Wrongful Discharge Laws and Innovation[1]

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Abstract

Wrongful Discharge Laws and Innovation

We show that wrongful discharge laws – laws that protect employees against unjust dismissal – spur innovation and new firm creation. Wrongful discharge laws, particularly those that prohibit employers from acting in bad faith *ex post*, limit employers' ability to hold up innovating employees after the innovation is successful. By reducing the possibility of hold-up, these laws enhance employees' innovative efforts and encourage firms to invest in risky, but potentially mould-breaking, projects. We develop a model and provide supporting empirical evidence of this effect using the staggered adoption of wrongful discharge laws across the U.S. states.

JEL: F30, G31, J5, J8, K31.

Keywords: Dismissal laws, Good-faith exception, R&D, Law and finance, Entrepreneurship, Growth.

1 Introduction

A recent strand of the literature emphasizes the critical role that laws and contracts play in fostering innovation and economic growth. Manso (2011) shows that the optimal contract to motivate innovation not only exhibits tolerance for short-term failure but also rewards interim failure to create the incentives for successful innovation in the long-term; Ederer and Manso (2010) find evidence supporting this thesis. Acharya and Subramanian (2009) show that the ex-post inefficient continuations engendered by debtor-friendly bankruptcy laws encourage ex-ante risk-taking and thereby promote firm-level innovation and country-level economic growth. In this overarching theme, we ask the following question: Can legal protection against unjust dismissal from employment spur innovative effort by employees and encourage firms to choose ex-ante risky yet value-enhancing innovative activities? We develop a theoretical model to highlight that this may indeed be the case; furthermore, we provide empirical evidence in support of the theory, in particular, that wrongful discharge laws can be instrumental in advancing innovation and entrepreneurship.

As highlighted by the theory on property rights (Grossman and Hart, 1986; Hart and Moore, 1990; and Hart, 1995), bilateral relationships suffer from hold-up problems when contracts are incomplete. As the payoffs from a successful innovation are often large, innovative firms may armtwist employees that contributed considerable effort to a successful innovation to appropriate a larger share of the ex-post surplus. A recent high-profile court case filed against the video-game company Activision by its former employees highlights this issue (see Section 2.1 for details).

When employment contracts are incomplete, wrongful discharge laws (hereafter WDL) can help to limit such ability of the employer to hold up the innovating employee by imposing the burden of proof on the employer in the case of an alleged wrongful discharge. The so-called "good-faith exception" to employment-at-will, which applies when a court determines that an employer discharged an employee in bad faith, can be effective in limiting an employer's capacity for holding up the innovating employee. Since "...the opportunity for bad faith and the duty of good-faith are products of incomplete contracts" (Bagchi, 2003), specifically, we assume in our model that an employer and an employee cannot commit to a contract that prohibits either of them from acting in bad faith ex post. The likelihood of a hold-up dampens the innovative effort by the employee. WDL – in particular the good-faith exception – can thus enhance the employee's innovative effort by reducing the possibility of such hold-up and may therefore cause innovation to be quite valuable to firms. Furthermore, this effect is likely to be *disproportionately* more pronounced in innovative industries when compared to the "brick-and-mortar" ones.

To provide empirical evidence supporting these hypotheses, we exploit the natural experiment created by the passage of WDL by several U.S. states since the 1970s. States adopted these laws in the form of common law exceptions to the employment-at-will doctrine. This setting is highly appealing from an empirical standpoint for two reasons. First, the motivation behind the passage of these laws centered around state courts' determination to assure legally binding policy principles, address the changing nature of labor relations, and assure the consistency with contract principles (see Walsh and Schwarz, 1996). Fortuitously, as these laws were not passed with the intention of promoting either innovation or entrepreneurship, potential effects on our outcomes of interest are likely to be an unintended consequence of the passage of these laws. Second, the staggered adoption of these laws across U.S. states enables us to identify their effect in a difference-in-difference setup.[1]

To develop proxies for innovation, we use data on patents issued to U.S. firms by the United States Patent and Trademark Office (USPTO) and link these data to Compustat. Apart from a simple count of patents, we use citations to patents to capture the economic importance of innovations. To estimate the difference-in-difference, we compare changes in innovation in states that passed such laws to the changes in states that did not. Our panel

[1]Cross-country studies (e.g., Botero et al., 2004) cannot easily control for time-varying country-level unobservables while U.S. studies investigating the impact of federal labor law encounter difficulties in disentangling the effect of the federal statute from contemporaneous changes in other relevant variables (see Donohue and Heckman, 1991; Donohue, 1998; Autor et al., 2006).

regressions include the following controls for confounding factors. First, we include firm and year fixed effects to capture invariant firm-level unobserved factors as well as secular trends in innovation. Second, we include firm-level characteristics (Tobin's Q, firm size, R&D) as well as state and industry-level factors (competition, industry-level ratio of value added, real state GDP, population, number of colleges, college enrollment, and unemployment benefits) to account for time-varying firm, state and industry level omitted variables. Third, we follow Autor et al. (2006) in adding interactions between the year dummies and indicators for the four census tract regions, which enable us to account for any confounding linear and/or non-linear regional trends in innovation. We find that the passage of WDL leads to more innovation, with the good-faith exception having the strongest positive effect. Economically, the adoption of the good-faith exception results in a rise in the annual number of patents and citations by 12.2% and 18.8% respectively.

Our theoretical model predicts that the increase in innovation due to the passage of WDL stems from increased employee effort in innovative projects. To provide evidence of this channel, we repeat our tests with a modified set of dependent variables that measure employee effort: patents and citations scaled by the number of employees and by R&D expenditure. The findings for these dependent variables are in line with the previous results. We also show that the impact of the good-faith exception is positive and significant only in high innovation-intensive industries, while the effect is insignificant in industries that have a lower propensity to innovate.

WDL are part of "common law" that evolved through seminal court decisions, which were unlikely to be determined by aggregate trends in innovation. Nevertheless, to alleviate any concerns about omitted variable bias and reverse causality, first, we examine potential determinants of the timing of the passage of the good-faith exception and find that pre-existing patterns of innovation are uncorrelated with the same. Second, in our tests of the effect of WDL on innovation, we control for economic growth as well as the political leanings of state governments and find that our results are unchanged. Third, we examine the dynamic effect of the passage of the good-faith exception on innovation as in Bertrand and Mullainathan (2003). While there is no effect on innovation prior to the passage of the good-faith exception, we find that the effect starts manifesting two years after the law passage, consistent with the long-run nature of innovation.

We then entertain alternative interpretations of our results. First, during our sample period, California (CA) and Massachusetts (MA) provided particularly strong protection to employees against dismissal and accounted for about 20% of U.S. patents filed. Furthermore, it is possible that firms may have specifically re-located to these two states to avail the benefits of strong employment protection on firm-level innovation. However, excluding observations from the states of CA and MA leads to similar results as with the full sample. Second, our findings could be a manifestation of firms shifting to labor-saving technologies rather than the result of stronger incentives provided for innovation. Shifting to labor-saving technologies would lead to an observable increase in Research and Development (R&D) investment. However, we do not find a significant impact of any WDL on firm investment of that type. Finally, it is also possible that the creation of the U.S. Court of Appeals of the Federal Circuit in 1982, which is often credited with at least partially causing a surge in U.S. patenting, is driving our results. We split the sample into two separate time periods – before 1982 and thereafter – and find that our results are similar in either sub-sample, thereby ruling out this possibility.

An important residual concern relates to the effect of legal restrictions on the mobility of human capital. Fulghieri and Sevilir (2011) argue in a theoretical model that such restrictions (through the strict enforcement of non-compete agreements) have a negative impact on employee effort to innovate. If states that passed WDL are also less likely to enforce non-compete agreements, then our above results may be spurious. To distinguish the effect of WDL from the effect of legal restrictions on mobility of human capital, we extend our basic model to consider the possibility of employee effort generating both firm-specific and generic innovations.[2] In this extension to the basic model, we show that while WDL encourage innovation by limiting the firm's ability to hold up the employee when the innovation is a firm-specific one, legal restrictions on the mobility of human capital limit the employee's ability to hold up the firm when the innovation is generic. Thus, if innovations are either firm-specific or generic, then the marginal effects of WDL and legal restrictions on the mobility of human capital work independent of each other. We confirm that this prediction holds in our empirical tests as well.

In the extended model, we also show that WDL increase creation of new firms by increasing employee effort in innovation (thereby also raising the likelihood of generic innovations that are optimally implemented by new firms). Since new firms need employees, WDL may also lead to greater employment creation. Using *novel* data from the Business Dynamics Statistics database, we investigate the effect of the passage of WDL on the creation of new firms as well as concomitant effects on job creation. Employing specifications that are similar to those in our tests of innovation, we find that states that adopt the good-faith exception experience a 12.4% increase in new establishments due to start-up firms and a 8.4% increase in job creation by such establishments.

Taken together, these tests enable us to conclude that innovation and firm creation are indeed fostered by laws that limit firms' ability to ex post discharge their employees at will. Thus, we surmise that employment protection laws present a trade-off: while they may cause ex-post inefficiencies in the labor market (Lazear, 1990, Ljungqvist and Sargent, 1998, Botero et al., 2004), they can have positive ex-ante effects by fostering innovation and entrepreneurship. As a large influential literature on endogenous growth (see Aghion and Howitt, 2006) argues that innovation and entrepreneurship contribute significantly to a country's economic growth and development, our study points out the need to factor in these incentive effects in any analysis of the net welfare implications of employment protection laws.

[2] As illustrated by the celebrated start-ups Adobe and 3Com spun out of the research efforts at Xerox's Palo Alto Research Center, innovative effort by employees can indeed lead to firm-specific as well as generic innovations that are optimally developed inside and outside existing firms respectively.

The rest of the paper is organized as follows. Section 2 provides background information on WDL and describes a case study to motivate the theoretical model. Section 3 presents the basic model which considers the possibility of the employer holding up the employee. Section 4 documents empirically the effect of WDL on innovation. In Section 5, we extend the basic model to incorporate the possibility of the employee holding up the employer. We show theoretically and empirically that the results in Section 4 are robust to controlling for the effect of laws governing mobility of human capital; we also derive empirical implications for the creation of new firms. Section 6 presents the results on the effect of WDL on entrepreneurship. In Section 7, we discuss related literature. Section 8 concludes.

2 Wrongful Discharge Laws

Since the 1970s, the vast majority of U.S. states have adopted common law exceptions to the employment-at-will doctrine. These so-called "wrongful discharge laws" are part of the common law, i.e., law created by court decisions (in this case, state courts). The legal profession distinguishes three distinct WDL: the public-policy exception, the good-faith exception, and the implied-contract exception. In a given state, courts recognize anywhere from zero to all three of these exceptions. We refer the reader to Dertouzos and Karoly (1992), Aalberts and Seidman (1993), Walsh and Schwarz (1996), Abraham (1998), Miles (2000), Kugler and Saint-Paul (2004), Autor et al. (2006), and MacLeod and Nakavachara (2007) for a detailed discussion.

The public-policy exception. This WDL assures that an employer cannot discharge an employee for declining to violate lawful public policy, taking actions that are in the public's interest, or refusing to commit an illegal act. By 1999, 43 U.S. states recognized this WDL.

The implied-contract exception. This WDL is applied in situations where the employer implicitly indicates that termination shall only occur due to just cause. Although 41 states recognized the implied-contract exception by 1999, legal scholars claim that this exception offers limited leverage in reducing employers' ability to unilaterally decide the fate of an employment relationship.

The good-faith exception. The good-faith exception applies in situations where a court determines that an employer discharged an employee for "bad cause". Importantly, unjust dismissal can arise even when no implied contract exists between the employer and the employee (for example, even if no indication had been made that the employment contract was long-term). Many legal scholars deem the good-faith exception to be the *most far-reaching WDL* (see Kugler and Saint-Paul, 2004). Due to the applicability of tort law – which entails damages to punish the defendant and thereby deter future wrongdoing – the good-faith exception is a potentially very costly one for employers. Between 1970 and 1999, the good-faith exception was adopted in 13 states (Autor et al., 2006).[3]

Figures 1 and 2 show the adoption of all three WDL in U.S. states from 1970–1999.

Evidence on the costs of wrongful discharge trials. Dertouzos et al. (1988) examine WDL trials in CA from 1980 to 1986. Plaintiffs win in 68% of the trials and on average are awarded $650,000, of which about 40% constitute punitive damages. These amounts are significant since the annual average salary of a plaintiff in their sample amounts to $36,254. Jung (1997) studies WDL jury verdicts in CA and Texas between 1992 and 1996. In CA, plaintiffs prevail in 54% of the cases brought to trial. Average compensatory damages equal approximately $449,000, while average punitive damages are about $675,000. Such awards were not exclusive to CA (see Edelman et al., 1992; Abraham 1998). Overall, the evidence indicates that WDL trials, especially when punitive damages are applied, can be costly for employers.

2.1 Wrongful Discharge in Innovative Industries: A Case Study

On the 3^{rd} of March 2010, the attorney firm O'Melveny & Myers LLP filed a lawsuit against Activision Publishing, Inc. in the Los Angeles County Superior Court, on behalf

[3]These states were: Alaska (adopted in 1983), Arizona (1985), California (1980), Connecticut (1980), Delaware (1992), Idaho (1989), Louisiana (1998), Massachusetts (1977), Montana (1982), New Hampshire (adopted in 1974, repealed in 1980), Nevada (adopted in 1987), Oklahoma (adopted in 1985, repealed in 1989), Wyoming (adopted in 1994).

of video game developers Jason West and Vince Zampella ("WZ"), who were in charge of Activision's Infinity Ward ("IW") subsidiary.[4] The lawsuit alleges "wrongful discharge and breach of the implied covenant of good faith and fair dealing":[5]

> "(The plaintiffs) are among the most talented and successful videogame developers in the world. They created for Activision two videogame franchises, *Call Of Duty* and *Modern Warfare*, that became the most successful in the company's – indeed, the industry's – history, lining Activision's pockets with billions of dollars in revenue and creating a die-hard fan base in the millions. In November 2009, after over two years of nearly 'round-the-clock work, Messrs. West and Zampella, and the rest of the Infinity Ward Studio delivered to Activision *Modern Warfare 2* – a video game that has already been responsible for over $1 billion in sales and was recently hailed by Activision itself as the largest launch of any entertainment product ever. Just weeks before Messrs. West and Zampella were to receive the royalties for their hard work on Modern Warfare 2, Activision fired them in the hope that by doing so, it could avoid paying them what they had rightfully earned,..."

On the other hand, Activision alleged in the counter-suit filed on the 9^{th} of April 2010 that WZ attempted to "steal" IW, "hold hostage" Modern Warfare 2, "delayed pre-production" on Modern Warfare 3, and deliberately withheld royalty cheques from IW employees, in addition to embezzling a significant fraction of the royalties. Activision maintains that WZ are guilty of the following: (1) threatening to bring production of Modern Warfare 2 to a stop in order to extort more control over the Call Of Duty franchise and the IW studio from Activision; (2) engaging in discussions with Activision's closest competitor and discussing their plans with employees to persuade them to leave Activision and join them.

[4] For further details about the case, we refer the reader to a news article published at http://ve3d.ign.com/articles/news/54192/Activision-Counter-Sues-Fired-Infinity-Ward-Founders-Suit-Scanned-Broken-Down-Transcribed

[5] This quote is taken from the original text of the complaint filed by West and Zampella in 2010 against Activision in the Superior Court of the State of California (County of Los Angeles).

Two observations from the above case are pertinent as they play a crucial role in the theoretical model below. First, the hold-up claims made by WZ relate to the breach of the implied covenant of good faith and fair dealing. Second, the claims made by both sides suggest ways in which one party can hold up the other after effort has been exerted and the project (or innovation) has proven successful. After the success of the project, the employer can threaten to fire the employee in an attempt to reduce the employee's bargaining power. Furthermore, innovating employees may adopt tactics to retain bargaining power vis-a-vis the employer, which may, in turn, prompt the employer to replace existing employees with new ones who would possess little bargaining power. These observations, as we will see later, will play an important role in both the theoretical model, as well as our empirical tests.

3 Theoretical Motivation

We develop a model in which a firm (F) chooses between two projects which differ in their degree of innovation. We denote the "routine" project by R and the "innovative" project by I. The firm employs an employee (E) who works on the project chosen by the firm.

Figure 3 shows the timing and sequence of events. There are three cash flow dates, $t = 0, 1, 2$. At date 0, the firm recruits an employee and chooses to invest in either the innovative or the routine project. The projects require the same initial investment and generate cash-flows at date 2. At date 1, the employee exerts firm-specific effort $e_j \in [0, 1]$, which affects the project outcome. We assume the effort to be *observable but not verifiable.* The employee incurs a personal cost which we assume to be $\frac{e_j^2}{2}$. At date 1.5, i.e., before the actual cash-flows accrue at date 2, all agents learn whether the project chosen at date 0 produced an innovation or not. If the employee chooses effort e_j in project j then the project generates a successful, firm-specific innovation with probability e_j.

As in Grossman and Hart (1986), Hart and Moore (1990) and Hart (1995), we assume that E and F cannot write complete contracts ex ante (i.e., at date 0). As a result, at date 1.5, i.e., after E has made the firm-specific effort and it is known that the project has generated a successful innovation, E is exposed to the possibility of hold-up by F. Once the project has generated a successful innovation, F could threaten to fire E and develop the innovation by employing an alternative employee E' who has limited bargaining power vis-a-vis F. We model the bargaining process between E and F as the $50:50$ Nash Bargaining solution with outside options.

To derive the outside options *endogenously*, we model the following extensive-form game between E and F. After knowing whether the innovation was successful or not, F decides whether to retain E or fire him. If F fires E after the project is known to be successful, then F's action violates the "covenant of good faith and fair dealing" in an employment relationship. So, E sues F for "wrongful discharge." In contrast, if F fires E after the project fails to generate an innovation, then no WDL claim can be made by E on F.

WDL require the firm to prove in a court of law that the dismissal was not "unjust", which it may or may not be able to prove. Note that WDL *do not* make firing a worker impossible; rather, they require the firm to ex post justify the dismissal in a court of law. This facet of WDL is captured by assuming that E wins the WDL suit with probability μ; the more stringent the WDL, the greater the difficulty faced by the firm in justifying that the dismissal was not unjust, which corresponds to a higher probability of E winning the lawsuit (i.e., μ is greater). If E wins the lawsuit, the court orders the firm to pay a fixed penalty C to the wrongfully dismissed employee.[6] 'Employment-at-will' nests as a special case since the firm does not have to justify its dismissal as "just" in a court of law and therefore does not have to pay a penalty, which corresponds to $\mu = 0$ in the model.

At date 2, cash-flows are realized and allocated based on bargaining outcomes at date 1.5. For project j, $j \in \{I, R\}$, the project cash-flow equals α_j if the project yields a successful innovation, and $\beta_j \leq \alpha_j$ if the project fails to generate an innovation, where:

$$\beta_j \leq \alpha_j < 1 \tag{1}$$

[6] As evidence of such penalties, see Section 2.

Since the employee makes a firm-specific effort, the innovation generated is a specific one. In other words, the cash-flows generated by E and F working together to implement the innovation are significantly greater than the cash-flows generated when F implements the innovation with another employee E', in which case the cash-flows equal $b\alpha_j$ $(0 < b < \frac{1}{2})$. Since the innovation is firm-specific, E cannot implement it without F. Furthermore, we assume the labor market to be competitive with employees earning their reservation utility in equilibrium, which we normalize to zero. Finally, the common discount rate equals zero.

3.1 Incompleteness of contracts

We assume that project cash-flows and the employee's effort are observable but not verifiable ex ante. The non-verifiability of the employee's effort as well as that of the cash-flows stems from the fact that the contract at date 0 cannot specify in detail all the different contingencies that may arise – a situation that Tirole (1999) labels "indescribable contingencies." This assumption is natural to settings involving innovation (e.g., Aghion and Tirole, 1994) because it involves considerable exploration (see Manso, 2011). Given these "unknown unknowns" involved in innovative endeavors, it is unlikely that the firm and the employee will be able to contract upon the specific details of either the employee's effort or the nature of the signal. Furthermore, given such uncertainty, at date 0, the two parties cannot commit to a contract that would not be renegotiated at date 1.5. As Tirole (1999) points out, indescribability results in contracts being incomplete when renegotiation is possible.

Specifically, we assume that E and F cannot write down a "good faith" clause that prohibits either of them from acting in bad faith ex post. The duty of good faith is a background condition imposed on all contracts that limits the negative effects of unequal bargaining power. However, its enforcement is particularly challenging in the context of most employment relationships since the employer typically has disproportionate bargaining power. In fact, as Bagchi (2003) avers: "The opportunity for bad faith and the duty of good faith go together. There is no need to impose a legal duty of good faith where there is no opportunity for bad faith." Therefore, it is natural to assume that an iron clad "good faith" clause cannot be written ex ante and enforced ex post.

3.2 Innovative vs. Routine Project

Routine projects face risks mainly due to uncertainty in market demand and competition. In contrast, innovative projects entail additional risks associated with the process of exploration and discovery. Therefore, in our model, the key difference between these projects is that the innovative project is riskier than the routine one. We capture this difference as:

$$\beta_R = \alpha_R = R; \beta_I = 0, \alpha_I = A \tag{2}$$

Finally, we assume that the penalties a firm has to pay for wrongful discharge are bounded:

$$C < 0.5A \tag{3}$$

3.3 Analysis

Since the payoff from the routine project is fixed ($= R$), it is not affected by employee effort. Therefore, we focus on the game that results if the firm chooses the innovative project I. We solve this game by backward induction. Consider first the extensive form game played at date 1.5. Let us denote E's and F's expected payoffs at date 1.5 as U and V respectively.

If the project generates a successful innovation and F fires E, E sues F for wrongful discharge. If E wins, the court orders F to pay damages equal to C. Since F produces with E' after dismissing E, the aggregate cash-flows from implementing the innovation equal bA. As the labor market is competitive, F has all the bargaining power with E' and gets the entire payoff bA in its bargaining with E'. However, F has to pay E penalties equal to C. Therefore, F's payoff equals $bA - C$ while E's payoff equals C.

If E loses the lawsuit, then E's and F's payoffs are respectively 0 and bA. Thus, E's and F's expected payoffs if F fires E after a successful innovation equal μC and $bA - \mu C$

respectively. These are the values of E's and F's outside options when they bargain with each other if the innovation is successful and F decides to retain E. Since the total cash-flows when F retains E equal A, $50:50$ Nash bargaining yields the payoffs for E and F as $U = \mu C + 0.5(1-b)A$ and $V = bA - \mu C + 0.5(1-b)A$. In equilibrium, F retains E since F's payoffs are greater in this case than when F fires E.

If the project does not generate a successful innovation, then the payoff from the project equals 0. Furthermore, even if F were to fire E, E cannot sue F for wrongful discharge. Since the payoff with or without E equals 0, F is indifferent between firing or retaining E.

Since the probability of a successful innovation is e_I, E's expected payoff at date 1 is:

$$\overline{U}(e_I) = e_I \cdot [\mu C + 0.5(1-b)A] - 0.5e_I^2 \tag{4}$$

where $\mu C + 0.5(1-b)A$ captures E's payoff when the innovation is successfully implemented within the firm and $0.5e_I^2$ equals E's private cost of effort. Thus, the equilibrium level of effort, which is chosen by E to maximize $\overline{U}(e_I)$, is:

$$e_I^* = \mu C + 0.5(1-b)A \tag{5}$$

To highlight the effect of contractual incompleteness, consider the first-best benchmark scenario when complete contracts can be written between E and F so that F can incentivize E to choose effort to maximize the total surplus generated from the project I:

$$e_I^{FB} = \arg\max_{e_I} \left[Ae_I - 0.5e_I^2\right] = A \tag{6}$$

3.4 Results

Proposition 1 *The equilibrium level of effort exerted by an employee when contracts are incomplete is lower than that in the first-best benchmark case when contracts are complete:*

$$e_I^* < e_I^{FB} \tag{7}$$

When contracts are incomplete, the employer cannot commit to not hold up the employee after finding out that the innovation is successful. Since increased innovative effort by the employee increases the likelihood of successful innovation, the likelihood of hold-up by the employer decreases the employee's effort in the innovative project.

Proposition 2 *As WDL become more stringent, the innovative effort exerted by an employee increases, which brings his effort closer to the first-best level.*

$$\frac{de_I^*}{d\mu} > \frac{de_I^{FB}}{d\mu} = 0 \tag{8}$$

As WDL become more stringent, the employee has a greater defense against hold-up by the employer, which increases the outside option and thereby increases his share of the surplus generated from a successful innovation. Therefore, more stringent WDL increase the employee's innovative effort when contracts are incomplete.

Proposition 3 *An increase in the stringency of WDL disproportionately increases the employee's effort in the innovative project relative to the increase in the routine project:*

$$\frac{de_I^*}{d\mu} > \frac{de_R^*}{d\mu} \tag{9}$$

Given our assumption that the routine project generates the same cash-flows whether the innovation is successful or not, it follows that effort in the routine project equals a constant. Therefore, we can infer using Proposition 2 that an increase in the stringency of WDL disproportionately increases the employee's effort in the innovative project when compared to the increase in his effort in the routine project.

Since the labor market is competitive, employees earn their reservation wage in equilibrium. Therefore, the firm chooses between innovative and routine project at date 0 depending on which one produces a greater joint payoff, which we denote by W_j, where $j\epsilon\{I, R\}$.[7] Then, Propositions 4 and 5 summarize the effect of WDL on the ex-ante expected surplus from pursuing an innovative project versus that from pursuing a routine project.

Proposition 4 *An increase in the stringency of WDL increases the value of the innovative project disproportionately more than the value of the routine project.*

$$\frac{d\overline{W}_I^*}{d\mu} > \frac{d\overline{W}_R^*}{d\mu} \tag{10}$$

Proposition 5 *Given some parametric restrictions (see Appendix B), there exists a* $\widehat{\mu} \in (0, 1)$ *such that the value from the routine project is higher than the value from the innovative project when WDL are not stringent; the reverse is true when WDL are stringent*

$$\mu \leq \widehat{\mu} \Rightarrow \overline{W}_I^*(\mu) \leq \overline{W}_R^*(\mu) \tag{11}$$

$$\mu > \widehat{\mu} \Rightarrow \overline{W}_I^*(\mu) > \overline{W}_R^*(\mu) \tag{12}$$

The intuition for both the above propositions follows directly from Proposition 3. Since the employee receives a greater share of the surplus generated from innovation when WDL are more stringent, the underinvestment in effort becomes disproportionately lower for the innovative project than for the routine project as WDL become more stringent. Therefore, the ex-ante expected surplus from undertaking an innovative project increases disproportionately more than that from undertaking a routine project, which explains the fact that innovation becomes the more attractive choice for the firm when WDL are more stringent.

[7] Lemma $A2$ in the Appendix formalizes this observation.

Thus, the increased employee effort in innovation generated by WDL translates into a positive effect on the expected firm value from innovation as well.

3.5 Discussion

A key driving assumption of our model is lack of complete contracts between the firm and the employee. A natural question arises: Could parties commit to contractual features in the employment contract, such as generous severance packages, to avoid inefficiencies stemming from contractual incompleteness? Note that given indescribability and renegotiation, revenue-sharing rules contracted at date 0, incentive contracts that specify severance payments at date 2, contracts that explicitly specify performance at date 2, or mechanisms that involve messaging between the two parties or to third parties, cannot fully address the incentive problem that is analyzed in this paper (see Hart, 1995, for details).[8] As Hart (1995) explains, any ex-ante contractual features cannot lead to credible commitment against hold-up in a setting such as ours. Given the ex-ante uncertainty associated with innovation, ex-post efficient renegotiation cannot be ruled out, which destroys the credibility of any ex-ante commitment through such contractual features.

Empirical evidence also indicates that for employees that do not constitute senior management in a firm, such severance packages are quite uncommon. Narayanan and Sundaram (1998) examined a sample of Fortune 1000 and S&P 500 non-financial firms from 1980–1994. They find that while 55% of the firms had a "golden parachute" agreement with top management, only 7% of the firms had "tin parachutes", i.e., severance agreements for employees who are not officers of the company. Furthermore, they found that such "tin parachutes" are limited to change-of-control events such as a merger or acquisition. In the context of innovative firms, this rarity of severance payments in employment contracts of employees below the level of senior management is consistent with the argument in Manso (2011), who

[8] For instance, while pre-committed severance packages may be written upfront to address the hold-up problem, they would in general be "incomplete" given the indescribability of all ex-post outcomes in such contracts. In other words, the extent of commitment the firm provides by agreeing to incur the cost of severance packages would be insufficient in some states of the world to avoid the hold-up problem.

shows that even when complete contracts can be written, the firm may find it prohibitively costly ex ante to commit to not fire its employees ex post.

4 Wrongful Discharge Laws and Innovation

In this section, we empirically examine the effect of WDL on firm-level innovation. Propositions 3, 4 and 5 respectively lead to the following testable hypotheses:

HYPOTHESIS 1: *Passage of WDL – particularly that of the good-faith exception – leads to greater innovation.*

HYPOTHESIS 2: *Passage of WDL – particularly that of the good-faith exception – leads to a larger increase in employee effort in innovative projects compared to more routine projects.*

HYPOTHESIS 3: *Passage of WDL – particularly that of the good-faith exception – leads to relatively more innovative effort by employees as well as relatively more innovation in the innovation-intensive industries than in the traditional industries.*

Next, we test these hypotheses by employing proxies for innovation.

4.1 Data and Main Proxies

We now describe the data, our proxies for innovation and the changes in WDL.

4.1.1 Proxies for Innovation

To construct proxies for innovation, we use patents filed with the U.S. Patent and Trademark Office (USPTO) and citations to these patents, compiled in the NBER Patents File (Hall et al., 2001). The NBER patent dataset provides among other items: annual information on patent assignee names, number of patents, number of citations received by each patent, technology class of the patent, and year that the patent application is filed. In this study we focus on patents filed by U.S. firms. To link the patent data with Compustat, we exploit the fact that each assignee in the NBER patent dataset is given a unique and time-invariant identifier. After matching these assignee names to the names of divisions and subsidiaries belonging to a corporate family from the *Directory of Corporate Affiliations,* we match the name of the corporate parent to Compustat.

We use two different proxies for innovation. First, we count the annual number of patents filed by a firm. Second, we measure the number of subsequent citations to a firm's patents that have accumulated until a given year. Citations capture the *importance* and drastic nature of innovation. This proxy is motivated by the recognition that a simple count of patents does not distinguish breakthrough innovations from less significant or incremental technological discoveries.[9] Intuitively, if firms are willing to further invest in a project that builds upon a prior patent, the cited patent has been influential and economically significant.

We follow the patent literature in dating our patents according to the year in which they were applied for. This avoids anomalies that may be created due to the lag between the date of application and the date of granting of the patent (Hall, Jaffe and Trajtenberg, 2001). Note that although we use the application year as the relevant year for our analysis, the patents appear in the database only after they are granted. Hence, we use the patents actually granted (rather than patent applications) for our analysis.

To examine Hypothesis 1, we use patents and citations as aggregate measures of innovation. To test Hypotheses 2 and 3, we employ patents and citations per employee and per dollar of R&D by complementing NBER patent data with data from Compustat.

4.1.2 Wrongful Discharge Laws

Following the recent literature, we use Autor et al.'s (2006) coding of the passage of WDL. This coding is particularly appealing as it attributes a law change to the year in which a precedent-setting court decision occurs, which ensures that unexpected changes in the law are employed to assess its effect on outcome variables. As the reason for the adoption of the WDL was unrelated to our outcome variables of interest, employing these unexpected changes alleviates any residual concerns about the endogeneity of these law passages. We

[9] Pakes and Shankerman (1984) show that the distribution of the importance of patents is extremely skewed, i.e., most of the value is concentrated in a small number of patents. Hall et al. (2005), among others, demonstrate that patent citations are a good measure of the value of innovations.

link the WDL data to our NBER-Compustat data using the variable 'postate' in the NBER dataset, which lists the state in which the patent was filed.

We follow the previous literature in including separate indices for each WDL in our regressions. Specifically, the variable GF_{st} takes the value of one if a given state s has a good-faith exception in place in year t, zero otherwise; the other two WDL indices (IC_{st} and PP_{st}) are defined analogously. As seen in Figures 1 and 2, the three WDL indices exhibit substantial cross-sectional as well as time-series variation, which enables our identification.

4.1.3 Summary Statistics

Panel A of Table 1 lists the mean, median, standard deviation, and data sources for the variables used in our tests on innovation. Our sample encompasses the years 1971–1999, which is the time-span for which the Autor et al. (2006) coding of the WDL is available and we can match Compustat firms to NBER patent assignees. Also, though the NBER patent data is in principle available until 2002, the data beyond 1999 suffer from severe truncation problems, particularly in the case of patent citations. Therefore, we end our sample in 1999.

Our sample includes 5,698 firms that can be merged from the NBER patent data file to Compustat, which corresponds to about one-third of the relevant NBER data consisting of patent assignees located in the U.S. Since the NBER data also includes patents assigned to privately held firms while Compustat focuses on publicly listed firms, this reduction in the sample size is expected. While our dataset without any control variables has 104,504 firm-year observations, this sample reduces to 48,433 observations for which we have data on all our control variables.[10] Since we use the log transformation, we have fewer observations when using citations as the dependent variable due to patents with zero citations. Although our results are unchanged when we use log of (*1* + citations), we use log of (citations) to be consistent with the other dependent variables, namely log of (citations/R&D) and log

[10]The *NCA* enforcement score, as well as the *Ratio of Value Added* are only available from 1976 and 1977 onwards, respectively. The point estimates and significance of the main explanatory variables vary slightly across specifications with and without control variables. As we show in Appendix Table A1 and the corresponding discussion, these differences are due to the impact of the control variables rather than the change in sample size.

of (citations/employees). When using these latter two dependent variables, the number of observations is slightly reduced due to missing values for R&D and number of employees.

4.2 Empirical Strategy

We investigate whether the passage of WDL in the U.S. led to greater innovation. Figure 4 depicts the effect of the passage of the good-faith exception on innovation in adopting states relative to non-adopting states. On the y-axis, the graph shows the logarithm of the number of citations received to patents filed in a given year; the x-axis shows the time relative to the year of adoption of the good-faith exception (ranging from five years prior to adoption until ten years after). The two dashed lines in the figure correspond to the 90% confidence intervals of the coefficient estimates.[11] This figure clearly illustrates that innovation increases after the passage of the good-faith exception. Consistent with the notion that innovation practices in firms take some time to change, the increase in innovation particularly manifests several years after adoption of this WDL, with a persistent long-run effect.

U.S. state courts adopted the three different WDL in different states and years during the sample period. Thus, we can examine the before-after effect of a change in WDL in affected states (the "treatment group") vis-à-vis the before-after effect in states where such a change was not effected (the "control group"). This is a difference-in-difference test design in a multiple treatment groups, multiple time periods setting as employed by Bertrand, Duflo and Mullainathan (2004) and Imbens and Wooldridge (2009). We implement this test

[11] We broadly follow Autor, Donohue, and Schwab (2006) in constructing this graph. The graph plots the point estimates and 90% confidence intervals (based on standard errors which are clustered by state of location of the patent assignee) of the parameters β_τ from the following regression:
$y_{ist} = \beta_t + \sum_{\tau=-10}^{10} \beta_\tau * Good\_Faith_{st}^{\tau} + \varepsilon_{ist}$
where y_{ist} is the log of the number of citations (+1) received for patents applied for in year t by patent assignee i in state s. $Good\_Faith_{st}^{\tau}$ is a variable indicating the year relative to the adoption of a good-faith exception in state s and year t. For example, $Good\_Faith_{st}^{0}$ is a variable taking the value of one in the year of adoption of the good-faith clause in state s and year t, zero otherwise; $Good\_Faith_{st}^{6}$ is a variable taking the value of one in the sixth year after adoption of the good-faith clause in state s and year t, zero otherwise. β_t is a set of year dummies. The time span underlying the regressions is 1970–1999; patent data is from the NBER Patents File (Hall et al., 2001), with data limited to patent assignees residing in the US.

through the following panel regression:

$$y_{i,s\to r,t} = \beta_i + \beta_t + \beta_r \times \beta_t + \beta_1 GF_{st} + \beta_2 PP_{st} + \beta_3 IC_{st} + \beta X_{ist} + \varepsilon_{ist} \tag{13}$$

where $y_{i,s\to r,t}$ measures innovation by firm i in state s (of U.S. census region r)[12] in year t.[13] β_i and β_t denote respectively firm and application year fixed effects. The application year fixed effects enable us to control for inter-temporal technological shocks as well as the fact that citations to patents applied for in later years would on average be lower than those in earlier years. Similarly, the firm fixed effects also allow us to control for time-invariant differences in patenting and citation practices across firms. In order to alleviate concerns from autocorrelation, we cluster standard errors at the state level. GF_{st}, PP_{st}, and IC_{st} measure whether a given WDL is in place in a given state and year. As explained by Imbens and Wooldridge (2009), the employed fixed effects lead to β_1–β_3 being estimated as the *within-state* differences *before* and *after* the WDL change vis-à-vis similar before-after differences in states that did not experience such a change during the same period. These tests are less subject to the criticism that geographical or industry-level unobserved factors influencing innovation are correlated with the level of dismissal laws in a state. X_{ist} denotes the set of time-varying control variables.

As in Autor et al. (2006), we also control for regional time trends through the interaction of region dummies with year dummies ($\beta_r \times \beta_t$). We include these region-specific time trends to control for potential sources of endogeneity in the passage of WDL. First, Autor et al. (2004) point out that the Southern states lagged behind the non-Southern states in enacting these laws. Furthermore, over the time-period 1940-2000, the Southern states lagged behind non-Southern states in filing patents. Second, the adoption of the good-faith exception – the main focus of our theory and empirical tests – was more common in the West, particularly the North-Western U.S. region. Therefore, $\beta_r \times \beta_t$ enable us to non-parametrically account

[12]The U.S. Census Bureau distinguishes four U.S. regions: Northeast, South, Midwest, and West.

[13]Howells (1990) and Breschi (2008) show that large firms locate their R&D facilities close to the company's headquarters and do not disperse them geographically.

for time-varying differences between geographical regions of the U.S. in innovation as well as in the enactment of WDL. We also account for additional differences between Northern and Southern states of the West region in additional tests (see Appendix C).

4.3 Results

4.3.1 Tests of Hypothesis 1

Hypothesis 1 states that the adoption of WDL, in particular the good-faith exception, leads to greater innovation. Table 2 provides support for this hypothesis by using patents and citations as the dependent variables. Columns 1 and 2, which report the results for the tests without control variables (except for year and firm fixed effects), show that the passage of WDL led to an increase in firm-level innovation as measured by both patents and citations; specifically, we observe that the good-faith and implied-contract exceptions had a positive and significant impact on innovation; the coefficient of the public-policy exception is positive and statistically significant in Column 2 but not in Column 1. The good-faith exception particularly pertains to the mitigation of hold-up problems (which are at the center of our model and theoretical predictions). Furthermore, as we mentioned in Section 2, legal scholars deem the good-faith exception to be the most far-reaching WDL. Consistent with this, our results show that the good-faith exception has the largest effect on our innovation measures.

Columns 3–4 show the results after controlling for regional trends (through the interaction of region and year dummies), as well as other variables that may affect innovation:

Firm-level controls To account for the possibility that larger firms might innovate more on average, we include firm *Size*, which is the natural logarithm of assets (in 2005 dollars); we also include $Size^2$, which is $Size * Size$, to capture possible non-linear effects of firm size on innovation. To control for investment opportunities, which may also affect a firm's innovation policies, we include *Market-to-Book*.[14] Furthermore, R&D constitutes an impor-

[14]Market value of assets is total assets (Compustat item *at*) plus market value of equity minus book value of equity. The market value of equity is calculated as common shares outstanding (*csho*) times fiscal-year

tant input into the innovation process, and our hypotheses (specifically, Hypothesis 2) imply that stricter dismissal laws should entail more innovation for a given level of R&D spending. Therefore, we include the log of R&D to Sales in the tests.

State-level controls Aghion et al. (2005) find that competition and innovation share an inverted U-shaped relationship. Therefore, we control for in-state competition (variable *Competition*) and its square (variable *Competition*^{2}).[15] A key determinant of innovation is the comparative advantage that a state possesses in its different industries, which could affect our interpretation of the effect of the passage of WDL on innovation. We control for this effect via our variable *Ratio of Value Added*.[16] We also account for various *time-varying* state characteristics in our regressions. Since richer and larger states may innovate more and may also be more likely to pass employment protection legislation, we include the logarithm of real GDP in a state and year (*ln(Real State GDP)*). As we stated above, over the time-period 1940-2000, the Southern states lagged behind non-Southern states in filing patents. If the non-Southern states were more likely to invest in education than the Southern states, such factors may have led to these differences in patenting. Therefore, we also control for a state's intellectual resources via the number of degree-granting institutions of higher education in a given state (*ln(Colleges)*), as well as via enrollment in institutions of higher education (*ln(Enrollment)*). We also control for number of state inhabitants through the logarithm of annual state population.[17]

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closing price (*prccf*). Book value of equity is defined as common equity (*ceq*) plus balance sheet deferred taxes (*txdb*). In order to eliminate the impact of outliers, we winsorize *Market-to-Book* at 1% and 99%.

[15] We define *Competition* as the fraction of total (2-digit SIC) industry sales generated by competitors in a given state. The state corresponds to the location of the firm's headquarters; Howells (1990) and Breschi (2008) show that large firms locate their R&D facilities close to the company's headquarters and do not disperse them geographically. Note that to construct the variable *Competition*, we use sales information for all Compustat firms in a given state and industry, not only sales from firms in our patent data-Compustat matched sample. In order to eliminate the impact of outliers, we winsorize *Competition* and *Competition*^{2} at 1% and 99%.

[16] In order to construct the variable *Ratio of Value Added*, we obtain data on the gross state product (GSP) per sector, state and year from the U.S. Bureau of Economic Analysis (available for the years 1977–1999). We combine the 63 BEA sectors to 18 sectors based on the BEA classification of two-digit SIC codes. In each year, the variable *Ratio of Value Added* corresponds to the GSP in a given sector and state divided by the total GSP in that state.

[17] Data on both state GDP as well as population is from the U.S. Bureau of Economic Analysis. The data on the number of colleges and college enrollment is taken from the annual Statistical Abstracts from the

Labor Unemployment Risk Agrawal and Matsa (2011), using changes in state unemployment insurance benefit laws, show that firms adopt conservative financial policies (i.e., lower corporate leverage, ceteris paribus) to mitigate worker exposure to unemployment risk. Similarly, employees in firms that are located in states with generous unemployment insurance benefit laws may be more willing to take more risk when choosing innovative projects. To control for this possibility, we use data on unemployment benefits provided by states. Following Agrawal and Matsa (2011), we employ the logarithm of the maximum total unemployment benefit (calculated as the maximum number of weeks that the benefit can be obtained times the maximum weekly benefit amount) as a proxy for the total unemployment insurance benefits that a claimant can receive in a given state and year.

Employing the full set of these covariates does not change our results materially. In particular, the point estimates and significance of the impact of the passage of the good-faith exception are almost unchanged. The control variables have the expected sign: firms with more R&D expenditure innovate significantly more. As in Aghion et al. (2005), in-state competition has an inverted U-shaped effect on innovation. Consistent with the notion that more insurance may encourage more risk-taking, we find that increases in state unemployment insurance benefits are associated with more innovation; this effect is (marginally) significant for one of our two innovation proxies.

Economic magnitudes In addition to being statistically significant, the economic magnitude of the impact of WDL on innovative activity is also large. In particular, if we use Columns 3 and 4 of Table 2 to estimate these economic magnitudes, we find that the adoption of the good-faith clause led to an increase in the annual number of patents and citations by 12.2% and 18.8% respectively, when compared to firms located in states which did not pass this WDL; the effect of the adoption of the public-policy exception on the two innovation proxies is 6.7% and 8.2% respectively while the implied-contract exception has no significant effect. Overall, these results confirm our main Hypothesis 1.

U.S. Census Bureau (1970-1999). For a few years, this data is not available (1973, 1979, 1989, 1993, 1996, 1998); in these cases, we replace a given missing year's value with the preceding year's value.

4.3.2 Tests of Hypothesis 2

To test Hypothesis 2, we repeat our tests of equation (13) using patents and citations scaled by the number of employees and, alternatively, by R&D expenditure (see Table 2, Columns 5–8). *Ln(Patents/Employee)* is the log of the number of patents per 1,000 firm employees; *ln(Patents/R&D)* is the log of the number of patents per million R&D dollars. *Ln(Citations/Employee)* and *ln(Citations/R&D)* are defined analogously. Both dependent variables provide a more direct measure of employee effort.

The results reported in Columns 5 & 6 of Table 2 confirm our Hypothesis 2: after the passage of WDL, patents and citations scaled by the number of employees increased significantly. In other words, innovative effort per employee increased significantly as WDL were adopted. This finding is robust to employing the full set of control variables described earlier. As before, it is again the good-faith exception that has the largest positive impact on innovation. We find that patents and citations per 1,000 employees increase by respectively 12.3% and 19.0% in states that adopt a good-faith exception vis-à-vis states that do not. Columns 7 & 8 of Table 2 further underscore these findings. From Columns 7 and 8, we find that adopting a good-faith exception increases patents and citations per million dollars of R&D by 12.9% and 19.5% respectively.[18]

4.3.3 Tests of Hypothesis 3

Hypothesis 3 suggests that the effect of the passage of WDL, in particular the good-faith exception, should be stronger in innovation-intensive industries than in other industries. In order to test this, we divide industries into those which have a high (low) propensity to innovate; our industry classification is based on the 48 Fama-French industries. Specifically, the dummy variable $High\_Intensity$ takes the value of one if the median number of patents filed in a given Fama-French industry in a given year exceeds the median value of these median number of patents across all industries in that year; $Low\_Intensity$ is $(1 - High\_Intensity)$.

[18] To avoid mechanical correlation of the dependent variable with our regressors, we do not use ln(R&D/Sales) as a control variable in these tests.

These dummy variables are then interacted with the indicator for the good-faith exception. The results can be seen in Table 3. Columns 1 and 2 report the results for patents and citations as the dependent variables, while Columns 3 & 4 (5 & 6) employ patents and citations scaled by the number of employees (scaled by R&D dollars). All regressions employ the full set of control variables. The results are striking: we find that the effect of the good-faith exception in high innovation-intensive industries is highly significant, while it is virtually absent in low innovation-intensive industries. The difference between high- and low-innovation intensive industries of the effect of the passage of the good-faith exception on innovation is significant in all six specifications (at the 10% level or higher).

Summary In sum, we find strong support for our hypotheses relating to innovation. Consistent with the theory, the passage of WDL, particularly the good-faith exception, leads to more innovation overall as well as to more innovative effort per employee and R&D dollar. Furthermore, these effects are stronger in the innovation-intensive industries.

4.3.4 Endogeneity concerns

We address concerns about other sources of omitted variable bias and the direction of causality in this section. As mentioned in Section 2, Walsh and Schwarz (1996) argue that states passed WDL for reasons largely orthogonal to the objective of promoting state-level innovation. In fact, the judicial decisions in the precedent setting cases were mainly concerned with enhancing fairness in employment relationships and consistency with general contracting principles rather than economic concerns.[19] Furthermore, WDL were based on judicial decisions, which are more likely to be driven by the merits of the case than political economy considerations. Nevertheless, to address residual concerns about omitted variable bias and reverse causality, we examine the potential determinants of the passage of WDL.

[19]For example, the precedent setting case in California ("Cleary v. American Airlines, Inc. (10/29/80), 168 Cal. Rptr. 722 (Cal. Ct. App. 1980)") involved an airline employee who argued that he was wrongfully dismissed by his former long-term employer, American Airlines, Inc. During the trial, the court decided that it was necessary to extend contracting principles from another law domain into employment contracts. Specifically, the court concluded that the "concept of good faith and fair dealing was first formulated by the California courts in insurance contracts. But it is clear that it has reference to all contracts."

The adoption of WDL may have been driven by underlying political or economic conditions at the state-level. For example, the passage of the laws may follow a period of low economic growth, and the positive trend in innovation after law adoption may merely reflect mean reversion in economic (and hence patenting) activity. We confirm in Table 4 that the timing of the adoption of the good-faith principle, which is the main focus in our theory and tests, was *not* a function of political, economic, or other prior observable factors. We estimate different Weibull Hazard models where the "failure event" is the adoption of the good-faith exception in a given U.S. state. Columns 1 and 2 show that the adoption of the good-faith exception was unrelated to pre-existing state-level innovation activity (as measured by the log of patents and citations per state-year, respectively). In the remaining columns, we additionally control for other state-level factors, including lagged GDP growth, the political balance in a given state (measured as the ratio of Democrat to Republican state representatives in the House of Representatives), and the state's unemployment rate. Only the wealth of a U.S. state (as measured by real state GDP) increases the "hazard" of adoption of the good-faith exception. None of the other variables significantly load, which indicates that such factors did not determine the timing of the adoption of good-faith exceptions by state courts. Indeed, Autor (2003, p.16) points out that "because a court's issuance of a new precedent is an idiosyncratic function of its docket and the disposition of its justices, the timing of a change to the common law is likely to be in part unanticipated." The fact that the adoption of these laws was at least partly unanticipated allows us to identify their causal effect on innovation by firms.

Table 5 further highlights that political and economic factors that may accompany the adoption of WDL are not accounting for our findings. In these tests, we examine the impact of the good-faith exception on innovation by firms, but in addition to our usual set of explanatory variables we also control for lagged state GDP growth, as well as for a state's political climate. While lagged GDP growth is not related to innovation by firms, we find that a higher ratio of Democrat to Republican state representatives in the House of Representatives has a negative impact on innovation by firms. Importantly, however, we find that the adoption of the good-faith exception continues to have a positive and (statistically and economically) significant impact on innovation by firms.

4.3.5 Dynamic effects

In Table 6 we examine the dynamic effect of the passage of the good-faith exception on innovation. We follow Bertrand and Mullainathan (2003) in decomposing the passage of the good-faith exception into separate time periods for each state: *Good Faith (-2,-1)* is a dummy that takes the value of one in the two years before the passage, zero otherwise; *Good Faith (0)* is a dummy that takes the value of one in the year of the passage, zero otherwise; *Good Faith (+1)* is a dummy that takes a value of one in the year after the passage, zero otherwise. Finally, *Good Faith* ($\geq +2$) that takes the value of one for the second year after the passage and thereafter, zero otherwise. Similar to what we observed in Table 4, pre-existing patterns of innovation are not correlated with the passage of the good-faith exception as seen in the coefficient of *Good Faith (-2,-1)* being statistically indistinguishable from zero in all but one specification. Furthermore, consistent with the long-run nature of innovation, the posited positive effect on innovation is robustly evident from two years after the passage of the good-faith exception onwards (as seen in the coefficient of *Good Faith* ($\geq +2$)).

4.3.6 Alternative Interpretations

We now examine several alternative interpretations for our above results.

Effect of California and Massachusetts CA and MA are two U.S. states known for their innovative vigor. For example, both states have high-tech industrial districts: Silicon Valley in CA and Route 128 in MA. In addition, both states had all three WDL in place from the late 1980s onwards and offered their employees significant protection against unjust dismissal.[20] Therefore, we would like to ascertain that our results are not driven entirely by

[20] In particular, California was not only the first state to adopt a wrongful discharge law, but also the state whose Court of Appeals ruled on the most influential good-faith case according to legal scholars (*Cleary v. American Airlines, 1980*). Furthermore, the good-faith exception in California was the most far-reaching one, at least in the first decade after the ruling. This exception barred Californian employers from dismissing

these two states. To alleviate these concerns, we estimate our main specification (equation (13)) with the full set of control variables and for all dependent variables (as in Table 2), but exclude observations from CA and MA. We do not report results from these tests in a separate table to conserve space. As in the full sample, the coefficient on the good-faith exception stays positive and significant (at the 5% level or higher) in all specifications. Furthermore, the coefficient magnitudes are very similar to those obtained using the full sample, which suggests that the effect of WDL was similar in CA and MA to that in other states.[21]

Shift to labor-saving technologies The positive effects of WDL on innovation may stem from firms' efforts to save on labor costs by shifting to less labor-intensive and more-innovative technologies. Indeed, if a majority of firms shifts to labor-saving technologies, this should manifest as an observable increase in the investment in R&D after the passage of WDL. We however do not find any evidence of such increases. In unreported tests, we run regression (13) using log of R&D scaled by sales (or assets) as the dependent variable and do not find any significant impact of any of the three WDL on the investment in R&D.

Creation of the Court of Appeals of the Federal Circuit The U.S. Court of Appeals of the Federal Circuit (CAFC) was created by Congress in 1982, and its main jurisdiction are appeals made regarding U.S. patent law. Following the establishment of the court, there was a large surge in patenting in the U.S. which was commonly ascribed to the creation of the Court, but which Kortum and Lerner (1999) attribute to other factors such as changes in the management of research. The spur in patenting activity also overlaps with the period when many WDL were adopted (see Figure 1).

any worker without good cause (see Autor et al., 2007). Finally, Californian state courts tended to be most receptive to wrongful discharge litigation (see Edelman et al., 1992).

[21] In our Theoretical Motivation, we argued that the passage of WDL enabled firms to commit to their employees not to hold them up in the case of successful innovation. Therefore, a possible alternative interpretation for our results is that innovation-driven firms (re-)located to states that offered their employees greater protection against wrongful discharge. As CA and MA arguably provided the strongest legal protection of this type, firms pursuing innovation may have been inclined to re-locate to either CA or MA after the passage of these laws. If this alternative interpretation were true, the passage of WDL would significantly further innovation in CA and MA, but not in the other states. However, as our results are robust to the exclusion of CA and MA from the sample, this does not appear to be the case.

To ensure that our results are not driven by the creation of the CAFC in 1982, we divide the sample period into pre-1982 and post-1982. We then re-run our difference-in-difference regressions (equation (13)) for each sub-sample, using the full set of control variables. In unreported results, we find that in both sub-periods, the impact of the passage of the good-faith exception on innovation remains consistent with the results from the full sample. This also highlights that the adoption of good-faith exceptions was quite evenly spread out over time across states. However, importantly, our findings allow us to rule out that the establishment of the CAFC in 1982 is causing our results.

More Patenting by Firms to Offset Employees' Increase in Bargaining Power WDL increase employees' bargaining power vis-a-vis employers. As a result, even if firms do not become more innovative, they may be more prone to patent their inventions in order to counter possible attempts of rent appropriation by employees.[22] Hence, the surge in corporate patenting activity after the passage of good-faith exceptions may reflect an increased propensity to patent inventions, rather than an increase in innovation per se.

We indirectly address this in our main tests by showing that not only do firms patent more after the passage of good-faith exceptions, but citations to these patents also rise. As citations capture the economic importance of patents, this does indicate that innovation increases, not just patenting activity. However, in Column 9 of Table 2 and Column 7 of Table 3, we also examine the ratio of citations to patents filed, which provides an alternative test of the hypothesis that innovation increases after the good-faith exception passage. Indeed, as *citations per patent* increase, these results confirm that innovation by firms increases after the adoption of good-faith exceptions, particularly so in innovation-intensive industries.[23]

[22] We are grateful to an anonymous referee for pointing this out.

[23] Another alternative interpretation of our results may be that passage of WDL leads to firms filing more patents because the adoption of these laws may be correlated with an increase in the probability of intellectual property litigation. In other words, is it the case that our results are an outcome of firms' increased efforts to protect themselves against intellectual property litigation? Since citations to patents capture the economic value of an innovation, our results indicate that not only do firms file more patents after the passage of WDL but they file more valuable patents. An effort to patent more to protect against possible litigation should not necessarily lead to firms filing more *valuable* patents.

Other robustness tests We conduct additional robustness tests, the results of which are omitted for brevity. First, we collapse the innovation proxies (patents and citations) at the state, year level by computing their aggregate measures by state, year and find in panel regressions that include state and year fixed effects that our results are similar. Second, in figure 4, we observe a post-event trend in innovation in the treatment group of states vis-à-vis the control group. Since identification in difference-in-difference settings comes from a before-after comparison in levels between the treatment and control groups, the counterfactual trend behavior of treatment and control groups should be the same (Angrist and Pischke, 2008, pp. 165). Figure 4 and Table 4 suggest that this requirement is satisfied in our setting. Nevertheless, to check purely for a difference in trend due to the good faith exception (rather than a difference in trend over and above the difference in levels), we run regressions where we interact the dummy for the good faith exception with a linear time trend and exclude the level of the good faith exception. Consistent with the observation in figure 4, we find that the trend for innovation is greater after the passage of the good faith exception (see Appendix C).

5 Robustness to Mobility of Human Capital

Fulghieri and Sevilir (2011) argue in a theoretical model that legal restrictions on the mobility of human capital (through the enforcement of non-compete agreements) have a negative impact on employee effort to innovate. If states that passed WDL are also less likely to enforce non-compete agreements, then the effect of WDL on innovation we documented so far may be spurious. To distinguish the channels through which WDL and legal restrictions on mobility of human capital affect innovative effort, we extend the basic model to allow for the effect of laws restricting human capital mobility. We then empirically examine the robustness of our result to controlling for the effect of such legal restrictions.

5.1 Extension of the basic model

In our basic model in Section 3, we allowed for the possibility of hold-up by the employer only. As we highlighted in Section 2.1 using the case of Activision, both the entrepreneur and the employee could, in principle, hold each other up. Therefore, in this section, we extend the basic model by introducing the possibility of employee E holding up employer F by implementing the innovation outside the firm with the help of a Venture Capitalist. E's ability to hold up F is reduced by the legal restrictions placed on the mobility of human capital in a state. If courts do not enforce non-compete clauses in employment agreements, then human capital is perfectly mobile. However, if such clauses are enforced rigidly, then human capital mobility is restricted, which reduces E's ability to hold up F.

To model a scenario where both E and F can hold each other up, we allow for the innovative project to generate both generic and firm-specific innovations. To motivate the possibility that innovative projects could fall into these two categories, consider the innovations generated by Xerox's Palo Alto Research Center (PARC). Since the late 1970s, PARC pursued a research agenda that was intended to: (i) support Xerox's existing businesses by enhancing scientific understanding of its core technologies; and (ii) create new growth opportunities for the company to move beyond its current businesses. Of the many innovations at PARC, Xerox selected those that fit its businesses and provided a graceful exit to those innovations that were deemed not to fit its core businesses (Chesbrough, 2003). For example, the ethernet networking protocol was a firm-specific innovation developed to connect Xerox Star workstations to Xerox laser printers. However, the generic local area networking technology that it created formed the basis for the start-up company 3Com. Similarly, the technology underlying Adobe was developed as a component for the Xerox Star, a networked workstation intended for the corporate office environment. However, this innovation helped to create the generic "desktop publishing" market pioneered by Adobe.

Appendix A develops the extended model in detail. Here, we describe the salient differences with respect to the basic model in Section 3 and state the results that we obtain from this extended model. After recruiting the employee E at date 0, we assume that the firm F invests to increase the generic human capital of E; such investment can be interpreted in a variety of ways such as training E to be innovative and entrepreneurial, as well as introducing him to suppliers, customers, venture capitalists, etc.[24] Such generic investment introduces the possibility that E generates an innovation that falls outside the core business of F.

We assume that commercializing a generic innovation outside F with the help of an investor such as a Venture Capitalist (VC) generates greater value than commercializing it inside F. Conversely, commercializing a firm-specific innovation inside F generates greater value than commercializing it outside F.

Finally, before F decides whether to retain or fire E, E chooses either to stay with F and commercialize the innovation within F or to start a new firm and commercialize the innovation with the support of the VC. If E chooses to start a new firm, F sues the departing employee for violation of *non-compete agreements.*

Proposition 6 *Propositions 3, 4 and 5 and the corresponding Hypotheses 1-3 remain robust to the effect of laws restricting the mobility of human capital in a state.*

Intuitively, WDL limit the firm's ability to hold up the employee when the innovation is firm-specific (and therefore has to be implemented within the incumbent firm). In contrast, legal restrictions on the mobility of human capital limit the employee's ability to hold up the firm when the innovation is generic (and is therefore optimally implemented through a new firm). Since innovations can be either firm-specific or generic, the effect of WDL on innovation survives the presence of legal restrictions on mobility of human capital.

As in Fulghieri and Sevilir (2011), the extended model also predicts that legal restrictions on the mobility of human capital have a negative impact on employee effort to innovate, and thereby on the value from innovation.

[24] The firm's generic investment in the employee can be rationalized based on the argument in Acemoglu and Pischke (1999), who show that if labor market frictions reduce the wages of skilled workers relative to wages of un-skilled workers, firms may provide and pay for general training.

5.1.1 Controlling for legal restrictions on mobility of human capital in the tests

In Table 7, we examine whether the results are consistent with Proposition 6 in two separate ways. First, in Panel A, we explicitly control for the legal restrictions on the mobility of human capital in a given state and year. For this purpose, we obtain data on the enforceability of non-compete agreements from Bird and Knopf (2010), who extend the coding of Garmaise (2010) back to 1976.[25] Higher values of the variable NCA indicate more pronounced non-compete enforcement and, in turn, greater legal restrictions on the mobility of human capital. Second, in Panel B, we exclude states which *changed* the enforcement of such non-compete agreements during our sample period.[26] As predicted by Proposition 6, the positive effect of the good-faith exception on innovation remains positive and significant.

We find the coefficient of NCA to be negative but insignificant. This is possibly because even though the employees' effort to innovate decreases with an increase in NCA, as predicted by our theoretical model and in Fulghieri and Sevilir (2011), an increase in NCA increases the firm's incentives to invest in the employee, which may in turn increase employees' effort. Garmaise (2010) formalizes both these effects simultaneously and finds that consistent with both these effects being at play, NCA does not have a statistically significant effect on R&D. Similarly, we do not find the effect of NCA on innovation to be significant.

6 Wrongful Discharge Laws and Entrepreneurship

Apart from showing that our results on the impact of WDL on innovation are robust to the effect of legal restrictions on mobility of human capital, the extension to the basic model described in Section 5.1 above also generates testable implications relating the passage of WDL to entrepreneurship, i.e., creation of new firms. Proposition A6 formally stated in Appendix A generates the following testable implication:

Hypothesis 4: *Passage of WDL – particularly that of the good-faith exception – leads to*

[25] We mainly employ the Bird and Knopf (2010) coding (from 1976 to 1991); from 1992, when the Garmaise (2010) coding starts, we complement it with the coding in Garmaise (2010).

[26] These states are Florida, Louisiana, Massachusetts, Michigan, Montana, Texas, Virginia, and Wyoming.

(a) creation of new firms; and (b) greater employment from the creation of new firms.

The intuition behind this result is as follows. WDL improve the employee's effort in innovation by reducing the possibility of hold-up by the firm. An increase in the employee's effort increases the possibility of both generic and firm-specific innovations. Since the generic innovation is optimally implemented by creating a new firm, this increased possibility of generic innovation leads to the increase in creation of new firms. Part (b) follows from the fact that the creation of a new firm also leads to employment creation.[27]

6.1 Data and Proxies

The analysis in this section employs a *novel* data set developed by the Center for Economic Studies of the U.S. Census Bureau, the Business Dynamics Statistics (henceforth simply "BDS") database.[28] The data encompass measures of establishment openings, firm startups, and job creation from new establishments.[29] In particular, the BDS database covers all non-agricultural sectors in the U.S. economy for the years 1977–2005. The data is made available in annual aggregates by categories, such as industry sector, firm age, state where the establishment is located, and the size of the establishment, where size in year t is defined as the average of the number of employees in years $t-1$ and t.

This dataset is particularly suited for the empirical analysis of entrepreneurship since the age of an establishment is defined based on the age of the ultimate *parent firm*. Specifically, establishment age is defined as the difference between the current year of operation and the ultimate parent firm's birth year. Therefore, age-zero establishments correspond to those created by new firms. The most detailed data available in the BDS database are by "category triples". As the state of location and establishment age are the most important categories

[27]This empirical prediction is consistent with the Xerox view of entrepreneurial spawning highlighted by Gompers, Lerner and Scharfstein (2005), where entrepreneurial spawning from incumbent firms is high not because of any sort of inefficiency at these firms, but rather because these firms wisely choose to focus on their core business or "core competence."

[28]The BDS data are drawn from the Longitudinal Business Database, which is a database of U.S. business establishments and firms. Most of the information on the BDS database discussed below is drawn from the *BDS Technical Note*, available at the U.S. Census website: *http://www.ces.census.gov/index.php/bds*

[29]An establishment is defined as a fixed physical location where economic activity occurs; a firm may consist of one or more such establishments.

for our empirical analysis, we use data by *establishment age*, *size*, and *state of location*.[30]

6.1.1 Proxies for Entrepreneurship

Hypothesis 4 predicts that the passage of WDL leads to greater firm creation, with attendant effects on job creation. To test this, we use the following dependent variables which are all measured annually by firm size and state of establishment location:[31] *Ln(Establishments created by start-ups)* corresponds to the log of the number of establishments of age zero. Since the age of an establishment corresponds to the age of its ultimate parent in the BDS dataset, this variable captures only those establishments that are created by new firms. The majority of new firms are single-establishment firms. *Ln(Establishment entries)* measures the log of the number of establishment entrants, defined in the database as establishments with positive employment in the current year and zero employment in the prior year. Establishment entries can be either due to greenfield firm start-ups (as captured by the variable *Ln(Establishments created by start-ups)* above) or due to existing firms opening a new establishment. Finally, *Ln(Job creation from new establishments)* measures the number of new jobs resulting from the creation of new establishments.

6.2 Results

For our tests on entrepreneurship, we employ a difference-in-difference strategy similar to that described in Section 4.2, implemented by following panel regression:

$$y_{klst} = \beta_l + \beta_s + \beta_t + \beta_r \times \beta_t + \beta_1 GF_{st} + \beta_2 PP_{st} + \beta_3 IC_{st} + \beta X_{klst} + \varepsilon_{klst} \qquad (14)$$

where y_{klst} is a measure of the dependent variable for establishment size category k, firm age category l in state s and year t. β_l, β_s, and β_t denote respectively firm age, state and year fixed effects. In some specifications, we also control for regional trends through $\beta_r \times \beta_t$

[30] The second BDS data "triple" currently available is the triple *establishment age*, *size*, and *industry sector*, which is less useful for our purposes due to the lack of information on the state of establishment location (which we need to link with the wrongful discharge law data).

[31] A more detailed description of the variables is available on the U.S. Census homepage; see $http://webserver03.ces.census.gov/index.php/bds/bds\_home$.

(interaction between region and year dummies).[32] Furthermore, all specifications include the following set of state characteristics: *ln(Real GDP p.c.)*, the logarithm of real (in 2005 $) state GDP per million state residents and year; *ln(Colleges p.c.)*, the logarithm of the number of degree-granting institutions of higher education in a given state per million state residents and year; and *ln(Enrollment p.c.)*, the logarithm of enrollment in institutions of higher education in a given state per million state residents and year. *NCA* is the score of non-compete enforcement per state and year; finally, *UI* is the logarithm of the maximum total potential benefit available under the unemployment insurance system in a given state and year.[33] As in our tests for innovation, we cluster standard errors at the state level. Summary statistics for all dependent and explanatory variables are reported in Panel B of Table 1.

6.2.1 Test of Hypothesis 4

In Table 8, we investigate the effect of WDL on the creation of new establishments. The results are reported in Column 1 (resp. 4, which additionally includes regional trends). We find a statistically significant positive effect of the passage of the good-faith exception on establishments created by start-up firms. The economic magnitude of the effect is quite large: based on the specification with region trends (Column 4), the adoption of the good-faith clause in a state led to an increase in the entry of establishments by 12.4% in that state when compared to the control group of states which did not adopt this particular WDL. The other two exceptions do not have statistically significant effects.

We also examine the effect of WDL on establishments created by all firms, i.e., not only by start-up firms. The results are displayed in Column 2 (resp. 5, with regional trends) of Table 8. We find a statistically significant positive effect of the good-faith exception on the entry of establishments. As before, the other two exceptions do not seem to matter. Based on estimates from Column 5, the adoption of the good-faith clause in a state led to an

[32] When focussing on start-ups, which by definition have a firm age of zero, we do not include age dummies.

[33] Unlike the tests for innovation, we cannot employ firm-level control variables. Also, since the dataset does not have the industry level granularity, we cannot include competition or the ratio of value-added.

increase in the entry of establishments by 8.7% in that state when compared to the control group of states which did not adopt this particular WDL.

In Column 3 (resp. 6, with regional trends), we explore the concomitant effect on employment due to the creation of new establishments. We find that the passage of the good-faith clause resulted in a significant increase in job creation from new establishments (by 8.4%, according to the estimate in Column 6) vis-à-vis states that did not adopt this WDL. Overall, we find strong support for Hypothesis 4.

7 Related Literature

Existing theoretical arguments make conflicting predictions about the welfare implications of employment protection laws. Early studies argued that such laws lead to inefficient resource allocation because firms cannot at their sole discretion terminate jobs that have lost their productive value. Furthermore, if job destruction is made difficult, it may lead to less job creation and higher unemployment (Lazear, 1990; Ljungqvist and Sargent, 1998).

However, more recent theoretical work argues that employment protection may also have positive economic effects. Bertola (2004) shows that employment protection can increase aggregate output when job switching is costly because such protection enables risk-neutral firms to insure risk-averse employees against negative income shocks. Baumann (2010) argues that employment protection laws may improve the average productivity of hired workers by equalizing the share of low-productivity workers across the states of employment and unemployment and, thereby, reducing adverse selection in labor markets. Our study complements Bertola (2004) and Baumann (2010) by highlighting the positive incentive effects of employment protection on innovative output when contracts are incomplete.

In other related work, Sevilir (2010) shows that established firms' investment in their employees' human capital leads to the creation of entrepreneurs as well as greater innovation within the firm. In contrast, we model how WDL and the enforcement of non-compete clauses limit holdup by the employer and the employee respectively to show that the two effects operate independent of each other.

Autor et al. (2007) study whether WDL reduce productivity by distorting production choices. They find that wrongful discharge protection reduces employment fluctuations and firm entry rates; furthermore, these provisions led to changes in production techniques that resulted in a decline in plant-level total factor productivity.[34] These results, however, are not at odds with the findings in our paper. First, while Autor et al. (2007) employ data drawn from the Annual Survey of Manufacturers (ASM), which is exclusively from manufacturing plants, our study includes all innovating industries, including high-tech sectors. Second, the ASM sample "focuses on intensive adjustments in large plants operating in stable business climates; by conditioning on survival, the extensive margin is suppressed" (p.F198). This sample restriction will clearly not cover many highly innovative firms operating in unstable business climates, e.g., high-tech or other innovating firms. Furthermore, as we argue in Hypothesis 4 and the corresponding tests on entrepreneurship, a significant part of the increased innovative activity attributable to the passage of the good-faith exception is likely due to changes at the extensive margin. Third, the negative effect of the good-faith exception on TFP documented by Autor et al. (2007) is not statistically significant at conventional levels after accounting for plant fixed effects. Fourth, Autor et al. (2007) report that labor productivity significantly rose after the adoption of the good-faith exception, which is consistent with the findings supporting Hypothesis 2 in our study.

In contrast to the empirical studies that highlight the negative effects of WDL, MacLeod and Nakavachara (2007) find that the passage of WDL increased employment, particularly in occupations that required a high level of skill.[35] Theoretically, they argue that employers' mistakes in the subjective evaluation of employees may lead to lower wages and productivity by workers. However, WDL arrest decreases in wages and productivity by requiring employ-

[34]Bird and Knopf (2009), in a study focussing on the banking industry, find that the implied-contracts exception increased labor expenses and had a negative impact on profitability. Schanzenbach (2003) reports that the adoption of the implied-contract exception increased job tenure, while returns to tenure as well as wages did not increase.

[35]Dertouzos and Karoly (1992), Miles (2000), Autor (2003), Autor et al. (2004), Kugler and Saint-Paul (2004) and Autor et al. (2006) are other empirical studies that examine the effect of WDL on employment.

ers to put into place systems of employee evaluation that produce verifiable information that is usable in court. Since *a priori* subjective evaluations are more likely to be erroneous in occupations that require a high level of skill, this effect is greater in such occupations.

8 Conclusion

Can laws that limit employment-at-will encourage employees to undertake risks and get around the difficulties encountered by firms in promoting innovation and entrepreneurship? In this paper, we develop a model in which WDL limit the possibility of hold-up by a firm of its employees, and thereby encourage innovative effort by employees and innovative pursuits by firms. We provide empirical evidence to show that laws that inhibit the common-law doctrine of employment-at-will can indeed motivate firms and their employees to undertake innovative and entrepreneurial pursuits. We provide this evidence by studying the effects of the staggered passage of WDL across several U.S. states (as a series of natural experiments) on patent- and citation-based measures of innovation in a comprehensive sample of U.S. firms and on establishment-level measures of entrepreneurship and job creation.

This evidence complements the findings in Acharya, Baghai, and Subramanian (2012), who show in a cross-country setting that stringent dismissal laws lead to greater innovation. Given the corroborating results of this paper, we conclude that laws affecting employment and dismissal are an important part of the policy toolkit for promoting innovation and possibly economic growth. An interesting and open question pertains to the relative merits and interactive effects of various laws such as creditor right laws, labor laws, and protection of intellectual property rights on innovation and economic growth. This appears to be a fruitful area for further inquiry.

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Figure 1: **Adoption of Wrongful Discharge Laws Across States in the U.S.**

The figure shows the annual number of U.S. states that have adopted a given wrongful discharge law. The sample spans the years 1970 to 1999. The data is from Autor, Donohue, and Schwab (2006).

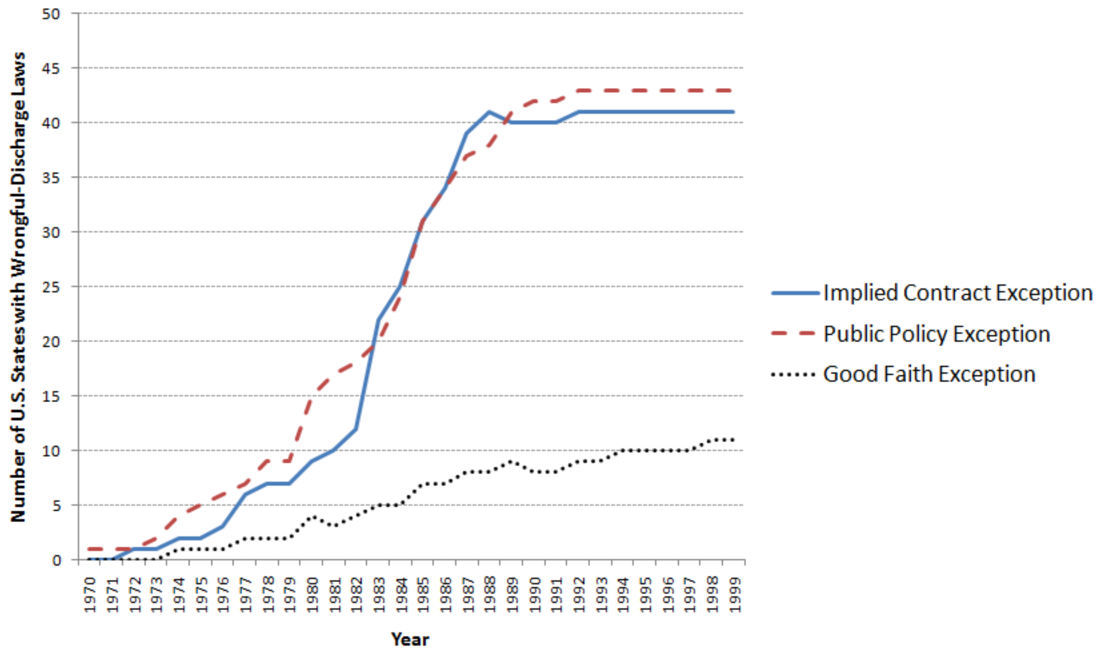

Figure 2: **Cross-Sectional and Time-Series Variation in the Wrongful Discharge Laws**

The figure shows the evolution of the wrongful discharge laws across U.S. states and time (1970–1999). Each line represents a unique U.S. state. Specifically, we plot the aggregate annual number of wrongful discharge laws adopted by a given state. The wrongful discharge data coding is from Autor, Donohue, and Schwab (2006).

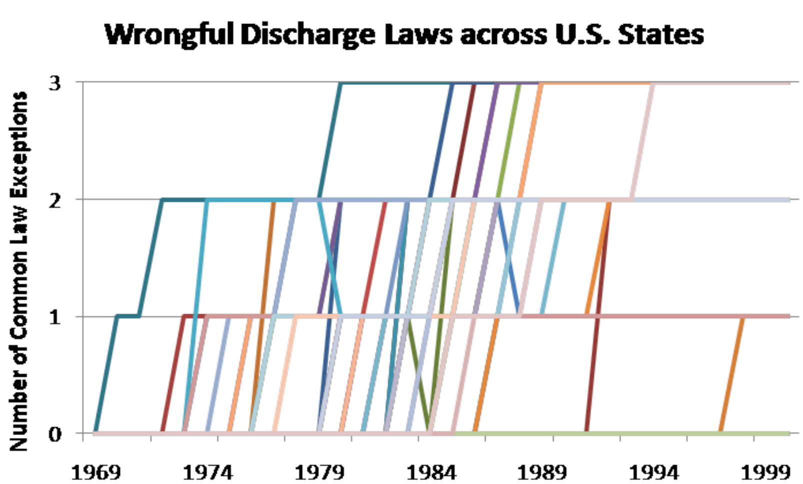

Figure 3: **Timing of Basic Model.**

This figure illustrates the timing of events in our basic model from Section 3.

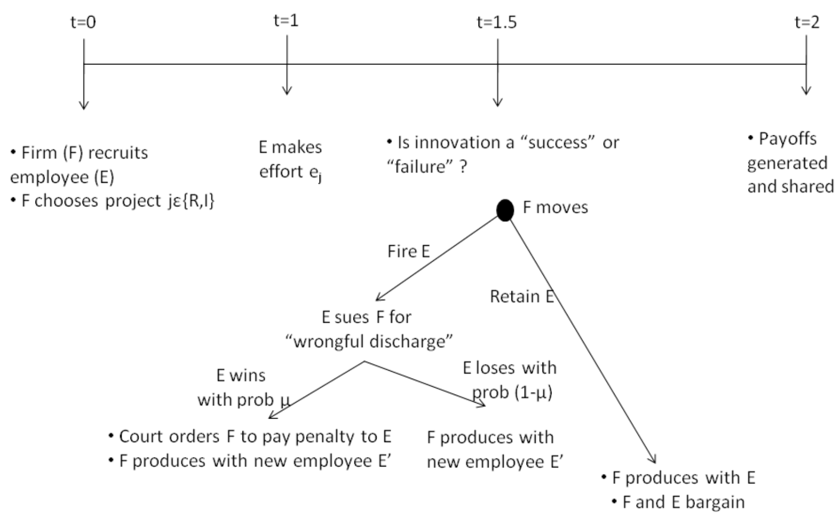

Figure 4: **Effect of the Passage of the Good-Faith Exception on Innovation.**

This figure shows a visual difference-in-difference examining the effect of the passage of the good-faith exception on innovation in adopting states relative to non-adopting states (see Autor, Donohue, and Schwab, 2006, for similar graphs). On the y-axis, the graph plots the logarithm of the number of citations filed; the x-axis shows the time relative to the year of adoption (ranging from five years prior to adoption until 10 years after the passage of the good-faith exception). The dashed lines in the figure correspond to the 90% confidence intervals of the coefficient estimates; the confidence intervals are based on standard errors which are clustered by state of location of the patent assignee.

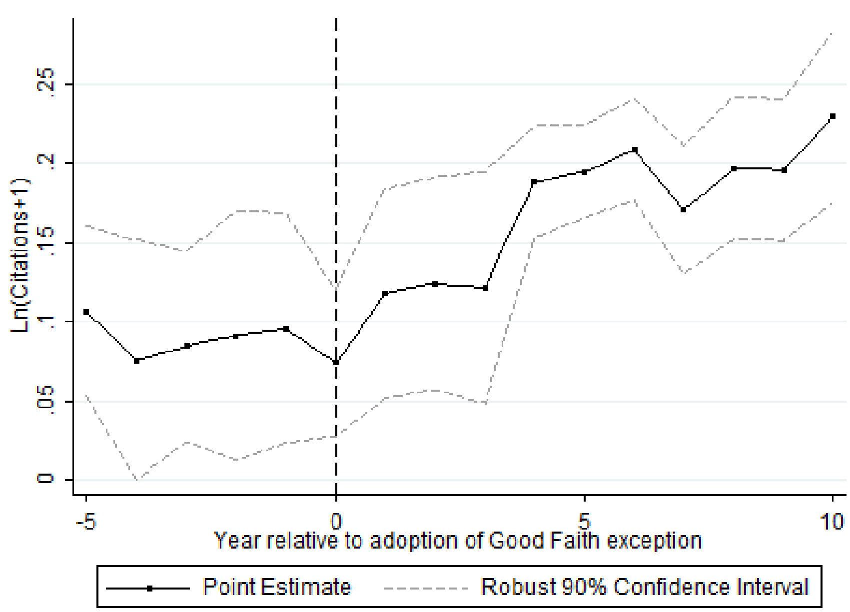

Table 1: **Summary Statistics.**

Panel A reports summary statistics for the variables used in the innovation tests (see Tables 2–7). The *dependent variables* are: *ln(Patents)*, *ln(Citations)*; *ln(Patents/Employee)*, the log of the number of patents per 1,000 firm employees; *ln(Patents/R&D)*, the log of the number of patents per million R&D dollars; *ln(Citations/Employee)* and *ln(Citations/R&D)* are defined analogously. Finally, *ln(Citations/Patent)* is the natural logarithm of the ratio of citations to patents. The *explanatory variables* are: *Good Faith* is a dummy that takes a value of one if a state has adopted a good-faith exception to the employment-at-will doctrine in a given year, and zero otherwise; *Implied Contract* and *Public Policy* are defined analogously. *Market-to-Book* ratio is the market value of assets to total book assets. Market value of assets is total assets plus market value of equity minus book value of equity. The market value of equity is calculated as common shares outstanding times fiscal-year closing price. Book value of equity is defined as common equity plus balance sheet deferred taxes. *Size* is the natural logarithm of assets (deflated to 2005 dollars); $Size^2$ is $Size * Size$. *ln(R&D/Sales)* is the natural logarithm of the ratio of research and development expenditures to firm sales. *Competition* is the fraction of total (2-digit) industry sales generated by competitors in a given state and year (the state variable is based on the location of the firm's headquarters). $Competition^2$ is $Competition * Competition$. *Ratio of Value Added* corresponds to the annual gross state product (GSP) in a given sector and state divided by the total GSP in that state (data for 1977–1999). *ln(Colleges)* is the logarithm of the number of degree-granting institutions of higher education in a given state per year. *ln(Enrollment)* is the logarithm of enrollment in institutions of higher education in a given state per year (in thousands). *ln(Real State GDP)* is the logarithm of annual real state GDP (in 2005 $ millions). *Real State GDP Growth* is the continuously compounded real state GDP growth per state and year. *ln(Population)* is the logarithm of a state's population (in million) in a given year. *UI* is the logarithm of the maximum total potential benefit available under the unemployment insurance system in a given state and year. *Political Balance* is the ratio of Democrat to Republican representatives in the Lower House (House of Representatives) for a given state and year; this variable is not available for the state of Nebraska, as it has a nonpartisan legislature (unicameral body) whose members are elected without party designation. *NCA* is the score of non-compete enforcement per state and year (data for 1976–1999). *Unemployment Rate* is a state's unemployment rate in a given year (data for 1976–1999). The sample spans 1971–1999, unless indicated otherwise above.

Panel B reports summary statistics for the variables used in the entrepreneurship tests (see Table 8). The *dependent variables* are: *ln(Establishments Created by Start-Ups)*, the logarithm of the number of start-up establishments; *ln(Establishment Entries)*, the logarithm of the number of establishment entrants (new and existing firms); *ln(Job Creation from new Establishments)*, the log of the number of new jobs resulting from the creation of new firm establishments. The *explanatory variables* are: *Good Faith* is a dummy that takes a value of one if a state has adopted a good-faith exception to the employment-at-will doctrine in a given year, and zero otherwise; *Implied Contract* and *Public Policy* are defined analogously. *NCA* is the score of non-compete enforcement per state and year. *UI* is the logarithm of the maximum total potential unemployment benefit available per state and year. *ln(Real GDP p.c.)* is the logarithm of real (in 2005 $) state GDP per million state residents and year. *ln(Colleges p.c.)* is the logarithm of the number of degree-granting institutions of higher education (colleges) in a given state per million state residents and year. *ln(Enrollment p.c.)* is the logarithm of enrollment in institutions of higher education in a given state per million state residents and year. The sample spans 1977–1999.

Variable	**Obns.**	**Mean**	**Median**	**Std. Devn.**	**Data Source**
				Panel A: Innovation Sample	
Number of patents	104,504	6.552	2	25.326	NBER Patents File (Hall et al., 2001)
Number of citations	104,504	52.438	11	216.107	NBER Patents File (Hall et al., 2001)
ln(Patents)	104,504	0.831	0.693	1.098	NBER Patents File (Hall et al., 2001)
ln(Citations)	96,849	2.608	2.485	1.514	NBER Patents File (Hall et al., 2001)
ln(Patents/Employee)	81,935	-1.296	-1.548	2.229	NBER Patents File (Hall et al., 2001); data on employees from Compustat
ln(Patents/R&D)	73,496	-2.373	-2.339	2.279	NBER Patents File (Hall et al., 2001); data on R&D from Compustat
ln(Citations/Employee)	76,012	0.438	0.247	2.451	NBER Patents File (Hall et al., 2001); data on employees from Compustat
ln(Citations/R&D)	68,175	-0.575	-0.535	2.555	NBER Patents File (Hall et al., 2001); data on R&D from Compustat
ln(Citations/Patent)	96,849	1.723	1.792	1.012	NBER Patents File (Hall et al., 2001)
Good Faith	104,504	0.193	0	0.394	WDL coding from Autor et al. (2006)
Public Policy	104,504	0.622	1	0.485	WDL coding from Autor et al. (2006)
Implied Contract	104,504	0.558	1	0.497	WDL coding from Autor et al. (2006)
Market-to-Book	75,658	1.706	1.247	1.371	Compustat
Size	83,891	7.188	7.545	2.356	Compustat
$Size^2$	83,891	57.224	56.922	32.164	Compustat
ln(R&D/Sales)	73,101	-3.432	-3.509	1.405	Compustat
Competition	78,301	0.056	0.024	0.079	Compustat
$Competition^2$	78,301	0.009	0.001	0.026	Compustat
Ratio of Value Added	67,838	0.091	0.082	0.051	U.S. Bureau of Economic Analysis

Table 1: —*Panel A: Innovation Sample – continued*

Variable	**Obns.**	**Mean**	**Median**	**Std. Devn.**	**Data Source**
ln(Colleges)	104,504	4.636	4.691	0.796	Annual Statistical Abstracts of the U.S. Census Bureau
ln(Enrollment)	104,504	6.001	6.016	0.908	Annual Statistical Abstracts of the U.S. Census Bureau
ln(Real State GDP)	104,504	12.310	12.374	0.936	U.S. Bureau of Economic Analysis
Real State GDP Growth	104,504	0.033	0.035	0.032	U.S. Bureau of Economic Analysis
ln(Population)	104,504	2.047	2.049	0.854	U.S. Bureau of Economic Analysis
UI	104,504	8.438	8.505	0.515	Data from Agrawal and Matsa (2011)
Political Balance	103,980	2.163	1.415	4.090	Annual Statistical Abstracts of the U.S. Census Bureau
NCA	87,324	3.873	5	2.077	Data based on coding from Bird and Knopf (2010) and Garmaise (2010)
Unemployment Rate	87,324	6.411	6.200	1.973	U.S. Bureau of Labor Statistics
			Panel B: Entrepreneurship Sample		
ln(Establishments Created by Start-Ups)	6,532	5.332	5.127	2.102	Business Dynamics Statistics database of the U.S. Census Bureau
ln(Establishment Entries)	52,990	3.561	3.296	1.586	Business Dynamics Statistics database of the U.S. Census Bureau
ln(Job Creation from new Establishments)	52,990	6.119	5.911	1.651	Business Dynamics Statistics database of the U.S. Census Bureau
Good Faith	94,861	0.156	0	0.363	WDL coding from Autor et al. (2006)
Public Policy	94,861	0.713	1	0.452	WDL coding from Autor et al. (2006)
Implied Contract	94,861	0.681	1	0.466	WDL coding from Autor et al. (2006)
NCA	94,861	4.307	5	1.726	Data based on coding from Bird and Knopf (2010) and Garmaise (2010)
UI	94,861	8.592	8.600	0.351	Data from Agrawal and Matsa (2011)
ln(Real GDP p.c.)	94,861	10.296	10.284	0.222	U.S. Bureau of Economic Analysis (BEA)
ln(Colleges p.c.)	94,861	2.727	2.724	0.363	Annual Statistical Abstracts of the U.S. Census Bureau; BEA
ln(Enrollment p.c.)	94,861	10.864	10.860	0.169	Annual Statistical Abstracts of the U.S. Census Bureau; BEA

Table 2: **Effect of Wrongful Discharge Laws on Innovation.**

The OLS regressions below implement the following model:
$y_{i,s\to r,t} = \beta_i + \beta_r \times \beta_t + \beta_r + \beta_t + \beta_1 * GF_{st} + \beta_2 * PP_{st} + \beta_3 * IC_{st} + \beta \cdot X_{ist} + \varepsilon_{ist}$
where $y_{i,s\to r,t}$ is a measure of innovation for firm i from state s (belonging to region r) in year t. β_i and β_t denote respectively firm and application year fixed effects. $\beta_r \times \beta_t$ captures general regional trends through the interaction of region dummies with year dummies (Columns 3–9); region dummies are based on four U.S. regions as defined by the U.S. census: Northeast, South, Midwest, and West. X_{ist} denotes the set of control variables; variable descriptions can be found in Table 1.
The sample spans 1971–1999 in Columns 1&2, 1977–1999 in Columns 3–9. Robust standard errors (clustered at the state level) are given in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	(1) ln(Patents)	(2) ln(Citations)	(3) ln(Patents)	(4) ln(Citations)	(5) ln(Patents /Employee)	(6) ln(Citations /Employee)	(7) ln(Patents /R&D)	(8) ln(Citations /R&D)	(9) ln(Citations /Patent)
Good Faith	0.124**	0.180***	0.115**	0.172**	0.116**	0.174**	0.121**	0.178**	0.050***
	(0.051)	(0.054)	(0.055)	(0.067)	(0.055)	(0.067)	(0.058)	(0.069)	(0.018)
Public Policy	0.082	0.108**	0.065**	0.079*	0.065**	0.079*	0.068*	0.084*	0.017
	(0.056)	(0.052)	(0.032)	(0.041)	(0.032)	(0.041)	(0.034)	(0.043)	(0.020)
Implied Contract	0.095**	0.142***	-0.024	-0.020	-0.035	-0.029	-0.033	-0.030	0.010
	(0.044)	(0.041)	(0.032)	(0.036)	(0.032)	(0.035)	(0.035)	(0.038)	(0.017)
ln(R&D/Sales)			0.057***	0.092***	0.091***	0.130***			0.030**
			(0.012)	(0.015)	(0.013)	(0.016)			(0.011)
Market-to-Book			0.006	-0.002	-0.009	-0.019*	-0.042***	-0.048***	-0.015**
			(0.006)	(0.008)	(0.007)	(0.011)	(0.011)	(0.013)	(0.006)
Size			0.145***	-0.025	-0.807***	-0.997***	-0.801***	-0.990***	-0.173***
			(0.046)	(0.059)	(0.062)	(0.070)	(0.084)	(0.088)	(0.029)
Size^2			-0.001	0.004	0.015***	0.022***	0.014***	0.021***	0.005**
			(0.003)	(0.004)	(0.003)	(0.004)	(0.004)	(0.005)	(0.002)
Competition			5.109***	5.404***	5.168***	5.501***	4.893***	5.264***	0.145
			(0.815)	(0.996)	(0.827)	(1.006)	(0.867)	(1.036)	(0.252)
Competition^2			-8.027***	-7.981***	-8.335***	-8.401***	-7.452***	-7.640***	0.281
			(1.780)	(2.133)	(1.769)	(2.124)	(1.839)	(2.174)	(0.597)
Ratio of Value Added			0.352	0.268	0.499	0.412	0.321	0.210	-0.023
			(0.562)	(0.615)	(0.606)	(0.642)	(0.616)	(0.655)	(0.163)
ln(Colleges)			-0.054	-0.111	-0.055	-0.113	-0.057	-0.114	-0.060**
			(0.064)	(0.076)	(0.064)	(0.077)	(0.066)	(0.078)	(0.028)
ln(Real State GDP)			-0.118	-0.061	-0.082	-0.035	-0.138	-0.098	0.046
			(0.192)	(0.205)	(0.192)	(0.205)	(0.204)	(0.217)	(0.070)
ln(Enrollment)			-0.174	-0.053	-0.181	-0.058	-0.195	-0.069	0.156***
			(0.173)	(0.194)	(0.175)	(0.196)	(0.174)	(0.199)	(0.057)
ln(Population)			0.413	0.282	0.389	0.267	0.466*	0.346	-0.148*
			(0.263)	(0.296)	(0.261)	(0.294)	(0.271)	(0.306)	(0.088)
UI			0.114	0.178*	0.111	0.174*	0.126	0.188*	0.068***
			(0.081)	(0.091)	(0.081)	(0.091)	(0.085)	(0.095)	(0.025)
Firm and Year dummies	Y	Y	Y	Y	Y	Y	Y	Y	Y
Region x Year dummies	N	N	Y	Y	Y	Y	Y	Y	Y
Observations	104,504	96,849	48,433	44,718	48,072	44,398	48,686	44,915	44,718
Adjusted R-squared	0.157	0.218	0.178	0.244	0.778	0.690	0.743	0.671	0.422

Table 3: **Relative Impact of Wrongful Discharge Laws on Innovation in Different Industries based on their Innovation Intensity.**

The OLS regressions below implement the following model:
$y_{i\to j,s\to r,t} = \beta_i + \beta_r \times \beta_t + \beta_r + \beta_t + \beta_1 * GF_{st} * High\_Intensity_{jt} + \beta_2 * GF_{st} * Low\_Intensity_{jt} + \beta_3 * High\_Intensity_{jt} + \beta_4 * PP_{st} + \beta_5 * IC_{st} + \beta \cdot X_{ist} + \varepsilon_{ist}$
where $y_{i\to j,s\to r,t}$ is a measure of innovation for firm i (belonging to industry j) from state s (belonging to region r) in year t. β_i and β_t denote respectively firm and application year fixed effects. $\beta_r \times \beta_t$ captures general regional trends through the interaction of U.S. Census region dummies with year dummies. $High\_Intensity_{jt}$ takes the value of one if the median number of patents filed in a given Fama-French 48 industry in a given year exceeds the median value of these median number of patents across all industries in that year; $Low\_Intensity_{jt}$ is given by $(1 - High\_Intensity_{jt})$. X_{ist} denotes the set of control variables. In the table below *Controls* denotes the following set of variables: *ln(R&D/Sales)* (not included in Columns 5 & 6), *Market-to-Book*, *Size*, *Size*^{2}, *Competition*, *Competition*^{2}, *Ratio of Value Added*, *ln(Real State GDP)*, *ln(Colleges)*, *ln(Enrollment)*, *ln(Population)*, *UI*; for the description, see Table 1. The sample spans 1977–1999. Robust standard errors (clustered at the state level) are given in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	(1) ln(Patents)	(2) ln(Citations)	(3) ln(Patents /Employee)	(4) ln(Citations /Employee)	(5) ln(Patents /R&D)	(6) ln(Citations /R&D)	(7) ln(Citations /Patent)
Good Faith * High_Intensity	0.124**	0.183***	0.125**	0.185***	0.128**	0.186***	0.051***
	(0.055)	(0.066)	(0.055)	(0.066)	(0.057)	(0.068)	(0.017)
Good Faith * Low_Intensity	0.056	0.101	0.054	0.103	0.078	0.123	0.034
	(0.059)	(0.081)	(0.060)	(0.082)	(0.063)	(0.080)	(0.031)
High_Intensity	0.091***	0.046**	0.084***	0.039**	0.053**	0.015	-0.048***
	(0.018)	(0.017)	(0.020)	(0.019)	(0.020)	(0.021)	(0.013)
Public Policy	0.065**	0.078*	0.064*	0.078*	0.067*	0.084*	0.017
	(0.032)	(0.041)	(0.032)	(0.041)	(0.034)	(0.043)	(0.020)
Implied Contract	-0.024	-0.019	-0.035	-0.028	-0.032	-0.029	0.010
	(0.032)	(0.036)	(0.032)	(0.035)	(0.035)	(0.038)	(0.017)
Controls	*Y*	*Y*	*Y*	*Y*	*Y*	*Y*	*Y*
Firm and Year dummies	Y	Y	Y	Y	Y	Y	Y
Region x Year dummies	Y	Y	Y	Y	Y	Y	Y
Observations	48,433	44,718	48,072	44,398	48,686	44,915	44,718
Adjusted R-squared	0.179	0.244	0.778	0.690	0.743	0.671	0.422

Table 4: **Duration Model for Timing of Passage of Good-Faith Exception.**

The table below reports the coefficients from a Weibull hazard model where the "failure event" is the adoption of the good-faith exception in a given U.S. state. States are dropped from the sample once they pass the good-faith exception (which is adopted in 13 U.S. states during the sample period). The explanatory variables (all lagged by one year) include *ln(Patents)*, the log of the total number of patents applied for by U.S. inventors in a given state and year, and *ln(Citations)*, the log of the number of citations to these patents. The description of the other explanatory variables can be found in Table 1. $l\cdot$ in the table below denotes the lag operator; e.g., $l2$ denotes the second lag. The sample spans 1971–1999, except for Columns 7 & 8 where we control for the unemployment rate (available from 1976–1999) and political balance (no data for Nebraska). Robust standard errors (clustered at the state level) are given in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ln(Patents)	-0.233		0.469		0.480		0.411	
	(0.244)		(0.295)		(0.315)		(0.377)	
ln(Citations)		-0.165		0.418		0.423		0.247
		(0.220)		(0.273)		(0.279)		(0.292)
ln(Colleges)			-0.338	-0.315	-0.387	-0.362	-0.754	-0.824
			(0.848)	(0.838)	(0.879)	(0.865)	(0.894)	(0.809)
ln(Real State GDP)			2.533**	2.542**	2.385**	2.449**	2.569*	2.646*
			(1.115)	(1.089)	(1.191)	(1.156)	(1.403)	(1.406)
ln(Enrollment)			1.172	1.067	1.019	0.920	2.024	2.123
			(2.216)	(2.257)	(2.253)	(2.287)	(2.003)	(2.024)
ln(Population)			-4.327*	-4.196*	-3.988	-3.910	-4.684*	-4.606*
			(2.372)	(2.362)	(2.440)	(2.433)	(2.564)	(2.527)
UI			-1.641	-1.538	-1.579	-1.488	-1.948	-1.877
			(1.585)	(1.664)	(1.656)	(1.733)	(2.261)	(2.315)
l1(Real State GDP Growth)					-1.597	-1.901	-1.587	-2.132
					(4.947)	(4.890)	(4.699)	(4.796)
l2(Real State GDP Growth)					0.347	0.521	0.624	0.662
					(5.133)	(5.192)	(4.141)	(4.172)
l3(Real State GDP Growth)					4.020	3.796	2.604	2.651
					(3.269)	(2.934)	(3.112)	(3.077)
Political Balance							-0.116	-0.124
							(0.140)	(0.132)
Unemployment Rate							0.131	0.106
							(0.112)	(0.113)
Observations	1,269	1,269	1,269	1,269	1,269	1,269	948	948

Table 5: **Robustness Test for the Effect of Wrongful Discharge Laws on Innovation after Accounting for Potential Endogeneity of Dismissal Laws.**

The OLS regressions below implement the following model:

$$y_{i,s\to r,t} = \beta_i + \beta_r \times \beta_t + \beta_r + \beta_t + \sum_{h=1}^{3} \beta_h * WDL_{hst} + \sum_{k=1}^{3} \beta_{(k+3)} * Growth_{s,t-k} + \beta_7 * Political\ Balance_{st} + \beta \cdot X_{ist} + \varepsilon_{ist}$$

where $y_{i,s\to r,t}$ is a measure of innovation for firm i from state s (belonging to region r) in year t. β_i and β_t denote respectively firm and application year fixed effects. $\beta_r \times \beta_t$ denotes the interaction of U.S. Census region dummies with year dummies. X_{ist} is the set of control variables. In the table below *Controls* denotes the following set of variables: *ln(R&D/Sales)* (not included in Columns 5 & 6), *Market-to-Book*, *Size*, *Size*^{2}, *Competition*, *Competition*^{2}, *Ratio of Value Added*, *ln(Real State GDP)*, *ln(Colleges)*, *ln(Enrollment)*, *ln(Population)*, *UI*; for the description, see Table 1. $l\cdot$ in the table below denotes the lag operator; e.g., $l2$ is the second lag. The state of Nebraska is omitted in these tests, as it has a nonpartisan legislature (unicameral body) whose members are elected without party designation. The sample spans 1977–1999. Robust standard errors (clustered at the state level) are given in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	(1) ln(Patents)	(2) ln(Citations)	(3) ln(Patents /Employee)	(4) ln(Citations /Employee)	(5) ln(Patents /R&D)	(6) ln(Citations /R&D)
Good Faith	0.135**	0.203***	0.138**	0.206***	0.140**	0.207***
	(0.054)	(0.063)	(0.053)	(0.063)	(0.056)	(0.065)
Public Policy	0.057*	0.069	0.056*	0.069*	0.061*	0.076*
	(0.032)	(0.041)	(0.032)	(0.041)	(0.034)	(0.043)
Implied Contract	-0.024	-0.012	-0.034	-0.020	-0.034	-0.024
	(0.033)	(0.037)	(0.034)	(0.037)	(0.036)	(0.040)
l1(Real State GDP Growth)	-0.139	-0.043	-0.275	-0.186	-0.310	-0.273
	(0.371)	(0.489)	(0.362)	(0.499)	(0.369)	(0.505)
l2(Real State GDP Growth)	0.221	0.400	0.317	0.515	0.191	0.361
	(0.317)	(0.473)	(0.315)	(0.480)	(0.324)	(0.479)
l3(Real State GDP Growth)	-0.465	0.091	-0.344	0.231	-0.323	0.211
	(0.348)	(0.395)	(0.360)	(0.410)	(0.351)	(0.392)
Political Balance	-0.021***	-0.029***	-0.023***	-0.031***	-0.019***	-0.028***
	(0.006)	(0.009)	(0.006)	(0.009)	(0.006)	(0.009)
Controls	*Y*	*Y*	*Y*	*Y*	*Y*	*Y*
Firm and Year dummies	Y	Y	Y	Y	Y	Y
Region x Year dummies	Y	Y	Y	Y	Y	Y
Observations	48,339	44,634	47,980	44,316	48,592	44,831
Adjusted R-squared	0.179	0.245	0.777	0.690	0.742	0.671

Table 6: **Dynamic Effect of Passage of Good-Faith Exception on Innovation.**

The OLS regressions below implement the following model:

$$y_{ist} = \beta_i + \beta_t + \beta_1 * Good\ Faith(-2,-1) + \beta_2 * Good\ Faith(0) + \beta_3 * Good\ Faith(+1) + \beta_4 * Good\ Faith(\geq +2) + \beta_5 * Public\ Policy_{st} + \beta_6 * Implied\ Contract_{st} + \varepsilon_{ist}$$

where y_{ist} is a measure of innovation for firm i from state s in year t. β_i and β_t denote respectively firm and application year fixed effects. We follow Bertrand and Mullainathan (2003) in decomposing the passage of the good-faith exception into separate time periods: *Good Faith (-2,-1)* is a dummy that takes the value of one in the two years before the passage, zero otherwise; *Good Faith (0)* is a dummy that takes the value of one in the year of the passage, zero otherwise; *Good Faith (+1)* is a dummy that takes a value of one in the year after the passage, zero otherwise. Finally, *Good Faith ($\geq$ +2)* is a dummy that takes the value of one for the second year after the passage and thereafter, zero otherwise. Robust standard errors (clustered at the state level) are given in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	(1) ln(Patents)	(2) ln(Citations)	(3) ln(Patents /Employee)	(4) ln(Citations /Employee)	(5) ln(Patents /R&D)	(6) ln(Citations /R&D)
Good Faith (-2,-1)	0.015	0.067	0.035	0.097	0.059	0.131*
	(0.047)	(0.057)	(0.054)	(0.064)	(0.064)	(0.069)
Good Faith (0)	-0.009	0.056	0.019	0.077	0.039	0.116
	(0.042)	(0.062)	(0.050)	(0.073)	(0.059)	(0.076)
Good Faith (+1)	-0.009	0.043	0.017	0.050	0.061	0.077
	(0.044)	(0.053)	(0.046)	(0.059)	(0.056)	(0.069)
Good Faith ($\geq$ +2)	0.137**	0.194***	0.131*	0.187**	0.130*	0.188**
	(0.056)	(0.058)	(0.074)	(0.075)	(0.075)	(0.076)
Public Policy	0.082	0.108**	0.113**	0.144**	0.144**	0.179***
	(0.056)	(0.053)	(0.056)	(0.055)	(0.060)	(0.058)
Implied Contract	0.097**	0.142***	0.096**	0.135***	0.113**	0.152***
	(0.044)	(0.041)	(0.048)	(0.044)	(0.055)	(0.051)
Firm and Year dummies	Y	Y	Y	Y	Y	Y
Observations	104,504	96,849	81,935	76,012	73,496	68,175
Adjusted R-squared	0.157	0.218	0.750	0.658	0.733	0.663

Table 7: **Robustness Test for the Effect of Wrongful Discharge Laws on Innovation after controlling for Changes in the Enforcement of Non-Compete Agreements.**

The OLS regressions below implement the following model:
$y_{i,s\to r,t} = \beta_i + \beta_r \times \beta_t + \beta_r + \beta_t + \beta_1 * GF_{st} + \beta_2 * PP_{st} + \beta_3 * IC_{st} + \beta_4 * NCA_{st} + \beta \cdot X_{ist} + \varepsilon_{ist}$
where $y_{i,s\to r,t}$ is a measure of innovation for firm i from state s (belonging to region r) in year t. β_i and β_t denote respectively firm and application year fixed effects. $\beta_r \times \beta_t$ captures general regional trends through the interaction of U.S. Census region dummies with year dummies. NCA_{st} is the score of non-compete enforcement per state and year. X_{ist} is the set of control variables. In the table below, *Controls* denotes the following set of variables: *ln(R&D/Sales)* (not included in Columns 5 & 6), *Market-to-Book*, *Size*, *Size*^{2}, *Competition*, *Competition*^{2}, *Ratio of Value Added*, *ln(Real State GDP)*, *ln(Colleges)*, *ln(Enrollment)*, *ln(Population)*, *UI*; for the description, see Table 1. Panel A explicitly controls for NCA enforcement, while Panel B excludes states which *change* NCA enforcement during the sample period. The sample spans 1977–1999. Robust standard errors (clustered at the state level) are given in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Controlling for NCA Enforcement

	(1) ln(Patents)	(2) ln(Citations)	(3) ln(Patents /Employee)	(4) ln(Citations /Employee)	(5) ln(Patents /R&D)	(6) ln(Citations /R&D)
Good Faith	0.114**	0.172**	0.115**	0.174**	0.120**	0.178**
	(0.055)	(0.067)	(0.055)	(0.067)	(0.057)	(0.069)
Public Policy	0.065**	0.079*	0.064*	0.079*	0.067*	0.084*
	(0.032)	(0.041)	(0.032)	(0.041)	(0.034)	(0.043)
Implied Contract	-0.028	-0.020	-0.038	-0.029	-0.037	-0.032
	(0.032)	(0.037)	(0.032)	(0.036)	(0.035)	(0.040)
NCA	-0.005	-0.001	-0.004	-0.000	-0.006	-0.002
	(0.011)	(0.013)	(0.011)	(0.014)	(0.012)	(0.014)
Controls	*Y*	*Y*	*Y*	*Y*	*Y*	*Y*
Firm and Year dummies	Y	Y	Y	Y	Y	Y
Region x Year dummies	Y	Y	Y	Y	Y	Y
Observations	48,433	44,718	48,072	44,398	48,686	44,915
Adjusted R-squared	0.178	0.244	0.778	0.690	0.743	0.671

Panel B: Excluding States that Change NCA Enforcement

	(1) ln(Patents)	(2) ln(Citations)	(3) ln(Patents /Employee)	(4) ln(Citations /Employee)	(5) ln(Patents /R&D)	(6) ln(Citations /R&D)
Good Faith	0.166***	0.230***	0.164***	0.230***	0.177***	0.242***
	(0.059)	(0.072)	(0.059)	(0.071)	(0.060)	(0.073)
Public Policy	0.061	0.063	0.061	0.063	0.057	0.062
	(0.045)	(0.055)	(0.046)	(0.055)	(0.048)	(0.058)
Implied Contract	-0.016	-0.013	-0.027	-0.024	-0.028	-0.027
	(0.038)	(0.040)	(0.037)	(0.037)	(0.040)	(0.041)
Controls	*Y*	*Y*	*Y*	*Y*	*Y*	*Y*
Firm and Year dummies	Y	Y	Y	Y	Y	Y
Region x Year dummies	Y	Y	Y	Y	Y	Y
Observations	38,477	35,499	38,195	35,250	38,693	35,666
Adjusted R-squared	0.186	0.255	0.784	0.699	0.751	0.680

Table 8: **Effect of Wrongful Discharge Laws on Creation of New Firms and Employment Creation due to New Firms**

The OLS regressions below implement the following model:
$y_{klst} = \beta_l + \beta_s + \beta_t + \beta_r \times \beta_t + \beta_1 * GF_{st} + \beta_2 * PP_{st} + \beta_3 * IC_{st} + \beta \cdot X_{klst} + \varepsilon_{klst}$
where y_{klst} is the dependent variable, measured at the establishment size (k), firm age (l), state (s) and year (t) level. β_l, β_s, β_t, and $\beta_r \times \beta_t$ denote respectively firm age, state and year fixed effects, and regional trends (interaction between U.S. Census region and year dummies). GF, PP, and IC measure whether a given wrongful discharge law is in place in a given state and year. X_{klst} denotes the time-varying control variables; descriptions can be found in Table 1. The sample spans 1977–1999. Robust standard errors (clustered at the state level) are given in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	(1) ln(Establishments Created by Start-Ups)	(2) ln(Establishment Entries)	(3) ln(Job Creation from new Establishments)	(4) ln(Establishments Created by Start-Ups)	(5) ln(Establishment Entries)	(6) ln(Job Creation from new Establishments)
Good Faith	0.116**	0.105***	0.106**	0.117*	0.083**	0.081*
	(0.053)	(0.036)	(0.043)	(0.064)	(0.035)	(0.042)
Public Policy	-0.051	0.014	0.037*	-0.063	0.013	0.019
	(0.051)	(0.019)	(0.020)	(0.052)	(0.020)	(0.018)
Implied Contract	-0.063	-0.026	-0.036*	-0.060	-0.027	-0.025
	(0.052)	(0.019)	(0.020)	(0.048)	(0.019)	(0.017)
NCA	-0.026	-0.009	0.002	-0.028*	-0.008	0.004
	(0.016)	(0.006)	(0.008)	(0.016)	(0.006)	(0.007)
UI	-0.150	-0.058	-0.062	-0.163	-0.063	-0.019
	(0.141)	(0.049)	(0.057)	(0.125)	(0.054)	(0.051)
ln(Real GDP p.c.)	0.433**	0.171**	0.558***	0.375*	0.171**	0.610***
	(0.162)	(0.075)	(0.088)	(0.195)	(0.082)	(0.085)
ln(Colleges p.c.)	-0.182*	-0.157***	-0.188**	-0.187*	-0.172***	-0.192***
	(0.104)	(0.049)	(0.073)	(0.104)	(0.048)	(0.067)
ln(Enrollment p.c.)	0.148	0.120	0.108	0.179	0.194*	0.079
	(0.349)	(0.091)	(0.133)	(0.350)	(0.096)	(0.126)
Age Group dummies	N	Y	Y	N	Y	Y
State and Year dummies	Y	Y	Y	Y	Y	Y
Region x Year dummies	N	N	N	Y	Y	Y
Observations	6,532	52,990	52,990	6,532	52,990	52,990
Adjusted R-squared	0.066	0.449	0.728	0.059	0.448	0.728