for truncation, I adjust citations per patent by the average number of citations received by patents in the same category and grant year. In addition to these adjustments, I control for firm and year variation in our statistical analysis.

4.1.1 Firm State Patent Data

The Harvard Patent Database includes the name and state of residence for patent inventors. This residence information allows me to attribute patents to different state establishments for patenting firms. For each patent, I determine which state the assignees are from. If there are multiple states

listed on the patent, I give each state an equal portion of credit for the patent and citations. Then, for each year, I take the sum of all patents a particular establishment applied for and calculate the total number of patents, citations, and adjusted citations. If a firm-state has previously patented, but does not patent in a given year, I assign 0 to its innovation measures.

4.1.2 Inventor Level Data

The Harvard Patent Database also provides additional information about to track inventors as they patent. Li et al. (2014) implemented a Bayseian supervised learning approach to identify unique inventors in the data. Since the USPTO only provides the name of the inventor and not a unique inventor number, it can be difficult to match multiple patents to an inventor. Li et al. (2014) use the full name of the inventor, the location of the inventor, and the patent classification to match inventors who reappear in the data set. They provide an unique inventor identifier that is generated by their learning algorithm.

Using a similar methodology as Bernstein (2015), I try to determine which inventors are new hires of the firm. I define a new hire as an inventor who previously patented at a different firm and first patents at the affected firm in a given year. To account for establishment size, which could vary by patenting location, I scale the number of new hires each year by the total number of inventors who have patented at that particular establishment in the last 10 years.

4.2 Bureau of Labor Statistics Data

I use public data from the Bureau of Labor Statistics (BLS) to measure industry level engineer and inventor employment. Each year the BLS surveys companies and tracks the occupation make up of each industry. Using broad occupation titles, I isolate engineering and science related occupations. For each industry-year, I aggregate total engineer and scientist count and total employee count. I classify an industry as High Tech if the industry engineer employment percentage is double the average industry engineer employment for that year (Hadlock et al., 1991; Hecker, 1999).

The BLS data begins in 1989 which limits the IDD adoption events I am able to examine. Also, the BLS changed the way it defines industries from sic codes to naics codes in 2002. Furthermore, the BLS switched from Office of Employment Statistic employment codes to Census Occupation codes in 1998. These changes to industry definitions and occupation codes should not have a large impact on the final results as they are only used to identify high technology firms.

4.3 Firm Financials

I collect firm financial information from the CRSP-COMPUSTAT merged database from 1989 to 2006. Using the match provided by HJT, I match financial information to firms in my sample. In particular, I use several measures of financial constraints including the Kaplan and Zingales (1997) index, the Whited and Wu (2006), and the Size-Age Index (Hadlock and Pierce, 2010). I calculate the INV and RD as capital expenditures and research and development spending scaled by total assets. Furthermore, I am able to match financial variables that have previously been associated with firm innovation such as Tobin Q, size, dividend dummy, fixed assets, cash holdings and return on assets. All continuous variables are winzorized at the 1% level.

4.4 Summary Statistics

Summary statistics are provided in Table 2. Panel A of Table 2 shows the summary statistics only for firm locations impacted by the IDD adoption. Panel B of Table 2 shows the summary statistics for the primary sample of the paper. This panel reports statistics for firm locations impacted by the IDD adoption and also non-treated locations of the same firm. Panel C of Table 2 shows firm level summary statistics for firms impacted by IDD adoption and industry matched peers.

5 Empirical Results

Motivated by theory, I examine how changes to the ease of departing with knowledge will affect firm innovation and investment. As a shock to the ability of employees to depart with knowledge, I use state adoption of IDD, which increases trade secret protections. First, I compare the impact of IDD when employee knowledge is high or low. Next, I test to see if these changes are driven by firm investment. Then, I provide evidence that the firm is able to attract better employees after IDD. Finally, I examine the impact when states reject IDD and look for a reversal.

5.1 Innovation Outcomes

The main test of the paper is to study how shocks to the ability of employees to depart with knowledge affect corporate innovation. In particular, I look at state court rulings on the Inevitable Disclosure Doctrine (IDD). When a state court rules to adopt IDD, employee mobility decreases for high skill workers (Klasa et al. (2015) and Png and Samila (2015)). In effect, firm ownership over projects and innovation increases at the expense of employees. This provides a natural setting to test the relationship between the allocation of innovation returns and corporate innovation.

Proposition 1 argues that there should be a non-monotonic relationship between the employee's outside options and total innovation. In particular, when employee outside options are high, a decrease in the employee's ability to depart the firm can lead to increases in total innovation. To proxy for the value of employee knowledge and inalienable human capital, I use the industry concentration of engineers and scientists. High technology industries, which employ more engineers and scientists, constantly improve their products to keep up with customer and consumer demand.[11] In these industries, new technologies rapidly replace existing products and methods. In lower technology industries, such as the lumber and furniture industries, product lines are more stable and are not often disrupted by new technologies. Thus, in high tech industries, the ability of the employee to leverage their knowledge and create new ideas is more valuable and more sought after

[11] Bill Gates, the founder and former CEO of Microsoft, once said "Intellectual property has the shelf life of a banana."

and their inalienable human capital is most valuable. Consistent with this notion, I use BLS data on occupation statistics to identify high technology industries, which employ a high percentage of engineers and scientists (Hadlock et al., 1991; Hecker, 1999).

In Figure 1, I compare the difference in response between high and low technology industries to IDD adoption. Using innovation data from firm establishments, i.e. state level innovation locations, I compare patent and patent citations three years before and after IDD adoption. In the first graph, I plot the average adjusted citations for low tech firms affected and unaffected by IDD adoption around the IDD adoption event. For these establishments, there is no difference before and after IDD adoption for either group. In the second graph, I plot the average adjusted citations for high tech firm establishments affected and unaffected by IDD adoption around the IDD adoption event. Compared to the non-treated establishments, the treated locations experience an increase in citations after IDD adoption. In the third graph, I compare the difference between treated and non-treated locations for high and low tech firms. It is clear that for the high tech locations, IDD increases citations. These graphs provide initial evidence that a decrease in the employee's allocation of innovation returns can lead to increases in corporate innovation.

To formally test the difference between the groups, I use a regression framework. To measure establishment level innovation output, I use the log of the number of patents, citations and adjusted citations each year for a state innovation location. First, I compare innovation outcomes in the three years before to the three years after IDD adoption for affected establishments only. This allows me to look at the overall effect of IDD adoption. Next, I compare patent and patent citations between high and low tech establishments before and after IDD adoption in a generalized difference-in-differences framework. The regressions specifications are given below:

$$
\begin{aligned}
innovation_{i,t} &= \beta_1 Post_{i,t} + \gamma_i + \lambda_t + \epsilon_{i,t} \\
innovation_{i,t} &= \beta_1 Post_{i,t} + \beta_2 Hi\,Tech_i \times Post_{i,t} + \gamma_i + \lambda_t + \epsilon_{i,t}
\end{aligned}
$$

In both of these regressions, I include establishment and year fixed effects to control for time invariant establishment characteristics and aggregate time varying changes. Additionally, I cluster

these regressions at the firm level.

The results of the regressions are presented in Table 3 Panel A. Again, my sample here are firm establishments affected by IDD adoption. In Columns 1-3, I compare innovation activity before and after IDD adoption. There is no significant difference in innovation outcomes. In Columns 4-6, I compare differences in innovation activity before and after IDD adoption between high and low tech firms and find that high tech firms increase innovation after IDD compared to low tech firms. Specifically, after IDD adoption, high tech firms increase citations by 9.19% relative to low tech and unaffected locations. This provides initial evidence in support of Proposition 1.

One potential concern is that establishments affected by IDD also experience a technology shock. To address this concern, I exploit the fact that firms often innovate in multiple establishments across several states, and I use the establishments that are not affected by IDD as natural controls for any technology shocks. First, I compare the difference in innovation outcomes in the three years before to the three years after IDD adoption for affected establishments to unaffected establishments of the same firm. Second, I compare patent and patent citations between high and low tech establishments before and after IDD adoption across affected and unaffected locations in a triple-differences framework. The regression specifications are given below:

$$
\begin{aligned}
innovation_{i,s,t} &= \beta_1 IDD_{i,s} \times Post_{i,t} + \gamma_{i,s} + \lambda_{i,t} + \epsilon_{i,s,t} \\
innovation_{i,s,t} &= \beta_1 IDD_{i,s} \times Post_{i,t} + \beta_2 IDD_{i,s} \times Post_{i,t} \times Hi\,Tech_i + \gamma_{i,s} + \lambda_{i,t} + \epsilon_{i,s,t}
\end{aligned}
$$

Again, in these regressions I am able to control for firm year level variation and firm state differences. I cluster these regressions at the firm level.

The regression results are presented in Panel B of Table 3. Again, in Panel B Columns 1 - 3, I examine the impact of IDD adoption on innovation comparing affected to unaffected locations pre- and post-IDD. Overall, there is no real impact of IDD on these innovation outcomes. In Table 3 Columns 4 - 6, I examine the differential impact of IDD on high tech industries compared to low tech industries and find that IDD adoption does have a positive effect for high tech firms. In these

high tech firms, the impact of IDD is positive and significant. The firm state establishment that is affected will have about 9% more patents, 22% more citations, and 10% more adjusted citations. The economic magnitudes of these coefficients are fairly large. A change in the IDD law for High Tech firms is associated with a 10% relative to mean increase in patents, citations, and adjusted citations.

These coefficients likely underestimate how IDD changes total innovation. Since IDD strengthens trade secret protections by decreasing employee mobility, the doctrine will also change the firm's incentive to patent new innovations. Kim and Marschke (2005) argue that firms with high employee mobility prefer to use patents, not trade secrets, to better protect ideas from employee expropriation. Therefore, IDD should have a negative impact on patenting at high technology firms relative to low technology firms. Moreover, since I document that high technology firms increase patenting relative to low technology firms, the effect I identify on patented innovations is likely a lower bound for the effect of IDD on total innovation.

Another concern is that firms that will benefit the most from IDD adoption spearhead the effort to bring cases before state courts. To address this concern, I remove firms in the same 2-digit SIC code as the industry that is directly involved in that state's IDD court case. This further limits my sample. I re-run the results on this smaller sample. The coefficients are given in Table 3 Panel C. The coefficients are still positive and significant for the high tech firms around IDD adoption. Moreover, the magnitude of the coefficients remains similar across the three specifications which provides additional proof that effect cannot be explained away by additional controls.

This analysis differs from and improves on previous studies that looked at investment and innovation response to non-compete laws. First, trade secret laws are applied more widely than non-competes and often are a precursor to non-compete enforcement. Every employee at a company signs an agreement, which makes them liable for misappropriation of trade secrets, and any differences in the enforcement of trade secret misappropriation come from state court decisions like adopting IDD. Second, I am able to compare differences within firm across states, which allows me to account for firm level technology shocks or difference in firm spending. Previous

studies mostly compared different companies in the same industry that are affected by changes to non-compete enforcement. These studies have a harder time accounting for company differences in those states. By comparing establishments within a firm, the policies toward innovation and technological development should be more standardized.

5.2 Synthetic Controls and Placebo Tests

This analysis assumes that other state level factors are constant around the state court's adoption of IDD. However, the state court might decide to adopt IDD as the state is trying other incentives to promote company investment and overall innovation in certain sectors. I address this concern in two ways. First, I run a Placebo Test to see if smaller, private firms that I think will be unaffected by IDD exhibit the same changes in innovation. Second, I use smaller, private firms as a synthetic control to account for state changes toward innovation policy that are unrelated to firm-employee incentives (Abadie et al., 2012).

First, I replicate the patenting behavior of firms that face the same state level changes, but do not respond to the differences in firm-employee incentives. In general, smaller firms and independent innovators that are not employed by large companies should not be impacted by IDD. In these private firms, each inventor and employee is more likely to own an equity stake in the company which reduces the chance of misaligned incentives. However, these firms should still be impacted by the same state level changes which might influence innovation such as banking deregulation (Amore et al. (2013), Chava et al. (2013), and Cornaggia et al. (2015)) and wrongful discharge laws (Acharya et al., 2014).

To replicate the innovation behavior of each establishment affected by the adoption of IDD, I follow a multi-step procedure. First, I take all patents not matched to compustat firms and aggregate the total number of patents and citations by state, patent category, and application year. Next, I measure patent category intensity for each firm establishment that is affected by IDD adoption. Finally, I replicate the firm establishment by taking a weighted sum of patent citations for each year around the IDD event using the firm's patenting intensity in each category as the weights.

I rerun the triple-differences result in Table 3 Panel B by substituting the innovation outcomes of establishments affected by IDD. This is a placebo test where the difference between high and low tech firms should no longer be significant. The results of the regression are presented in Table 4 Panel A. In Columns 1 - 3, I find that the impact of IDD is positive. That means for firms in states that adopted IDD there is an impact on overall innovation that is associated with IDD adoption. However, in Columns 4 - 6, the impact of IDD adoption on innovation measures is not different for low tech firms. Therefore, this placebo test shows that a state's friendliness to innovation and technology development is correlated with state courts adopting IDD laws, but cannot explain the difference between high and low technology firms.

Next, I verify that the actual establishments affected by IDD still exhibit increases in innovation above their synthetic controls. In particular, I run a triple difference regression where I compare establishments pre- and post- IDD adoption, between high and low technology firms, across real and synthetic observations. The results of the regression are presented in Table 4 Panel B. In Columns 1 - 3, I find that there is a decline in innovation overall after IDD compared to the synthetic control group. In Columns 4-6, I find that high tech locations experience an increase compared to low tech establishments. Thus, these results support the notion that these changes to employee mobility and investment incentives have a positive impact on high technology firms beyond any state differences.

5.3 Firm Investment

The main emphasis of this paper is that firm investment and employee effort decisions are intertwined. When employees become less able to depart with valuable knowledge, it affects both firm investment and employee effort. Corollaries 1 and 2 come from the insight that firm investment must increase if corporate innovation increases after decreasing employee allocation of innovation returns.

To test Corollary 1, I examine firm spending on research and development (RD). In order to confirm Corollary 1, I expect that high tech firms increase investment after IDD adoption relative

to unaffected peers and relative to low tech firms. Using only the firms that I can identify in the patent data set, I compare the level of RD and investment spending to industry peers in the 3 years around IDD adoption. I run the following regression:

$$investment_{i,t} = \beta_1 IDD_i \times Post_t + \beta_2 IDD_i \times Post_{i,t} \times Hi\,Tech_i + \gamma * X_{i,t} + \lambda_i + \mu_t + \epsilon_{i,t}$$

The coefficient estimates are presented in Table 5. In Column 1, I only include the IDD adoption indicator. I find that IDD adoption does not significantly impact investment. This confirms the result in Klasa et al. (2015), who look at firm leverage around IDD adoption and do not find increases in investment spending. In Column 2, I add the interaction term to compare investment differences between high tech firms. I find that high tech firms invest more after IDD relative to low technology firms and unaffected industry peers. In Column 3, I add in additional firm controls that have been used to explain investment and innovation and the result holds. Together this provides evidence that firms in the high tech area are likely to invest more after trade secrets become better protected. This is consistent with Png (2015), who studies firm investment around state adoption of the Uniform Trade Secrets Act.

To test Corollary 2, I look at innovation outcomes for firms that are financially constrained and unconstrained. Corollary 2 asserts that if investment is fixed then decreasing employee allocation cannot lead to increases in innovation. Therefore, firms that are likely financially constrained should have a harder increasing investment after IDD adoption and will not increase innovation.

In Table 6, I present the same triple difference regression specification as in Table 3 Panel B split by different measures of financial constraints – leverage, KZ, WW and SA. In each panel of Table 7, the positive and significant coefficients are present only in the firms that are likely unconstrained. These firms should be able to easily finance additional innovation investment by using internal cash flows or accessing bank lending. In firms that are likely constrained, there is a small, insignificant increase in innovation, which could be due to firms experiencing a slight

relaxation of financing constraints caused by increased pledgeability of intangible assets (Klasa et al. (2015) and Mann (2015)).

5.4 Employee Hiring

One benefit of the patent data is the ability to identify individual inventors. Using the inventor matches provided by Li et al. (2014), I can identify when an employee joins a new firm. Consistent with the literature, I define a new hire as an inventor who previously patented at a different firm then applied for a patent at the target firm (Bernstein, 2015). Furthermore, I measure the quality of a new inventor by checking if the inventor has a patent which ranked in the top 10 of citations compared to the patent's category-year cohort. Together this will let me test Proposition 2.

Proposition 2 states that, when employees can easily depart with knowledge, there will be a negative assortative match between employee quality and employee ability to depart. To test this, I examine new hires at different firm establishments and compare the difference between high and low technology establishments. Using the same methodology as Table 3 Panel B, I compare ability to hire new inventors before and after IDD adoption across affected and unaffected establishments between high and low technology firms. Specifically, I run the following regression:

$$new_{i,s,t} \quad = \quad \beta_1 IDD_{i,s} \times Post_{i,t} + \beta_2 IDD_{i,s} \times Post_{i,t} \times Hi\,Tech_i + \gamma_{i,s} + \lambda_{i,t} + \epsilon_{i,s,t},$$

where $new(new10, not10)$ is the number of new (high quality, low quality) hires in a state s of firm i in year t as a fraction of inventors in the 5 years before IDD adoption.

The results of the regression are presented in Table 8. In Columns 1 and 2, the dependent variable is all new hires. There is a slight increase in new hires by high tech firms, but it is not significant. In Columns 3 and 4, the dependent variable is high quality new hires. After IDD adoption, high tech firms are able to hire 2.45% more high quality new hires per year compared to low tech firms and unaffected firm locations. This result is economically significant since the average

a location only hires 1.17% high quality inventors a year. In Columns 5 and 6, the dependent variable is low quality new hires. Again the results are insignificant.

These results confirm Proposition 2–that decreasing the employee's ability to depart the firm will allow firms to hire better inventors. Intuitively, before the IDD, firm investment is low and high quality inventors would have better opportunities elsewhere. However, after IDD, the firm can commit to a large increase in investment anticipating the employee will provide more effort. This will increase the expected utility of the higher quality employees more leading to the firm to match with better employees.

5.5 Rejection of IDD laws

To add to the previous results, I am able to study the behavior of firms and employees when state courts reject IDD. The state courts of Florida (2001) and Texas (2003) rejected IDD.[12] The rejection of IDD by these state courts essentially increases the ability of employees to seek outside employment. However, rejection of IDD tends to be a much weaker signal than adoption. This is likely due to the mechanism in Hennessy and Strebulaev (2015) where rational agents do not fully react to the shock because they think there might be a future correction.

In Table 9, I present the effects of IDD rejection on total innovation output. This is the same regression specification as Table 3 Panel B. In this regression, I compare the effect of IDD rejection within a firm by comparing between different industries. I find that firm establishments have fewer patents and citations when IDD is rejected in those states, but not significantly so. This could be due to the two factors I talk about above or the fact that there are fewer states affected and the insignificant coefficient could be due to lack of power in the test.

[12]Michigan also rejected the IDD in 2004. However, Michigan only adopted the IDD in 2002. Thus there is not enough data to measure in the pre-treatment period.

6 Conclusion

The results of this paper are relevant to understanding the relationship between human capital and firm investment. This is relationship is will become even more important to the economy in the Information Age. When evaluating policies related to human capital and firm investment, it is important to consider the impact on both investing parties. Focusing only on one side will give an incomplete picture of the policy impact. This paper shows the counter intuitive result that decreasing the employee's ability to depart with valuable knowledge can lead to better overall outcomes for the firm.

The results of this paper are relevant to policy makers who are trying to increase innovation spending by firms while also providing labor protection for employees. This paper would recommend policy makers take a wholistic approach to incentivizing innovation by considering firm and employee decisions in tandem. This paper also provides insights for future trade secret and employee protection laws, such as the Defend Trade Secrets Act (S. 1890, H.R. 3326). For high tech industries, increasing trade secret protections should have a positive effect on innovation and investment. However, this paper does not speak to the impact of trade secret protection on other employees in the wider economy.

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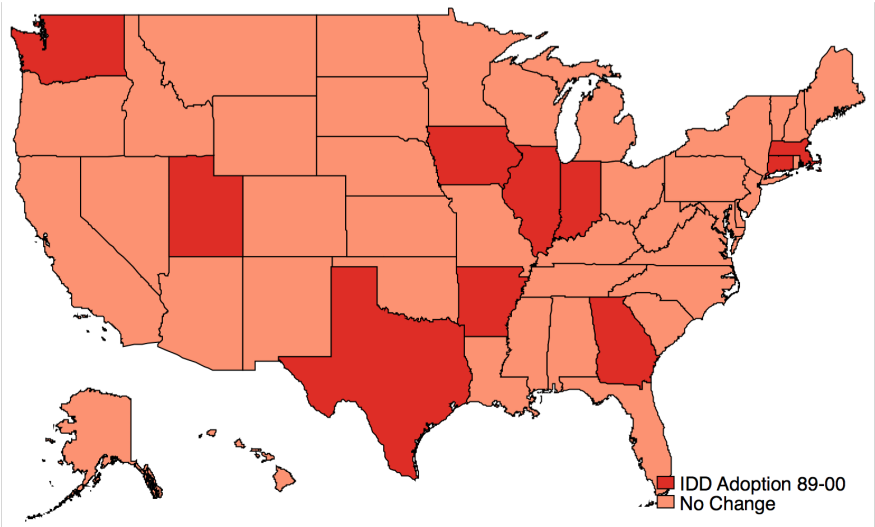
Table 1: Summary of State Stances on Inevitable Disclosure

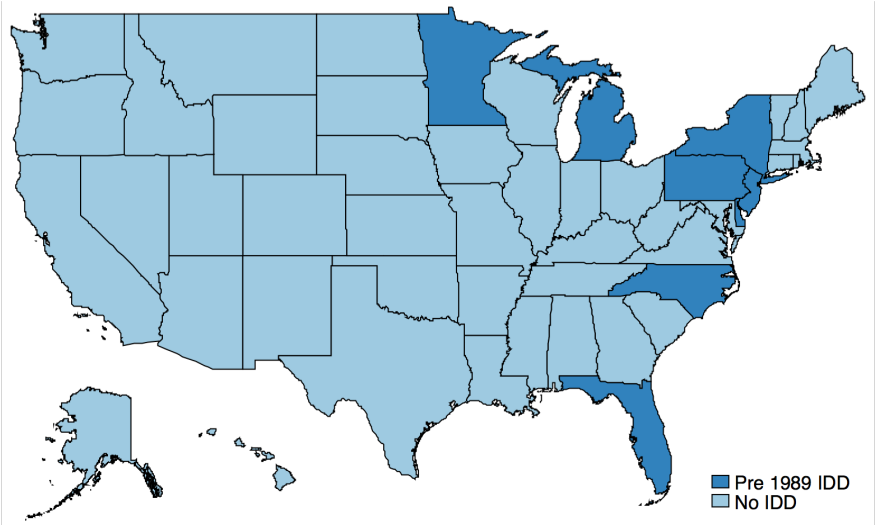
State Court Adoptions			
State	Primary Case(s)	Year	Industry (2D-SIC)
Arkansas	Southwestern Energy Co v. Eickenhorst	1997	13
Connecticut	Branson Ultrasonics Corp v. Stratman	1996	28
Deleware	E.I. DuPont de Nemours & Co. v. American Potash & Chemical Corp.	1964	
Florida	Fountain v Hudson Cush-N-Foam Corp.	1960	
Georgia	Essex Group, Inc, v. Southwire Co	1998	36
Illinois	Teradyne, Inc. v. Clear Communications Corp.	1989	38
Indiana	Ackerman v. Kimball International, Inc.	1995	36
Iowa	Uncle B's Bakery, Inc. v. O'Rouke	1996	20
Kansas	Bradbury CO. V Teissier-DuCros	2006	34
Massachusetts	Marcam Corp. v. Orchard	1995	15
Michigan	Allis-Chalmers Mfg. Co. v. Cont'l Aviation & Engineering Corp.	2002	
Minnesota	Surgidev Corp. v. Eye Tech., Inc.	1986	
Missouri	H& R Block Eastern Tax Services, Inc. v. Enchura	2000	64
New Jersey	National Starch & Chemical Corp. v. Parker Chemical Corp.	1987	28
New York	Eastman Kodak Co. v. Powers Film Prod.	1919	38
North Carolina	Travenol Labs., Inc v Turner	1976	
Ohio	Procter & Gamble Co., v. Stoneham	2000	28
Pennsylvania	Air Products & Chemical, Inc. v. Johnson	1982	
Texas	Rugen v. Interactive Business Systems, Inc.	1993	87
Utah	Norvell, Inc. v. Timpanogos Research Group, Inc.	1998	87
Washington	Solutec Corp Inc. v. Agnew	1997	20

Figure 1: Inevitable Disclosure Doctrine Adoption

(A) State Court IDD adoptions from 1989 - 2000



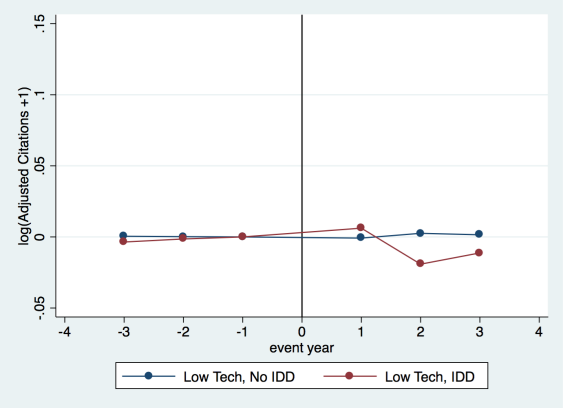
(B) State with IDD prior to 1989



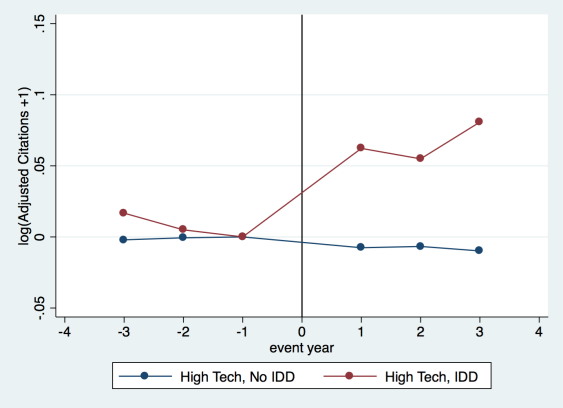
These figures map IDD adoption events across the United States. In Panel A, states that adopt IDD between 1989 and 2000 are colored dark red. These are the IDD shcoks I use in my paper. In Panel B, states that have adopted IDD before 1989 are colored dark blue. I plot these states to show the full slate of states that have adopted IDD.

Figure 2: Inevitable Disclosure Triple Differences

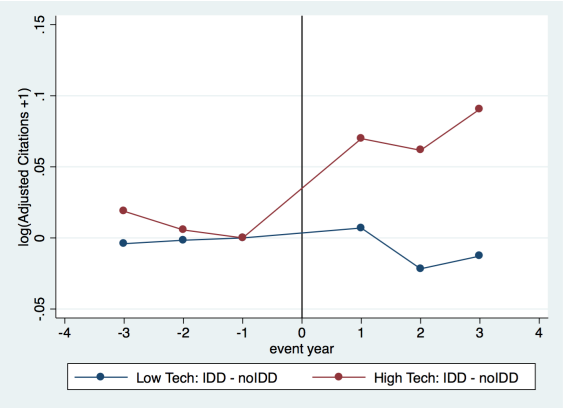
(A)



(B)



(C)



This figure graphics displays the impact of IDD on adjusted citations for high and low tech industries. I regress year dummies interacted with IDD treatment and firm technology level on firm innovation measured by the natural logarithm of adjusted citations. I include firm-year fixed effects in these regressions. I adjust these coefficients by setting the year prior to IDD adoption to 0. There are four main categories of establishments IDD and high tech, IDD and low tech, no IDD and high tech, and no IDD and low tech.

Panel A plots the difference between treated and untreated establishments before and after IDD for low tech firms. Panel B does the same for high technology firms. Panel C compares the differences between these two groups.

Table 2: Summary Statistics

Panel A: ALL IDD Firms Locations						
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	N	mean	sd	p10	p50	p90
Hi Tech	7,920	0.508	0.500	0	1	1
log(patents+1)	7,920	0.939	1.121	0	0.693	2.565
log(cites+1)	7,920	2.092	2.209	0	1.792	5.268
log(adj_cites+1)	7,920	0.928	1.218	0	0.378	2.792
Panel B: All Firm Locations						
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	N	mean	sd	p10	p50	p90
log(patents+1)	33,420	0.950	1.206	0	0.693	2.708
log(cites+1)	33,420	2.106	2.315	0	1.609	5.412
log(adj_cites+1)	33,420	0.934	1.288	0	0.285	2.832
Hi Tech	33,420	0.573	0.495	0	1	1
IDD	33,420	0.112	0.316	0	0	1
New Hire	33,420	0.0422	0.176	0	0	0.0769
Top New Hire	33,420	0.0177	0.110	0	0	0.0103

Table 3: Inevitable Disclosure and Innovation

Estimates are reported for Difference-in-Differences and Triple Difference regression specifications using state adoption of Inevitable Disclosure Doctrine as a treatment event. I use three years of data both pre- and *Post*-. In Panels B and C, I compare establishments affected by IDD to establishments of the same firm that are unaffected. The final difference comes from high and low tech industries which I split using BLS OES data on occupation. The main variables of interest are the natural logs of the number of patents, citations, and adjusted citations which are applied for in a given year (and eventually granted). In Panel A, I focus on firm locations that are in states that adopt IDD and compare the effects between high and low tech firms. In Panel B, I add in non-treated establishments of firms locations that are impacted by IDD. In Panel C, I remove firms in industries which are directly mentioned in the lawsuits. In Columns 1 - 3 of each panel, I compare innovation before and after IDD passes. In Columns 4-6, I compare the differences between firms in high and low tech industries. All specifications have firm-state fixed effects and year or firm-year fixed effects. Standard errors are clustered at the firm level and reported in parentheses below coefficient estimates.

Panel A: Overall Effects of IDD						
	(1)	(2)	(3)	(4)	(5)	(6)
	patents	citations	adj citations	patents	citations	adj citations
Post	0.0242	0.0669	0.0364	-0.0222	-0.0129	-0.0129
	(0.0231)	(0.0616)	(0.0283)	(0.0268)	(0.0704)	(0.0337)
Post × Hi Tech				0.0866***	0.149**	0.0919***
				(0.0290)	(0.0662)	(0.0327)
Observations	7,920	7,920	7,920	7,920	7,920	7,920
Adjusted R-squared	0.791	0.659	0.749	0.792	0.659	0.749
Firm-State FE	✓	✓	✓	✓	✓	✓
Panel B: Within Firm Effect of IDD						
	(1)	(2)	(3)	(4)	(5)	(6)
	patents	citations	adj citations	patents	citations	adj citations
IDD × Post	0.00908	0.0264	0.0298	-0.0432	-0.0918	-0.0285
	(0.0258)	(0.0580)	(0.0268)	(0.0375)	(0.0779)	(0.0369)
IDD × Post × Hi Tech				0.0935*	0.211**	0.104**
				(0.0497)	(0.107)	(0.0518)
Observations	33,420	33,420	33,420	33,420	33,420	33,420
Adjusted R-squared	0.847	0.723	0.817	0.847	0.723	0.817
Firm-State FE	✓	✓	✓	✓	✓	✓
Firm-Year FE	✓	✓	✓	✓	✓	✓
Panel C: Within Firm Removing Industries Involved in IDD cases						
	(1)	(2)	(3)	(4)	(5)	(6)
	patents	citations	adj citations	patents	citations	adj citations
IDD × Post	0.00578	0.0129	0.0283	-0.0416	-0.0922	-0.0267
	(0.0275)	(0.0641)	(0.0299)	(0.0378)	(0.0786)	(0.0372)
IDD × Post × Hi Tech				0.0907*	0.201*	0.105*
				(0.0527)	(0.119)	(0.0584)
Observations	30,816	30,816	30,816	30,816	30,816	30,816
Adjusted R-squared	0.847	0.724	0.817	0.847	0.724	0.817
Firm-State FE	✓	✓	✓	✓	✓	✓
Firm-Year FE	✓	✓	✓	✓	✓	✓

Table 4: Placebo Test and Synthetic Control

Estimates are reported for Triple Difference specifications using state adoption of Inevitable Disclosure Doctrine as a treatment event. I use three years of data both pre- and *Post*-. I compare establishments affected by IDD to establishments of the same firm that are unaffected. The final difference comes from high and low tech industries which I split using BLS OES data on occupation. The main variables of interest are the natural logs of the number of patents, citations, and adjusted citations which are applied for in a given year (and eventually granted). For each firm location affected by IDD adoption, I replace the innovation variables with the state level innovation weighted by the firm location's patenting characteristics. In Columns 1 - 3, I compare innovation before and after IDD passes. In Columns 4-6, I compare the differences between firms in high and low tech industries. All specifications have firm-state fixed effects and year or firm-year fixed effects. Standard errors are clustered at the firm level and reported in parentheses below coefficient estimates.

			Panel A: Placebo Test			
	(1)	(2)	(3)	(4)	(5)	(6)
	patents	citations	adj citations	patents	citations	adj citations
IDD × Post	0.0901***	-0.0107	0.0827***	0.0830***	-0.00318	0.0922***
	(0.0175)	(0.0342)	(0.0206)	(0.0256)	(0.0471)	(0.0293)
IDD × Post × Hi Tech				0.0127	-0.0134	-0.0171
				(0.0360)	(0.0684)	(0.0409)
Observations	33,420	33,420	33,420	33,420	33,420	33,420
Adjusted R-squared	0.956	0.869	0.945	0.956	0.869	0.945
Firm-State FE	✓	✓	✓	✓	✓	✓
Firm-Year FE	✓	✓	✓	✓	✓	✓
			Panel B: Synthetic Control			
	(1)	(2)	(3)	(4)	(5)	(6)
	patents	citations	adj citations	patents	citations	adj citations
Real × Post	-0.0846***	0.0173	-0.0689***	-0.201***	-0.127	-0.173***
	(0.0221)	(0.0504)	(0.0251)	(0.0440)	(0.0800)	(0.0468)
Real × Post × Hi Tech				0.210***	0.259**	0.188***
				(0.0696)	(0.116)	(0.0726)
Observations	7,512	7,512	7,512	7,512	7,512	7,512
Adjusted R-squared	0.948	0.893	0.941	0.948	0.893	0.941
Firm-State-Year FE	✓	✓	✓	✓	✓	✓

Table 5: IDD and Financial Investment

Estimates are reported for Triple Difference specifications using state adoption of Inevitable Disclosure Doctrine as a treatment event. I use three years of data both pre- and *Post*-. I compare firms affected by IDD to firms in the same industry that are unaffected. The final difference comes from high and low tech industries which I split using BLS OES data on occupation. The main variables of interest are research and development spending and capital expenditures divided by assets. In Columns 1 - 3, the main variables of interest are research and development spending divided by assets . In Columns 4-6, the main variables of interest are research and development spending and capital expenditures divided by assets. In Columns 3 and 6, I use TobinsQ, ln(Size), Dividend, ROA, Leverage, Cash, WW, and HHI as controls. All specifications have firm and year fixed effects. Standard errors are clustered at the firm level and reported in parentheses below coefficient estimates.

	(1)	(2)	(3)	(4)	(5)	(6)
	RD	RD	RD	INV	INV	INV
IDD × Post	-0.00164	-0.00457	-0.00400	0.00120	-0.00265	-0.00227
	(0.00210)	(0.00285)	(0.00245)	(0.00205)	(0.00207)	(0.00207)
IDD × Post × Hi Tech		0.00602*	0.00737**		0.00810**	0.00730*
		(0.00349)	(0.00365)		(0.00398)	(0.00435)
TobinQ			0.00370***			0.00227***
			(0.000609)			(0.000342)
Ln(Size)			-0.0270***			0.00426***
			(0.00202)			(0.00126)
Dividend			-0.000424			0.00318*
			(0.00197)			(0.00171)
ROA			-0.178***			-0.0144***
			(0.00893)			(0.00411)
Leverage			-0.0162***			-0.0374***
			(0.00613)			(0.00569)
Cash			-0.0686***			-0.0646***
			(0.00643)			(0.00453)
WW			-0.00531			-0.0210*
			(0.0162)			(0.0110)
HHI			-0.104**			-0.0698**
			(0.0447)			(0.0342)
Observations	54,756	54,720	54,720	54,756	54,720	54,720
Adjusted R-squared	0.785	0.785	0.846	0.505	0.506	0.522
Firm FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓

Table 6: IDD and Financial Constraints

Estimates are reported for Triple Difference regression specifications using state adoption of Inevitable Disclosure Doctrine as a treatment event. I use three years of data both pre- and *Post*- and compare establishments affected by IDD to establishments of the same firm that are unaffected. The final difference comes from high and low tech industries which I split using BLS OES data on occupation. The main variables of interest are the natural logs of the number of patents, citations, and adjusted citations which are applied for in a given year (and eventually granted). In Panel A, split the sample based on leverage. In Panel B, split the sample based on the KZ index. In Panel C, split the sample based on the WW index. In Panel D, split the sample based on SA index. In Columns 1 - 3 of each panel, report coefficient estimates for constrained firms. In Columns 4-6, report coefficient estimates for unconstrained firms.. All specifications have firm-state fixed effects and year or firm-year fixed effects. Standard errors are clustered at the firm level and reported in parentheses below coefficient estimates.

Panel A: Firms split by Leverage						
	High Lev			Low Lev		
	(1)	(2)	(3)	(4)	(5)	(6)
	patents	citations	adj citations	patents	citations	adj citations
IDD × Post	-0.0244	-0.0844	-0.00836	-0.0566	-0.113	-0.0463
	(0.0683)	(0.126)	(0.0642)	(0.0441)	(0.104)	(0.0470)
IDD × Post × Hi Tech	0.0355	0.130	0.0438	0.138**	0.309**	0.155**
	(0.0810)	(0.158)	(0.0800)	(0.0646)	(0.155)	(0.0717)
Observations	15,582	15,582	15,582	17,466	17,466	17,466
Adjusted R-squared	0.854	0.731	0.824	0.861	0.730	0.832
Firm-State FE	✓	✓	✓	✓	✓	✓
Firm-Year FE	✓	✓	✓	✓	✓	✓
Panel B: Firms split by KZ						
	High KZ			Low KZ		
	(1)	(2)	(3)	(4)	(5)	(6)
	patents	citations	adj citations	patents	citations	adj citations
IDD × Post	-0.0711	-0.151	-0.0598	-0.0284	-0.0604	-0.0119
	(0.0701)	(0.131)	(0.0677)	(0.0421)	(0.0975)	(0.0456)
IDD × Post × Hi Tech	0.0807	0.145	0.0672	0.109*	0.274**	0.139**
	(0.0841)	(0.170)	(0.0868)	(0.0601)	(0.139)	(0.0655)
Observations	13,560	13,560	13,560	19,860	19,860	19,860
Adjusted R-squared	0.828	0.714	0.798	0.857	0.727	0.826
Firm-State FE	✓	✓	✓	✓	✓	✓
Firm-Year FE	✓	✓	✓	✓	✓	✓

Panel C: Firms split by WW

	High WW			Low WW		
	(1)	(2)	(3)	(4)	(5)	(6)
	patents	citations	adj citations	patents	citations	adj citations
IDD × Post	-0.0302	-0.0399	-0.0117	-0.0367	-0.131	-0.0179
	(0.0476)	(0.103)	(0.0503)	(0.0558)	(0.125)	(0.0568)
IDD × Post × Hi Tech	0.0476	0.0214	0.0486	0.151**	0.439***	0.155**
	(0.0658)	(0.148)	(0.0720)	(0.0759)	(0.160)	(0.0738)
Observations	16,553	16,553	16,553	16,867	16,867	16,867
Adjusted R-squared	0.810	0.687	0.777	0.871	0.749	0.842
Firm-State FE	✓	✓	✓	✓	✓	✓
Firm-Year FE	✓	✓	✓	✓	✓	✓

Panel D: Firms split by SA

	High SA			Low SA		
	(1)	(2)	(3)	(4)	(5)	(6)
	patents	citations	adj citations	patents	citations	adj citations
IDD × Post	-0.0649	-0.140	-0.0511	-0.0330	-0.0816	-0.0212
	(0.0718)	(0.134)	(0.0689)	(0.0423)	(0.100)	(0.0465)
IDD × Post × Hi Tech	0.0689	0.133	0.0558	0.110*	0.297**	0.143**
	(0.0853)	(0.173)	(0.0877)	(0.0607)	(0.141)	(0.0662)
Observations	13,494	13,494	13,494	19,554	19,554	19,554
Adjusted R-squared	0.839	0.720	0.808	0.868	0.736	0.839
Firm-State FE	✓	✓	✓	✓	✓	✓
Firm-Year FE	✓	✓	✓	✓	✓	✓

Table 8: IDD and Firm New Hires

Estimates are reported for Triple Difference regression specifications using state adoption of Inevitable Disclosure Doctrine as a treatment event. I use three years of data both pre- and *Post*- and compare establishments affected by IDD to establishments of the same firm that are unaffected. The final difference comes from high and low tech industries which I split using BLS OES data on occupation. In Columns 1 and 2, the main variable of interest is the number of new hires as a fraction of patenting employees in the 5 years before IDD adoption at the firm location. In Columns 3 and 4, the main variable of interest is the number of new hires who have a previous top 10 patent as a fraction of patenting employees in the 5 years before IDD adoption at the firm location. In Columns 5 and 6, the main variable of interest is the number of new hires who do not have a top 10 patnet as a fraction of patenting employees in the 5 years before IDD adoption at the firm location. All specifications have firm-state fixed effects and year or firm-year fixed effects. Standard errors are clustered at the firm level and reported in parentheses below coefficient estimates.

	(1)	(2)	(3)	(4)	(5)	(6)
	new	new	top10	top10	no top10	no top10
IDD × Post	-0.00130	-0.0117	0.00663	-0.00709	-0.00793*	-0.00464
	(0.00700)	(0.00819)	(0.00594)	(0.00522)	(0.00469)	(0.00614)
IDD × Post × Hi Tech		0.0187		0.0245**		-0.00588
		(0.0132)		(0.0111)		(0.00899)
Observations	33,420	33,420	33,420	33,420	33,420	33,420
Adjusted R-squared	0.185	0.185	0.129	0.129	0.115	0.114
Firm-State FE	✓	✓	✓	✓	✓	✓
Firm-Year FE	✓	✓	✓	✓	✓	✓

Table 9: IDD Rejection

Estimates are reported for Triple Difference specifications using state rejection of Inevitable Disclosure Doctrine as a treatment event. I use three years of data both pre- and *Post*-. I compare establishments affected by IDD to establishments of the same firm that are unaffected. The final difference comes from high and low tech industries which I split using BLS OES data on occupation. The main variables of interest are the natural logs of the number of patents, citations, and adjusted citations which are applied for in a given year (and eventually granted). In Columns 1 - 3, I compare innovation before and after IDD is rejected. In Columns 4-6, I compare the differences between firms in high and low tech industries. All specifications have firm-state fixed effects and year or firm-year fixed effects. Standard errors are clustered at the firm level and reported in parentheses below coefficient estimates.

	(1) patents	(2) citations	(3) adj citations	(4) patents	(5) citations	(6) adj citations
IDD Rejection × Post	0.0188	0.0474	-0.0646	0.0596	0.156	-0.00908
	(0.0378)	(0.0741)	(0.0529)	(0.0519)	(0.102)	(0.0785)
IDD Rejection × Post × Hi Tech				-0.0725	-0.199	-0.133
				(0.0749)	(0.151)	(0.111)
Observations	18,584	18,584	18,584	16,676	16,676	16,676
Adjusted R-squared	0.863	0.760	0.777	0.864	0.759	0.775
Firm-State FE	✓	✓	✓	✓	✓	✓
Firm-Year FE	✓	✓	✓	✓	✓	✓

A Appendix

A.1 Employee Outside Option and Total Innovation

The equation for the total expected innovation is given in equation (7). From this, I can take the total derivative with respect to δ, the employee's outside option to see how total innovation will behave.

$$\begin{aligned}\frac{dR^*}{d\delta} &= (2\alpha(1-\delta)\delta)^{\frac{2\alpha}{1-2\alpha}} + \frac{\delta(2\alpha(1-\delta)\delta)^{\frac{2\alpha}{1-2\alpha}-1}(2\alpha)(2\alpha(1-2\delta))}{1-2\alpha} \\ &\propto \left(1-\delta+\frac{(2\alpha)(1-2\delta)}{1-2\alpha}\right)\end{aligned} \tag{A.1}$$

To understand the behavior of the derivative, all I need to do is focus on the simpler expression. Hence, I can set the expression equal to zero and determine what the critical value for δ.

$$\begin{aligned}0 &= \left(1-\delta+\frac{(2\alpha)(1-2\delta)}{1-2\alpha}\right) \\ \overline{\delta} &= \frac{1}{1+2\alpha}\end{aligned} \tag{A.2}$$

It is clear that the expression is decreasing in α. Thus $\frac{dER^*}{d\delta} > 0$ when $\delta < \overline{\delta}$ and $\frac{dER^*}{d\delta} < 0$ when $\delta > \overline{\delta}$.

A.2 Firm Investment

To prove Corollary 1, I need to determine the impact of δ on firm invest. Therefore, I need to take the total derivative of expected innovation with respect to δ.

$$\frac{dI^*}{d\delta} = (2\alpha(1-\delta)\delta)^{\frac{1}{1-2\alpha}-1}\frac{1}{1-2\alpha}(2\alpha(1-2\delta)) \tag{A.3}$$

The first two terms of the derivative, $(2\alpha(1-\delta)\delta)^{\frac{1}{1-2\alpha}-1}\frac{1}{1-2\alpha}$ will always be positive. If $\delta > \overline{\delta}$, then the last term is will be negative because $1-2\delta < 0$. Thus, when employee outside option decrease, firm investment will increase in this region.

To prove Corollary 2, I need to determine the impact of δ on innovation holding investment fixed.

$$\frac{d}{d\delta}R(e,\overline{I}) = \frac{d}{d\delta}\delta\overline{I}^{a+1} = \overline{I}^{a+1} \tag{A.4}$$

Therefore, it is clear that total innovation will decrease if employee outside options decrease and and investment is held constant.

A.3 Employee Matching

With heterogenous employee skill, I assume that employee there are differences in costs of effort. Specifically, employee with skill c will have disutility of effort of $\frac{e^2}{2c}$. Given this cost of effort I can solve for the employee's utility in equilibrium.

First, employee effort will be $e(I) = c\delta I^{\alpha}$. Next, firm investment in the project will be $I^* = (2\alpha c\delta(1-\delta))^{\frac{1}{1-2\alpha}}$. Thus, I can solve for employee utility and I will get $U_emp(c,\delta) = \frac{e^2}{2c} = \frac{c\delta^2}{2}(2\alpha c\delta(1-\delta))^{\frac{2\alpha}{1-2\alpha}}$.

A sufficient condition for assortative matching is to prove supermodularity of employee utility with respect to disutility of effort and employee outside options. It is obvious that employee utility is an increasing in $\frac{e}{\sqrt{c}}$. Thus, I will show that this is supermodular.

$$\begin{aligned}\frac{\partial\frac{e}{\sqrt{c}}}{\partial\delta} &= \frac{\partial\sqrt{c}\delta(2\alpha c\delta(1-\delta))^{\frac{\alpha}{1-2\alpha}}}{\partial(\delta)} \\ &= \sqrt{c}(2\alpha c\delta(1-\delta))^{\frac{\alpha}{1-2\alpha}}\left[1+\frac{\alpha(1-2\delta)}{(1-2\alpha)(1-\delta)}\right]\end{aligned} \tag{A.5}$$

This constant term at the end is less than 0 if $\delta > \hat{\delta} = 1-\alpha$.

$$\begin{aligned}\frac{\partial^2\frac{e}{\sqrt{c}}}{\partial\delta\partial c} &= \frac{\partial}{\partial c}\sqrt{c}(2\alpha c\delta(1-\delta))^{\frac{\alpha}{1-2\alpha}}\left[1+\frac{\alpha(1-2\delta)}{(1-2\alpha)(1-\delta)}\right] \\ &= \frac{\partial}{\partial c}c^{\frac{\alpha}{1-2\alpha}+\frac{1}{2}}(2\alpha\delta(1-\delta))^{\frac{\alpha}{1-2\alpha}}\left[1+\frac{\alpha(1-2\delta)}{(1-2\alpha)(1-\delta)}\right] \\ &= \left(\frac{\alpha}{1-2\alpha}+\frac{1}{2}\right)c^{\frac{\alpha}{1-2\alpha}-\frac{1}{2}}(2\alpha\delta(1-\delta))^{\frac{\alpha}{1-2\alpha}}\left[1+\frac{\alpha(1-2\delta)}{(1-2\alpha)(1-\delta)}\right]\end{aligned} \tag{A.6}$$

It is clear that this cross derivative will be the same sign as the previous derivative with respect to δ.

To interpret these equations, if $\delta > \hat{\delta}$, there will be a negative assortative match between cost of effort and employee outside options. Alternatively, there will be a negative assortative match between employee skill and employee outside options. In this region of high employee options, highly skilled employees will go where they have lower options. The opposite is true in regions with lower options.

Figure 3: Inevitable Disclosure Triple Differences

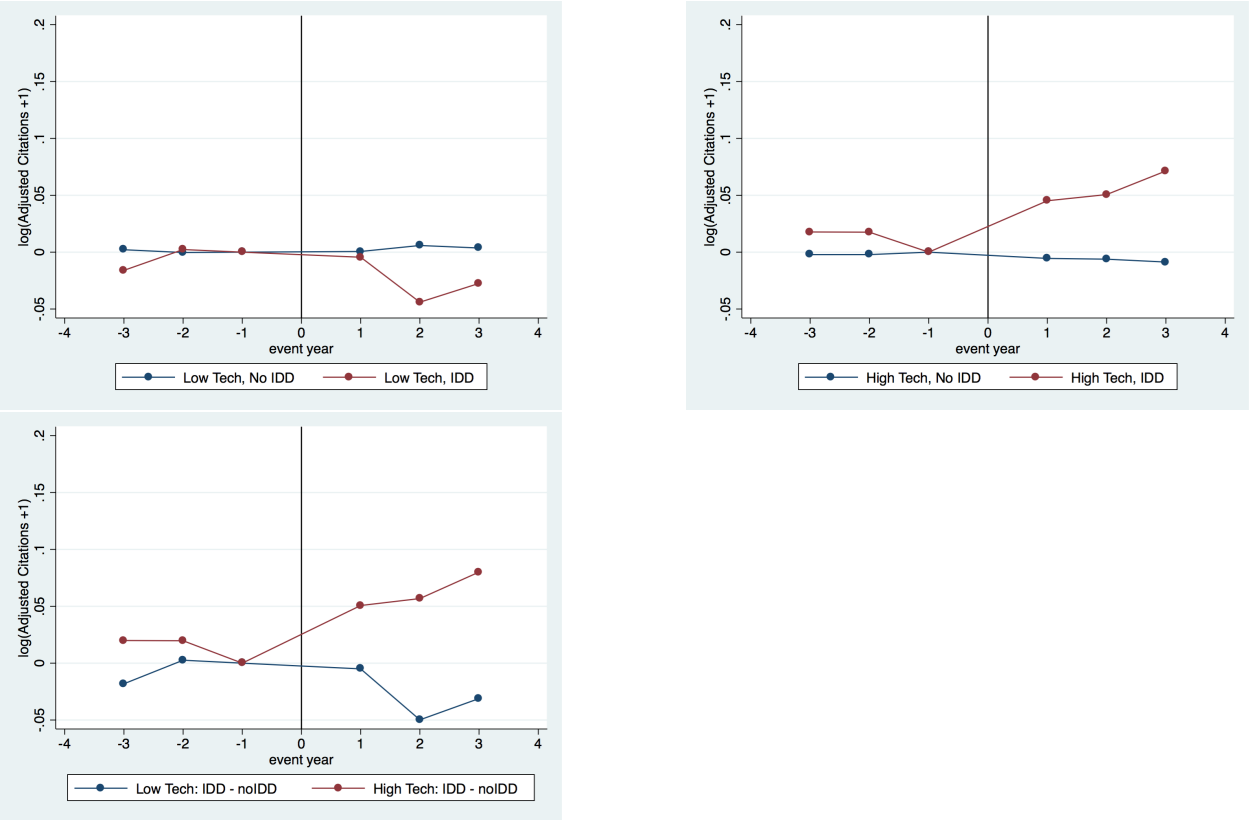


Figure 4: Inevitable Disclosure Triple Differences