Wrongful Discharge Laws and Innovation[1]

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Abstract

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We show that wrongful discharge laws – laws that inhibit the common-law doctrine of "employment-at-will" – spur innovation. In our model, wrongful discharge laws make it costly for firms to arbitrarily discharge employees. This enables firms to commit to not punish short-run failures of employees and thereby encourage employees to exert greater effort in risky but potentially mould-breaking projects. We provide supporting empirical evidence using the staggered adoption of wrongful discharge laws across the U.S. states. Using difference-in-difference tests, we show that firms and employees in the affected states engage in greater innovation, measured by the number of patents filed, citations to these patents, and the number of patents and citations per employee and per dollar of R&D expense. Using a novel dataset, we also document a "creative destruction" in the affected states: we find more new firms being created and more existing firms being destroyed, with an increase in both job creation and job destruction.

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

Keywords: Dismissal laws, R&D, Technological change, Law and finance, Entrepreneurship, Growth, Creative destruction.

1 Introduction

The appropriate degree of government intervention in private contractual relationships — particularly in employment law — remains a fraught public policy issue. In arguing the detrimental effects of laws that prevent employers from terminating labor contracts with employees, flexible labor market conditions in the U.S. — exemplified by the common-law "employment-at-will" doctrine — are often contrasted to the rigidities engendered by employment protection provisions in several European countries. Yet, two facets of this argument deserve closer scrutiny. First, the detrimental effects of laws that limit employment-at-will often center around their *ex-post* consequences.[1] Once a situation to terminate an employment contract arises, tying down an employer's hands from doing so can indeed lead to ex-post inefficient outcomes. However, these ex-post unfavorable effects may be mitigated by the positive effects that laws limiting employment-at-will may have on *ex-ante* incentives. In particular, these laws might have the countervailing effect of providing firms a commitment device to not punish short-run failures. Such commitment may spur employees to undertake risky but innovative activities that propel the gale of creative destruction.

Second, the image of a flexible U.S. labor market does not reflect substantive legal changes in the U.S. since the 1970s. The rapid adoption of a series of common-law doctrines called "wrongful discharge laws" by most U.S. states since the 1970s represents a significant departure from employment-at-will.

In this paper, we bring together both these facets. We develop a theoretical model to show that employment protection laws spur innovation. To investigate our model's empirical predictions, we exploit the *natural experiment* offered by the passage of wrongful discharge laws. Since the motivations behind the adoption of these laws were unrelated to either innovation or entrepreneurship, they offer a clean empirical setting to test our predictions. By exploiting their staggered passage across several U.S. states, we find that these employment protection laws indeed appear to have an *ex-ante* positive incentive effect by: (i) encouraging firms and their employees to engage in more successful, and more significant, innovative pursuits; and (ii) stimulating the creation of new firms and the destruction of existing ones.

We motivate our tests with a model in which an all-equity firm chooses between two projects that differ in their degree of innovation. Routine projects face risks mainly due to uncertainty in market demand and competition and have limited upside. In contrast, innovative projects result in higher terminal payoffs if successful, but entail additional risks associated with the process of exploration and discovery. Though innovative projects may differ from routine projects along other important dimensions, the difference in risk is sufficient to generate our testable empirical predictions.

A key friction in the model is that contracts are incomplete as in Hart (1995). Specifically, we assume that the firm cannot commit to the employee (through its ex-ante contract) that it will not fire her in those states where project failure occurs due to sheer bad luck. Following MacLeod

[1] Jacob (2009) provides evidence of the *ex-post* detrimental consequences of employment protection on worker productivity and firm output. Also, strong labor market regulation is often blamed to be one of the reasons for Europe's economic under-performance compared to the US (see e.g. a study by McKinsey Global Institute, 1997).

and Nakavachara (2007), we model the introduction of wrongful discharge laws as an increase in the ex-post costs that a firm incurs when firing an employee. Among others, the model generates the prediction that the lower threat of termination created by the passage of such laws acts as a commitment device for the firm to not punish the employee when the project is unsuccessful, thereby leading to an increase in the effort exerted by the employee. Furthermore, the passage of these laws *disproportionately* increases the investment by the employee in the innovative project vis-à-vis the routine project. Thus, the firm too finds innovative projects to be more value-enhancing than routine projects. Therefore, the adoption of wrongful discharge laws leads to more innovation.

The model also provides testable implications relating to entrepreneurship. According to Schumpeter (1942), innovative activity is intrinsic to entrepreneurial firms and its employees; furthermore, it is such innovative activity that feeds the "perennial gale of creative destruction." In fact, employees who choose to work on innovative projects are central to this concept of entrepreneurship (Schumpeter, 1911). Since the passage of wrongful discharge laws leads firms and their employees to invest in innovative projects, we extend our model's predictions to the Schumpeterian context and argue that the passage of wrongful discharge laws should also lead to greater creative destruction, i.e. creation of new firms as well as destruction of existing ones.

To test these theoretical predictions, first, we employ data on patents issued to U.S. firms by the United States Patent and Trademark Office (USPTO) and link this data to Compustat. Second, we employ a *novel* dataset on entrepreneurship developed by the U.S. Census Bureau – the Business Dynamics Statistics database. We use the passage of wrongful discharge laws across U.S. states to infer their *causal* impact on firm-level innovation and entrepreneurship.[2] From an empirical standpoint, the natural experiment created by the adoption of these laws across the U.S. states and time is highly appealing. 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). Hence, these law passages can be considered as *exogenous* to our outcomes of interest — firm-level innovation and entrepreneurship. Second, the staggered adoption of these laws across U.S. states enables us to assess their causal impact in a difference-in-difference setup.[3]

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. In estimating this effect, in addition to firm and year fixed effects, we control for firm-level characteristics (Tobin's Q, firm size, R&D) as well as state and industry-level characteristics (competition, industry-level ratio of value added, gross state product, population, anti-takeover laws, and number of colleges) to account for time-varying firm, state and industry level omitted variables. We find that, ceteris paribus, the passage of the

[2] By investigating the year in which a precedent-setting court decision occurs, Autor et al. (2006) code three kinds of wrongful discharge law passages over the period 1970-1999: (i) the public policy exception; (ii) the implicit contract exception; and (iii) the good faith exception (see Section 2 for the details).

[3] 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).

good faith exception results in a rise in the annual number of patents and citations by 9.1% and 17.4% respectively. Indeed, the passage of the good-faith exception – which is considered the most significant and broad among the three common law exceptions that constitute wrongful discharge laws (e.g. Kugler and Saint-Paul, 2004) – had the strongest positive effect.

Our theoretical model predicts that the increase in innovation due to the passage of wrongful discharge laws stems from increased employee effort in innovative projects. To provide supporting evidence, we repeat our tests with a modified set of dependent variables: patents and citations scaled by the number of employees and by R&D expenditure; both of these dependent variables can be interpreted as measures of employee effort. The findings for these dependent variables are in line with the previous results. We also show that the impact of these laws is positive in both high- as well as low-innovation intensive industries with the effect being larger in the former.

We entertain alternative interpretations of our results. First, during our sample period, California and Massachusetts 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. Therefore, it could be that these two states are driving our above results. However, when we re-run our tests by excluding observations from the states of California and Massachusetts, our results remain as strong as with the full sample, alleviating concerns about such alternative interpretations. The above results could also 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 manifest in an observable increase in Research and Development investment. However, we do not find a significant impact of any wrongful discharge law 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 – one before 1982 and another after – and find that our results are as strong for either sub-sample, thereby ruling out this possibility.

Next, we examine the effect of the passage of wrongful discharge laws on (i) the creation of new firms, and (ii) the destruction of old ones. Using *novel* data from the the Business Dynamics Statistics database, we investigate effects (i) and (ii), as well as attendant effects on job creation and destruction. Employing specifications that are similar to those in our tests of innovation, we find that states that adopt the good-faith exception experience a 10.1% increase in new establishments due to start-up firms, 3.7% increase in job creation by such establishments (though the effect is statistically weak), 6.7% increase in closure of existing establishments, and 7.4% increase in job losses due to establishment shut-downs. We also check the robustness of these results to including fixed effects for the firm age category to which the establishments belong. Also, by excluding California and Massachusetts from our sample, we verify that these results are robust to the alternative interpretations that were discussed above.

Taken together, these tests enable us to conclude that innovation, firm creation and firm destruction 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: although they may cause ex-post inefficiencies in the labor market, they can have positive ex-ante effects by fostering innovation and hastening the process of creative destruction. We discuss the literature highlighting the ex-post effects of employment protection laws in Section 6. Since a large influential literature on endogenous growth (see Aghion and Howitt, 2006) postulates that innovation and entrepreneurship contribute significantly to a country's economic growth and development, our study points out the need to factor in these ex-ante incentive effects in any analysis of the net welfare implications of employment protection laws.

The rest of the paper is organized as follows. Section 2 provides background information on wrongful discharge laws. Section 3 presents the theoretical model that motivates our empirical investigation. Section 4 discusses results documenting the effect of wrongful discharge laws on innovation, while Section 5 presents the effects of these laws on entrepreneurship. In Section 6, we discuss the related literature. Finally, Section 7 concludes.

2 Employment-at-will and Wrongful Discharge Laws

Until the latter half of the 20th century, U.S. labor relations were characterized by "employment at will", which implied that employers could "discharge or retain employees at will for good cause or for no cause, or even for bad cause without thereby being guilty of an unlawful act per se."[4] Blades (1967) observed that large corporations exert substantial influence over the lives and well-being of individuals, and that the law should recognize its obligation to protect the economically dependent employees from arbitrary acts by the employer. Consequently, since the 1970s onward, the vast majority of U.S. states have adopted common law exceptions to the employment-at-will doctrine. Walsh and Schwarz (1996) argue that states passed these exceptions to assure legally binding policy principles, address the changing nature of labor relations, and assure consistency with contract principles. These exceptions from the employment-at-will doctrine are part of the common law, i.e. law created by court decisions (in this case, state courts).

The legal profession distinguishes three distinct wrongful-discharge laws. In a given state, courts recognize anywhere from zero to all three of these exceptions. The three wrongful discharge laws are: the public-policy exception, the good-faith exception, and the implied-contract exception. 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. The public-policy exception assures that an employer cannot discharge an employee for declining to violate lawful public policy (such as performing jury duty), taking actions that are in the public's interest (e.g. exposing an employer's legal misconduct), or refusing to commit an illegal act. Violations of the public policy exception can trigger economic damages for lost earnings, non-economic damages for pain and suffering incurred, as well as punitive

[4]Source: Epstein (1984) who cites *Payne v. Western & Atl. R.R.*, 81 Tenn. 507, 518-19 (1884).

tort damages, which are awarded in order to punish the defendant and deter future wrongdoing. By 1999, 43 U.S. states recognized this wrongful discharge law.

The implied-contract exception. This wrongful-discharge law is applied in situations where the employer implicitly indicates that termination shall only occur due to just cause.[5] Although 41 states recognized the implied-contract exception by 1999, evidence suggests that this exception offers limited leverage in reducing an 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 in bad faith, i.e. in a manner deemed unfair.[6] Importantly, unfair 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). Although the good-faith exception has only been adopted in 11 states, many legal scholars deem the good-faith exception to be the *most far-reaching wrongful discharge law* (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.

Figures 1 and 2 show the adoption of wrongful-discharge laws in U.S. states during the years 1970–99.

2.1 Do employment protection laws affect white-collar employees?

A commonly prevailing perception is that employment protection laws, such as the wrongful discharge laws, matter to firms only with respect to their relationships with blue-collar workers. However, these laws are quite relevant to a firm vis-à-vis its professional/ white-collar employees as well. We provide case-based evidence to highlight this fact.

A leading case involving wrongful discharge of a *scientist* is Mehlman v. Mobil Oil (707 A.2d 1000; N.J. 1998). Mehlman was an internationally respected toxicologist who was employed by Mobil Oil. When Mehlman learned that Mobil was selling gasoline in Japan that contained more than 5% benzene,[7] he insisted that Mobil immediately stop this harmful practice. Mobil terminated Mehlman's employment one month after he objected to the high benzene concentrations. In the subsequent wrongful discharge trial, the jury ruled that Mobil had violated the public policy exception and awarded Mehlman US$ 3,440,300 in compensatory damages and US$ 3,500,000 in punitive damages.

[5]Such an implied contract can arise from statements made by the employer in internal personnel policy handbooks, from verbal statements, as well as from more circumstantial evidence such as the length of employment, salary and promotion history, and general company policies or established industry practices.

[6]The prototypical example of this wrongful discharge law is the case of *Fortune v. National Cash Register Co. (1977)*, where an employer fired a salesman in order to prevent him from obtaining a commission after a completed sale; the Massachusetts Supreme Court decided that the employer's actions violated the good-faith exception, and awarded the salesman compensatory and punitive damages.

[7]Compared to the gasoline that is sold in the USA, which must contain less than 1% benzene, the 5% benzene content in Japan was excessive.

Another famous case is Lorenz v. Martin Marietta Corp. (823 P.2d 100; Colo. 1992). Paul M. Lorenz was a mechanical engineer specializing in fracture mechanics of metals. Martin Marietta Corporation, a supplier of external tanks to NASA's space shuttles, terminated Lorenz's employment in violation of the public policy exception. Lorenz had "expressed his concern that the testing sequence proposed was inadequate" for an external tank for NASA's space shuttle. Lorenz was ordered by his supervisor to make modifications to the minutes of a meeting that had been prepared by Lorenz, which he refused to do. He had complained about the design and construction of a test fixture, in which Martin Marietta spent only 40% of the funds appropriated by NASA. He "was pressured by his superiors to attest to the adequacy of certain materials.... His refusal was based on his professional opinion that the materials had not been subjected to adequate testing." The Colorado Supreme Court affirmed an appellate court ruling in favor of the plaintiff, citing the employer's violation of the federal fraud statute (18 USC § 1001) as the relevant public policy violation in this case of wrongful discharge.

3 Theoretical Motivation

To derive sharp empirical predictions, we develop a model in which a firm chooses either of two projects; these projects differ only in their degree of innovation. We denote the *routine* project by R while we denote the *innovative* project by I.

Figure 3 shows the timing and sequence of events. There are three cash flow dates, $t = 0, 1, 2$. At date 0, the firm invests in either of the two projects. The projects require the same initial investment and generate cash flows at date 2. For project j, $j \in \{I, R\}$, the project cash flow is α_j if the project is successful and $\beta < \alpha_j$ if it fails. These cash flows are verifiable.

After deciding on a project, at date 0.5, the firm hires an employee to work on this project; we assume the employee to be wealth-constrained. Since the project cash flows are verifiable, the firm can offer her a compensation or wage contract tied to these cash flows:

$$\widetilde{w}_j\left(q_j^S, q_j^F, \alpha_j\right) = \begin{cases} q_j^F + q_j^S \alpha_j & \text{if the project is successful} \\ q_j^F & \text{if the project fails} \end{cases} \tag{1}$$

Thus the employee's compensation contract is characterized by $q_j = \left(q_j^S, q_j^F\right)$. Since the compensation is tied to project cash flows, the employee receives it at date 2. As we explain below, the employee receives the compensation only if she is retained by the firm.

At date 1, the employee makes specialized investment e_j which affects the project outcome. We assume the investment to be *observable but not verifiable.* The employee incurs a personal cost which is convex in the level of investment. For simplicity, we assume this cost to be $\frac{e_j^2}{2}$.

At date 1.5, i.e. before the actual cash flows accrue at date 2, a signal x_j $(j \in R, I)$ is obtained about these cash flows. We assume this signal to be also *observable but non-verifiable.* This signal x_j depends upon specialized investment e_j made by the agent:

$$x_j = e_j + \sigma_j \eta \tag{2}$$

where η is a uniform random variable distributed over the support $[0, 1]$ while σ_j captures the inherent risk of the project. Thus, the signal informs whether the project would be successful or not. If the signal is above (below) a threshold ξ, which is exogenously specified, the project is deemed to be successful (a failure).

After observing the signal, at date 1.5, the firm decides whether to retain the employee or to replace her. If replaced, the employee is given a severance payment by the firm, which we normalize to zero. We denote the project cash flow generated using the new employee to be $\gamma + \delta$, where δ is a uniformly distributed random variable over the support $[0, 1]$. To model a situation where the firm finds it optimal (sub-optimal) to replace the employee after observing a signal that indicates failure (success), we assume that the cash flow generated by the new employee is considerably greater (lower) than the cash flow upon failure (success):

$$\beta + 0.5 < \gamma < 0.5\alpha_j \tag{3}$$

At date 2, project cash flows are realized and the firm pays wages to its employees. For simplicity, we assume the project outcome to be perfectly correlated with the signal obtained at date 1.5. Therefore, the project cash flow is α_j if the signal is above the threshold ($x_j > \xi$) while the cash flow equals β if the signal is at or below the threshold ($x_j \leq \xi$) but the firm retains the original employee.

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

A key friction in our model is that contracts are incomplete as in Hart (1995). Specifically, we assume that the firm cannot commit that it will not fire the employee in those states where project failure occurs due to bad luck. This ex-ante inability to commit to not replacing the employee ex-post stems from (i) the non-verifiability of investment and, in turn, the cause for project failure; and (ii) the firm finding it advantageous ex-post to replace the original employee. We detail these assumptions below.

The non-verifiability of the investment as well as that of the signal 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." The assumption of indescribable contingencies is natural to settings involving innovation (see Aghion and Tirole, 1994, for example) because it involves considerable exploration (see Manso, 2009). Given these "unknown unknowns" involved with innovation, it is unlikely that the firm and the employee will be able to contract upon the specific details of either the employee's investment or the nature of the signal.

Formally, as seen in equation (2), project failure can be either due to bad luck or due to the employee's incompetence, i.e., a low level of investment by her. However, since we assume investment to be non-verifiable, the firm *cannot* commit through a state-contingent contract with the employee at date 0 that it will not fire the employee in those states of the world where failure resulted due to bad luck.

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:

$$\sigma_I > \sigma_R \tag{4}$$

The innovative project also generates greater cash flows if it is successful. For simplicity, we assume that each project, if successful, generates a return that is proportional to its risk:

$$\frac{\alpha_I}{\sigma_I} = \frac{\alpha_R}{\sigma_R} = k \tag{5}$$

We assume that the routine project possesses a minimum threshold level of risk:

$$\sigma_R > \overline{\sigma} \tag{6}$$

3.3 Risk Preferences

While the firm is assumed to be risk-neutral, the employee is averse to the risk of being fired. To ensure tractability, we model the employee's utility in the following simple manner:

$$U = \underbrace{E\left[\widetilde{w}\right]}_{\text{Utility from expected wage}} - \underbrace{\rho \cdot prob\left(fired\right) \cdot q^F}_{\text{Dis-utility from being fired}} \tag{7}$$

Thus, as usual, the employee derives utility from his wage income (the first term above). However, if fired, she experiences a dis-utility in the form of a "penalty" equal to the fixed wage q^F. This dis-utility increases with (i) her degree of risk-aversion, which we denote by ρ $(\rho > 0)$; and (ii) the probability of her getting fired.[8]

3.4 Wrongful Discharge Laws

As in MacLeod and Nakavachara (2007), we model the passage of 'wrongful discharge laws' as an increase in the costs incurred in firing a worker. Employment protection regulation can impose direct and indirect costs on firms with respect to dismissing employees. Direct costs can take the form of third party payments such as payments to courts and lawyers in the event of litigation and to the plaintiffs in the form of damages.[9] If the employee sues the firm upon dismissal, wrongful

[8] Gilson (1981) provides empirical evidence that when managers are fired from under-performing publicly listed companies, they do not find employment in another publicly listed company for three years on average. We are attributing a similar dis-utility to the firm's employees.

[9] As evidence of such costs incurred by employers, Dertouzos et al. (1988) find in a study of California court awards between 1980 and 1986 relating to wrongful discharge cases that plaintiffs were on average awarded $650,000 (the median was lower at $177,000). A significant fraction (40%) of these awards were for punitive tort damages. Such awards were not exclusive to California either (Edelman et al., 1992; Abraham 1998).

discharge laws require the firm to prove in a court of law that the dismissal was not unjust. Therefore, in the presence of wrongful discharge laws, firms also incur indirect costs to acquire verifiable information about the employee's effort. Note that wrongful discharge laws *do not* make firing a worker impossible; rather, they require the firm to provide a valid and *verifiable* reason for the dismissal. If the firm collects systematic records of the employee's performance, it can prove to a court of law that the employee performed at an unacceptable level. In this case, dismissal of the employee is justified. Thus, the evidentiary requirements of the legal system necessitate the firm to invest in verifying the employee's performance and obtain a better evaluation of the same.

We model this effect of wrongful discharge laws in a reduced form. After the passage of these laws, the firm has to incur a positive fixed cost θ when dismissing an employee. In contrast, under employment-at-will, there are no costs incurred in dismissing an employee. Thus, given $\theta \geq 0$, the employment-at-will regime is nested as a special case. To ensure that wrongful discharge laws do not make dismissals impossible in equilibrium, we assume:

$$\theta < \frac{\rho}{\rho+1} + \gamma - \beta \tag{8}$$

3.5 Analysis

We solve the model by backward induction. Consider the firm's decision at date 1.5 whether or not to replace the original employee. Let us first analyze the case where the signal indicates that the project will be a success. Since the value generated under the new employee γ is assumed to be lower than the cash flow conditional on success α_j (see (3)), the firm finds it optimal to retain the employee in this case.

Next, consider the case where the signal indicates that the project will fail. In this case, the value generated under the original employee is β while that generated under the replacement employee is given by $\gamma + \delta - \theta$. Therefore, the firm replaces the employee if $\gamma + \delta - \theta > \beta$, i.e. if $\delta > \beta - \gamma + \theta$. Thus, the probability of retaining the original employee, which we denote by μ, equals:

$$\mu = \max(\beta - \gamma + \theta, 0) \tag{9}$$

Since $\theta = 0$ under employment-at-will and $\gamma > \beta$ using (3) it follows that $\mu = 0$ in this case. Thus, under employment-at-will, the firm finds it optimal to replace the employee when the signal indicates project failure. Also, using (8) , it follows that $\beta - \gamma + \theta < 1$. Therefore, wrongful discharge laws do not make dismissals impossible.

Lemma 1 *If the signal indicates project success, the firm always retains the original employee. If the signal indicates project failure, the firm replaces the original employee with probability* $\min(1 + \gamma - \beta - \theta, 1)$.

Therefore, at date 1.5, there are three outcomes that are possible: (1) the signal indicates that the project will be successful; (2) the signal indicates that the project will fail but the firm does not fire the employee; and (3) the signal indicates that the project will fail and the firm fires the employee. The probability of these outcomes, the original employee's wage and her dis-utility are given in the following table:

Outcome:	Success	Failure but employee retained	Failure & employee replaced
Probability:	$1-\frac{\xi-e_j}{\sigma_j}$	$\left(\frac{\xi-e_j}{\sigma_j}\right)\mu$	$\left(\frac{\xi-e_j}{\sigma_j}\right)(1-\mu)$
Wage:	$q_j^F+q_j^S\alpha_j$	q_j^F	0
Dis-utility:	0	0	$-\rho q_F$

Given project j, let the employee's and firm's expected payoffs at date 0 be U_j and V_j respectively and the aggregate payoff be $W_j=U_j+V_j$. The employee's payoff is the expected value of her wage minus the dis-utility from being fired as given by (7). The firm's payoff is given by its expected cash flows, where the cash flow in a particular state equals the aggregate cash flow less the wage paid to the employee less any costs incurred in dismissing the employee. Also, when the firm replaces the original employee, the cash flow under the new employee equals $\gamma+\delta$. The resulting expressions for U_j and V_j are given in Appendix A in equations $(A-1)$ and $(A-2)$.

Then, given the project and the optimal compensation contract, the employee chooses investment $e_j^*(q_j)$ to maximize U_j. The expression for this investment is given in Appendix A in equation $(A-6)$. Using the expression for the investment chosen by the employee, we derive the firm value V_j. For given project j, the firmowners maximize V_j when choosing the optimal compensation contract q_j^*. Intuitively, the firm faces the following trade-off in deciding the optimal contract: While increasing the employee's fixed or variable compensation decreases the firm's payoff, increasing compensation incentivizes the employee to exert greater effort. This trade-off is formalized in Appendix A in equations (A-8).

Finally, since the labor market is competitive, employees earn their reservation wage in equilibrium. Therefore, the firm-owners choose between innovative and routine project at date 0 to maximize the joint payoff W_j. Lemma 2 formalizes this result.

Lemma 2 *The optimal project is chosen to maximize the aggregate payoff to the firm and the employee.*

3.6 Results

Given these steps for solving the model, we now derive the key results and discuss their testable empirical implications. The proofs for these results are provided in Appendix A.

Proposition 1 *If the employee is not risk-averse* $(\rho=0)$, *then the firm chooses not to pay her a fixed wage (part (a)). Under employment-at-will* $(\theta=0)$ *if the employee is risk-averse* $(\rho>0)$, *the firm pays the employee the entire cash flow in the case of failure as her fixed wage (part (b)). Under wrongful discharge laws* $(\theta>0)$, *if the employee is risk-averse* $(\rho>0)$, *then the firm pays* *her a fixed wage that is less than the cash flow in case of failure (part (c)).*

$$(a)\,\rho = 0 \Rightarrow q_j^{F*} = 0 \tag{10}$$
$$(b)\,\theta = 0, \rho > 0 \Rightarrow q_j^{F*} = \beta \tag{11}$$
$$(c)\,\theta > 0, \rho > 0 \Rightarrow 0 < q_j^{F*} < \beta \tag{12}$$

If the employee is not averse to the risk of being fired, the firm finds it optimal to incentivize her by providing a variable payoff when the project succeeds. Therefore, the firm decides to set the fixed portion of the employee's compensation to be zero. In contrast, if the employee is risk-averse but the firm cannot commit to not fire the employee (because wrongful discharge laws do not exist), the firm chooses to pay her the maximum fixed wage (which equals the entire cash flow in the event of project failure) to motivate the employee's effort. Wrongful discharge laws enable the firm to commit to not fire the employee in some states of the world. Therefore, the firm does not need to pay her the maximum fixed wage in this case.

Thus, interior solutions for *both* q_j^F and q_j^S are obtained only if wrongful discharge laws exist and the employee is risk-averse. In this case, the optimal compensation contract (q_j^{S*}, q_j^{F*}) is given in equations (A-13) and (A-14) in Appendix A. In turn, the optimal level of investment e_j^* given this optimal compensation contract is specified by:

$$e_j^* = \xi - \left[1 - \frac{\mu}{\rho\,(1-\mu)}\right]\sigma_j \tag{13}$$

The employee's equilibrium level of investment exhibits the following features. First, the investment in the innovative project is lower than that in the routine project. Second, an increase in the stringency of wrongful discharge laws increases the employee's investment. Third, an increase in the stringency of these laws disproportionately increases the investment in the innovative project when compared to the increase in investment in the routine project. Finally, an increase in the employee's risk aversion decreases her investment.

Proposition 2 *If wrongful discharge laws exist ($\theta > 0$) and the employee is risk-averse ($\rho > 0$), the employee chooses lower effort with the innovative project than with the routine project (part (a)). However, an increase in the stringency of wrongful discharge provisions disproportionately increases the investment by the employee in the case of the innovative project relative to the increase in the investment in the routine project (part (b)):*

$$(a)\,e_I^* < e_R^* \tag{14}$$
$$(b)\,\frac{de_I^*}{d\theta} > \frac{de_R^*}{d\theta} \tag{15}$$

The intuition for these results is as follows. Recall that the firm cannot commit to not firing the employee in those states of the world where failure occurs due to bad luck. Since the effect of investment on project success is lower with the innovative project than with the routine project (the probability of success decreases with σ_j), failure due to bad luck is more likely with the innovative project than with the routine project. Therefore, the firm's inability to commit to not firing in these states leads to the employee exerting lower effort with the innovative project.

Given the inherent riskiness of innovative projects, the insurance effect of wrongful discharge laws stemming from a lower threat of termination matters more for the innovative project than for the routine project. This insurance effect leads the employee to increase his investment relatively more with the innovative project than with the routine project.

Thus, the greater risk involved in the innovative project always generates an inefficiency in the form of reduced investment by the risk-averse employee. However, reducing the threat of termination induces the employee to invest more in the innovative project and thus reduces the inefficiency in investment. In other words, wrongful discharge laws act as a commitment device for the firm and thereby lead to a greater increase in the employee's investment.

Proposition 3 *Given a risk-averse employee ($\rho > 0$) and some restrictions on the level of her risk-aversion ($\rho < \overline{\rho}$), an increase in the stringency of wrongful discharge provisions increases the value of the innovative project disproportionately more than the value of the routine project.*

$$\frac{dW_I^*}{d\theta} > \frac{dW_R^*}{d\theta} \tag{16}$$

The intuition for this result follows directly from part (b) of Proposition 2. Since an increase in the employee's investment increases the likelihood of project success, a disproportionate increase in the employee's investment in the innovative project (relative to the routine project) leads to a similar increase in the value of the project. This explains the disproportionate increase in the value of the innovative project when compared to the routine project resulting from the adoption of more stringent wrongful discharge provisions.

This result generates the empirical prediction that the passage of wrongful discharge laws in a state would lead firms located in that state to prefer investing in innovation. Furthermore, since the increase in value from innovation becomes disproportionately greater, this effect of the passage of wrongful discharge laws would manifest more in the innovation-intensive industries than in the 'brick-and-mortar' industries.[10]

Proposition 4 *Given a risk-averse employee ($\rho > 0$) and some restrictions on the level of her risk-aversion ($\rho < \overline{\rho}$), there exists a $\widehat{\theta} \in (0, 1)$ such that the value from the innovative project is higher than the value from the routine project when wrongful discharge laws are not stringent $\left(\theta \leq \widehat{\theta}\right)$ and*

[10]Note that our model does not help answer whether the passage of wrongful discharge laws increases or decreases the value of the *routine* project. This is because we do not model the possibility that the employee might shirk in the presence of laws that reduce the threat of termination. Manso (2009) considers such an "exploit" strategy in addition to the innovative "explore" strategy, and shows that an increased threat of terminating the agent's employment upon failure prevents the agent from shirking, even though such an increased threat also dissuades the agent from exploring the new work method. Incorporating the possiblility of shirking into our setup would deliver the additional result that the value from the routine project would decrease due to the passage of wrongful discharge laws.

the reverse is true when such laws are stringent $\left(\theta > \widehat{\theta}\right)$

$$\theta \leq \widehat{\theta} \Rightarrow W_I^*(\theta) > W_R^*(\theta) \tag{17}$$

$$\theta > \widehat{\theta} \Rightarrow W_I^*(\theta) \leq W_R^*(\theta) \tag{18}$$

This result follows directly from the Proposition 3. Since the threat of dismissal is relatively higher when wrongful discharge laws are less stringent, the inefficiency in an employee's investment is disproportionately greater for the innovative project under such a regime, which explains the fact that innovation is less attractive when wrongful discharge laws are less stringent. Thus, the effect of wrongful discharge laws in enabling commitment by the firm translates into a positive effect on firm value as well.

The propositions from our model directly lead to the following testable hypotheses:

HYPOTHESIS 1: *Passage of wrongful discharge laws leads to greater innovation.*

HYPOTHESIS 2: *Passage of wrongful discharge laws leads to a larger increase in employee effort in the innovative projects when compared to the routine projects.*

HYPOTHESIS 3: *Passage of wrongful discharge laws leads to relatively more innovative effort by employees as well as relatively more innovation in the innovation-intensive industries than in the traditional industries.*

The above propositions also deliver testable implications about the effect of wrongful discharge laws on entrepreneurship. According to Schumpeter (1942), innovative activity is intrinsic to entrepreneurial firms and its employees and it is such innovative activity that feeds the "perennial gale of creative destruction." In fact, employees that choose to undertake innovative activities are central to Schumpeter's concept of an entrepreneur. For example, Schumpeter (1911) postulates that "... it is the carrying out of *new combinations* that constitutes an entrepreneur... we call entrepreneurs not only those 'independent' businessmen in an exchange economy who are usually so designated but all who fulfill the function by which we define the concept, even if they are, *as is becoming the rule, 'dependent' employees of a company*" (pp. 74-75; emphasis added). Since the passage of wrongful discharge laws leads firms and their employees to prefer innovative projects, it follows by applying the Schumpeterian interpretation that the passage of wrongful discharge laws should also propel the gale of creative destruction. Therefore, our model provides the following additional implications:

HYPOTHESIS 4: *Passage of wrongful discharge laws leads to (a) creation of new firms; and (b) greater employment from the creation of new firms.*

HYPOTHESIS 5: *Passage of wrongful discharge laws leads to (a) destruction of existing firms; and (b) job loss due to the destruction of existing firms.*

Next, we test these hypotheses by employing proxies for innovation and entrepreneurship. We organize our empirical analysis into two parts. In the first part, we examine the effect of the passage of wrongful discharge laws on innovation. In the second part, we examine their effect on entrepreneurship.

4 Wrongful Discharge Laws and Innovation

In this section, we examine the effect of wrongful discharge laws on firm-level innovation.

4.1 Data and Main Proxies

We now describe the data, our proxies for innovation and the changes in wrongful discharge laws that we employ to identify their effect on innovation.

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 the citations to these patents, compiled in the NBER Patents File (Hall, Jaffe and Trajtenberg, 2001). The NBER patent dataset provides among other items: annual information on patent assignee names, the number of patents, the number of citations received by each patent, the technology class of the patent and the year that the patent application is filed. Although the NBER dataset covers all patents filed with the USPTO by firms from around 85 countries, in this study we focus on patents filed by U.S. firms. To link the patent data with Compustat, we exploit the detailed information on patent assignees in the NBER patents file. Each assignee in the NBER patent dataset is given a unique and time-invariant identifier. We match these assignee names to the names of divisions and subsidiaries belonging to a corporate family from the Directory of Corporate Affiliations. We then match the name of the corporate parent to Compustat.

Patents have long been used as an indicator of innovative activity in both micro- and macroeconomic studies (Griliches, 1990). Although patents provide an imperfect measure of innovation, there is no other widely accepted method which can be applied to capture technological advances. Nevertheless, we are aware that using patents has its drawbacks. Not all firms patent their innovations, because some inventions do not meet the patentability criteria and because the inventor might rely on secrecy or other means to protect her innovation. In addition, patents measure only successful innovations. To that extent, our results are subject to the same criticisms as previous studies that use patents to measure innovation (e.g., Griliches, 1990; Kortum and Lerner, 1999).

Apart from a simple count of the number of patents, we use the subsequent citations made to patents as our second metric of innovative activity. Citations capture the *importance* and drastic nature of innovation. This proxy is motivated by the recognition that the simple count of patents does not distinguish breakthrough innovations from less significant or incremental technological discoveries.[11] Intuitively, the rationale behind using patent citations to identify important innovations is that if firms are willing to further invest in a project that is building upon a previous patent, it

[11] 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.

implies that the cited patent is influential and economically significant. In addition, patent citations tend to arrive over time, suggesting that the importance of a patent may be revealed over a period of time and may be difficult to evaluate at the time the innovation occurs.

We date 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 investigate Hypothesis 2, we employ patents and citations per employee and per dollar of R&D.

4.1.2 Wrongful Discharge Laws

Following the recent literature, we use Autor et al.'s (2006) coding of the passage of wrongful discharge laws. 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 adoption of the wrongful discharge laws was unrelated to our outcome variables of interest, employing these unexpected changes alleviates any residual concerns about the endogeneity of these law passages. We link the wrongful discharge 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 three separate indices, one for each wrongful discharge law (Good Faith, Implied Contract, and Public Policy) in our regressions. Specifically, the variable $Good\_Faith_{st}$ takes a value of one if a given state s has a good faith exception in place in year t, zero otherwise; the other two wrongful discharge law indices ($Implied\_Contract_{st}$ and $Public\_Policy_{st}$) are defined analogously.

As seen in Figures 1 and 2, the three wrongful discharge law indices exhibit substantial cross-sectional as well as time-series variation, which enables our identification.

4.1.3 Summary Statistics

Table 1 lists the mean, median, standard deviation, minimum, and maximum for the variables used in our tests on innovation. Our sample encompasses the years 1970–1999. 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.

4.2 Empirical Strategy

We investigate whether the passage of wrongful discharge laws in the U.S. led to greater innovation. As mentioned in Section 2, the reasons for the passage of these laws were quite orthogonal to firm-level innovation. Therefore, the natural experiment created by the passage of these laws across U.S. states and time is very appealing.

Figure 4 depicts a visual difference-in-difference examining the effect of the passage of the good faith exception in California in 1980. The graph plots on the y-axis the logarithm of the number of patents filed by firms in California over the years 1975-1991 vis-à-vis the same variable for the states that did not pass any wrongful discharge law during this period, which included Delaware, Florida, Georgia, Louisiana, Pennsylvania and Rhode Island. To enable comparison, we normalize the measure to 1 in 1980 for both California and the control group of states by dividing by the logarithm of the number of patents in 1980. This figure clearly illustrates that after the wrongful discharge law passage in 1980, firms in California filed significantly more patents in the years following the law passage compared to this difference for the control group of states.

As U.S. state courts adopted the wrongful discharge laws in different years during the sample period, we can implement the econometric variant of the above visual difference-in-difference in a multiple treatment groups, multiple time periods setting as employed by Bertrand, Duflo and Mullainathan (2004) and Imbens and Wooldridge (2009). Thus, we examine the before-after effect of a change in wrongful discharge laws in the affected state (the "treatment group") vis-à-vis the before-after effect in a state where such a change was not effected (the "control group"). This difference-in-difference test is implemented through the following panel regression:

$$\begin{aligned} y_{ist} &= \beta_i + \beta_t + \beta_1 * Good\_Faith_{st} + \beta_2 * Implied\_Contract_{st} \\ &\quad + \beta_3 * Public\_Policy_{st} + \beta \cdot X_{ist} + \varepsilon_{ist} \end{aligned} \tag{19}$$

where y_{ist} is a measure of innovation for firm i done in state s in year t. β_i and β_t denote respectively firm and application year fixed effects; note that the inclusion of firm dummies makes the coarser state dummies irrelevant. $Good\_Faith_{st}$, $Implied\_Contract_{st}$, and $Public\_Policy_{st}$ measure whether a given wrongful discharge law is in place in a given state and year. β_1, β_2 and β_3 measure the difference-in-difference effect of the passage of each of the three wrongful discharge laws (good-faith, implied-contract, public-policy exceptions respectively). X_{ist} denotes the set of time-varying control variables. The application year fixed effects enable us to control for inter-temporal technological shocks as well as the problem stemming from the truncation of citations, i.e., citations to patents applied for in later years would on average be lower than citations to patents applied for 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.

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 wrongful discharge law change vis-à-vis similar before-after differences in states that did not experience such a change during the same period (see Appendix B for a formal proof). These tests are less subject to the criticism that state or industry level unobserved factors influencing innovation are correlated with the level of dismissal laws in a state.

4.3 Results

4.3.1 Tests of Hypothesis 1

Based on Proposition 2 from our model, we expect that the adoption of wrongful discharge laws leads to greater innovation (Hypothesis 1). Table 2 provides support for this hypothesis by using patents and citations per firm-year as the dependent variables. Columns 1 and 2, which report the results for the tests without control variables, show that the passage of wrongful discharge laws 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. As we mentioned in Section 2, legal scholars deem the good-faith exception to be the most far-reaching wrongful discharge law. Our results buttress this claim: the good-faith exception consistently has the largest effect on our innovation measures.

Columns 3–4 show the results after controlling for 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 sales. To control for investment opportunities, as these might also have an impact on a firm's innovation policies, we include *Market-to-Book*.[12] Furthermore, R&D constitutes an important 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 logarithm of R&D to Sales (variable *ln(R&D/Sales)*).

State-level controls As Sapra et al. (2009) show that innovation is fostered by either an unhindered market for corporate control or strong anti-takeover laws that significantly deter takeovers, we include the number of antitakeover laws in the state in which the firm is incorporated (a time-varying *Anti-Takeover Index* from Bebchuk and Cohen (2003)). Furthermore, Garmaise (2007) finds that in-state competition affects the effect that the enforcement of employee non-compete covenants has on employee mobility and thereby firm-level investments in Research and Development. Aghion et al. (2005) find that competition and innovation share an inverted U-shaped relationship. Motivated by these studies, we control for in-state competition (variable *Competition*) and its square (variable $Competition^2$).[13]

A key determinant of innovation is the comparative advantage that a state possesses in its different industries, which could affect our interpretation of the difference-in-difference coefficient

[12] 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 closing price (*prccf*). Book value of equity is defined as common equity (*ceq*) plus balance sheet deferred taxes (*txdb*).

[13] We follow Garmaise (2007) in defining *competition* as the fraction of total (2-digit) industry sales (excluding those of the firm itself) generated by competitors in a given state (the state variable is based on the location of the firm's headquarters). Note that to construct the variable *competition*, we use sales information for all Compustat firms in a given state and industry which have their headquarters in the U.S., not only sales from firms in our patent data-Compustat matched sample. In order to eliminate the impact of outliers, we winsorize the variables *Market-to-Book*, *Size*, *competition*, and $competition^2$ at 1% and 99%.

measuring the effect of the passage of wrongful discharge laws on innovation. We control for this effect via our variable *Ratio of Value Added*.[14]

We also account for various *time-varying* state characteristics in our regressions. Since richer states may innovate more and are also more likely to pass employment protection legislation, we include the logarithm of GSP in a state and year (*ln(GSP)*). We also control for the state's population (*ln(Population)*) and its intellectual resources via the number of degree-granting institutions of higher education in a given state (*ln(College)*).[15]

Employing the full set of these covariates does not change our results materially. While the point estimates of the impact of the passage of dismissal laws are smaller, they largely remain statistically significant: in particular, we still find that adoption of the good-faith and public policy exceptions led to a significant increase in innovation. 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; the ratio of value added in a particular industry and state is positively correlated with innovation.

Economic magnitudes In addition to being statistically significant, the economic magnitude of the impact of wrongful discharge laws 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 9.1% and 17.4% respectively, when compared to firms located in states which did not pass this wrongful discharge law; the effect of the adoption of the public-policy exception on the two innovation proxies is 7.7% and 13.5% respectively. Overall, these results confirm our main Hypothesis 1.

4.3.2 Tests of Hypothesis 2

To test Hypothesis 2, we repeat our tests of equation (19) using patents and citations as scaled by the number of employees and, alternatively, by R&D expenditure (see Table 3). *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 1–4 of Table 3 confirm our Hypothesis 2: After the passage of wrongful discharge laws, patents and citations scaled by the number of employees increased significantly. In other words, innovative efforts per employee increased significantly as wrongful discharge laws were adopted by state courts. 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. From Columns 3 and 4 of Table 3, we find that patents

[14] 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 for the years 1977–2000. 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.

[15] Data on both state GSP as well as population is from the U.S. Bureau of Economic Analysis. The data for *ln(college)* is taken from the annual Statistical Abstracts from the U.S. Census Bureau (1970-2000). 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.

and citations per 1,000 employees increase by respectively 12.5% and 20.6% in states that adopt a good-faith exception vis-à-vis states that do not.

Columns 5–8 of Table 3 further underscore these findings. In these regressions, we report tests with patents (citations) scaled by R&D in million dollars as the dependent variable.[16] From Columns 7 and 8, we find that adopting a good faith exception increases patents and citations per million dollars of R&D by 12.0% and 19.5% respectively.

4.3.3 Tests of Hypothesis 3

Hypothesis 3 suggests that the effect of more stringent dismissal laws should be stronger in innovation-intensive industries than in the traditional industries. In order to investigate this hypothesis, we divide industries into those which have a high (low) propensity to innovate. Specifically, the dummy variable $High\_Intensity$ takes the value of one if the mean number of patents filed in a given 2-digit SIC industry in a given year exceeds the median value of these mean number of patents across all industries in that year; $Low\_Intensity$ is given by $(1 - High\_Intensity)$. These dummy variables are then interacted with the three wrongful discharge law indices (*Good_Faith*, *Implied_Contract* and *Public_Policy*). The results can be seen in Table 4. 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. For both the good faith and the public policy exceptions, we find that the effect of wrongful discharge laws in high innovation-intensive industries is almost double the effect in low innovation-intensive industries; furthermore, for these two exceptions, the effects are only significant for the high-intensity industries. Consistent with the results for our basic tests in Columns 3 and 4 of Table 2, the implied contract exception has no significant effect on either sets of industries.

Summary In sum, we find strong support for our hypotheses relating to innovation. The passage of wrongful discharge laws leads to more innovation overall as well as to more innovative effort per employee. Furthermore, these effects are stronger in the innovation-intensive industries. Finally, consistent with the claim made by legal scholars that the good-faith exception has the greatest effect among the wrongful discharge laws, we find this exception to have the largest effect on innovation.

4.3.4 Alternative Interpretations

We now examine several alternative interpretations for our above results.

Effect of California and Massachusetts California and Massachusetts are two U.S. states known for their innovative vigor. For example, both states have high-tech industrial districts: Silicon Valley in California and Route 128 in Massachusetts. Furthermore, according to our estimates based on the NBER patent data, firms (patent assignees) located in those two states account for 19% of the patenting output of all U.S. innovators between 1970 and 1999, while citations to patents

[16] 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.

owned by firms from California and Massachusetts account for 21% of total citations made to U.S. patents during the same period.

In addition, both states had all three wrongful discharge exceptions in place from the late 1980s onwards; thus these two states offered their employees significant protection against unjust dismissal. 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 *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).

For these reasons, California and Massachusetts are special, and we would like to ascertain that our results are not driven entirely by innovation in these states. Table 5 tries to alleviate these concerns. In this table, we report results for our main specification (equation (19)) with the full set of control variables, but the sample excludes all patents filed by firms in California or Massachusetts. Columns 1 and 2 report the results for patents and citations as the dependent variables, while Columns 3 & 4 (resp. 5 & 6) employ patents and citations scaled by the number of employees (resp. scaled by million R&D dollars). The tests indicate that our results are not driven by these two states alone: As in the full sample, the coefficients on the *Good_Faith* and *Public_Policy* exceptions stay positive and significant in all specifications. Furthermore, the coefficient magnitudes are very similar to those obtained using the full sample, which suggests that the effect of wrongful discharge laws was similar in California and Massachusetts to that in the other states.[17]

Shift to labor-saving technologies One could argue that the positive effects of wrongful discharge laws on innovation documented in this paper, instead of being an outcome of better incentives to innovate, are essentially a manifestation of firms' efforts to save on labor costs by shifting to less labor-intensive and more innovative technologies. Indeed, if a majority of the firms shifts to labor-saving technologies, this should manifest as an observable increase in the investment in Research and Development, as captured by e.g. R&D/Sales, after the passage of wrongful discharge laws. We however do not find any evidence of such increases: Running regression (19), but with R&D/Sales (or, alternatively, the natural logarithm of that ratio) as the dependent variable, we do not find any significant impact of any of the three wrongful discharge laws on the investment in Research and Development.

[17] In our Theoretical Motivation, we argued that the passage of wrongful discharge laws enabled firms to commit to their employees that they would not be fired in the case of project failure. 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 California and Massachusetts arguably provided the strongest legal protection of this type, firms pursuing innovation may have been inclined to re-locate to either California or Massachusetts after the passage of these laws. If this alternative interpretation were true, the passage of wrongful discharge laws would significantly further innovation in California and Massachusetts, but not in the other states. However, as we showed above (see Table 5), our results are as strong for other states as they are for California and Massachusetts.

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. Importantly, the spur in patenting activity also overlaps with the period when many wrongful discharge laws were adopted (see Figure 1). Therefore, we would like to ascertain that the positive effect of wrongful discharge laws on innovation is not spurious.

To show that our results are not driven by the creation of the CAFC in 1982, we divide the sample period into pre-1982 (1970–1982) and post-1982 (1983–1999). We then re-run our difference-in-difference regressions (equation (19)) for each sub-sample. Results are reported in Table 6; Panel A shows the results for sub-period 1970–1982, while Panel B reports the results for 1983–1999. We use all the previously discussed dependent variables (patents, citations, scaling by employees as well as by R&D), as well as the full set of control variables in these regressions. We find that in both sub-periods, the passage of the good faith exception leads to a positive and significant impact on innovation. The effect of the public policy exception on innovation is also positive in both sub-periods, but significant only in the first. The latter may result because most public policy exceptions were adopted prior to the mid-1980s, while the adoption of good faith exceptions was more evenly spread out over time. However, our findings allow us to rule out that the establishment of the U.S. Court of Appeals of the Federal Circuit in 1982 is causing our results.

4.3.5 Division/ Subsidiary level tests and Sample Selection

For the above tests, we used the firm-level sample that was generated by matching the NBER patent data to Compustat. To construct this sample, our NBER-Compustat data match was done at the assignee level (the subsidiary or division to which the USPTO assigns the patent). Hence, instead of using the firm-level sample, we can test our hypotheses using the more granular division/subsidiary level sample. Here, we can control for unobserved heterogeneity at the level of each division/subsidiary and therefore construct a more robust test of our hypotheses. Note however that using this sample, we cannot test Hypothesis 2: since information about employees in a division/subsidiary or the R&D spending of the division/subsidiary is not available, we cannot construct the proxies that we had used to test Hypothesis 2 above. Furthermore, we cannot include the firm-level control variables that we had employed in our tests above. Our regression specification is as follows:

$$y_{j\to i,st} = \beta_j + \beta_t + \beta_1 * Good\_Faith_{st} + \beta_2 * Implied\_Contract_{st} + \beta_3 * Public\_Policy_{st} + \varepsilon_{jst} \quad (20)$$

where $y_{j\to i,st}$ is a measure of innovation done by division/subsidiary j (of firm i) in state s in year t. β_j and β_t denote respectively division/subsidiary and application year fixed effects.

The results of these tests are described in Columns 1 and 2 of Table 7. We can see that the conclusions drawn from our earlier tests are unaffected here: the impact of wrongful discharge laws remains positive and significant, with the good-faith clause having quantitatively the largest effect, but the other two unjust wrongful discharge laws similarly having positive and significant effects.

Also, in the earlier tests, we used the link of the NBER patent data to Compustat. This enabled us to use firm-level variables like *Size, Market-to-Book* and *R&D Intensity* in the regressions. Furthermore, we were able to identify a firm's state of incorporation (Compustat item *incorp*) and use it as a link to the Bebchuk and Cohen (2003) *Anti-Takeover Index*. However, the Compustat–NBER patent data merge came at a cost: Not all U.S. firms (assignees) from the NBER patent data set could be matched to Compustat, resulting in a smaller sample that was possibly selected in systematic ways. In order to show that our results are not driven by sample-selection, we repeat the main tests with the *full* NBER patent data sample for all U.S. assignees. We therefore run regressions specified in equation (20) but for the full sample.

The results of these tests are reported in Columns 3 and 4 of Table 7. We can see that the conclusions drawn from our earlier tests are unaffected: In the full NBER patent data sample, the impact of wrongful discharge laws remains positive and significant, suggesting that our findings from the NBER-Compustat matched sample are not due to sample selection.

5 Wrongful Discharge Laws and Creative Destruction

In this section, we analyze the impact of the passage of the wrongful discharge laws on the process of creative destruction.

5.1 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.[18] The data encompasses measures of establishment openings and closings, firm startups, job creation and destruction. The BDS data are drawn from the Longitudinal Business Database, which is a longitudinal database of U.S. business establishments and firms spanning the years 1976–2005. In particular, the BDS database is constructed from information encompassing all non-agricultural sectors in the U.S. economy. The information is collected at the establishment level. An establishment is defined as a fixed physical location where economic activity occurs; a firm may consist of one or more such establishments. 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 firm's birth year, which is specified as the birth year of the establishment's ultimate parent. Therefore, establishments which have an age of zero years correspond to those that have started operating in that particular

[18] Most of the information on the BDS database discussed below is drawn from the *BDS Technical Note*, available at the U.S. Census website: $http://www.ces.census.gov/index.php/bds$

year, i.e. which are newly created firms. Overall, the firm age categories are as follows: 0 years; 1 year; 2; 3; 4; 5; 6 to 10; 11 to 15; 16 to 20; 21 to 25; and ≥26 years.

The most detailed data provided currently in the BDS database are by "category triples". Since the state of location and establishment age are the most important categories for our empirical analysis, we use data provided by the triple *establishment age*, *size*, and *state of location*.[19]

5.1.1 Proxies for Entrepreneurship

Hypotheses 4 and 5 predict that the passage of wrongful discharge laws leads to greater firm creation and firm destruction, with attendant effects on job creation and job destruction. To investigate these hypotheses, we employ the following dependent variables:

- *Establishments created by start-ups*: This variable corresponds to 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, i.e. all establishments that are new entrants to the database in that year. The vast majority of new firms are single-establishment firms.

- *Establishment entries*: This variable measures the number of establishment entrants; in the database, an establishment entrant is defined as an establishment 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 *"Establishments created by start-ups"* above) or due to existing firms opening a new establishment.

- *Establishment Exits*: This variable measures the number of establishment closures; specifically, an establishment exit is an establishment with zero employment in the current year and positive employment in the prior year.[20]

- *Job creation due to start-ups*: This variable measures the number of new jobs resulting from the creation of new firms.

- *Job destruction due to firm deaths*: For any year t, this variable measures the employment losses (from year $t-1$ to year t) that are attributed to establishments that are shutting down.

All these variables[21] are measured annually by firm size and state of establishment location and employ their natural logarithm. To avoid effects of outliers, we winsorize dependent variables at 5%. Summary statistics for these variables are reported in Table 8.

[19]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).

[20]There are some establishments that are temporarily closed and then re-opened and which are counted in the establishment entries and exits; however, the number of such establishments is negligible.

[21]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*.

5.2 Results

For our tests using the entrepreneurship sample, we employ a difference-in-difference strategy similar to that described in Section 4.2. The following panel regression implements these tests:

$$\begin{aligned} y_{klst} &= \beta_s + \beta_t + \beta_1 * Good\_Faith_{st} + \beta_2 * Implied\_Contract_{st} \\ &\quad + \beta_3 * Public\_Policy_{st} + \beta \cdot X_{klst} + \varepsilon_{klst} \end{aligned} \tag{21}$$

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. All the other variables are as defined before. As in our tests for innovation, we estimate standard errors that are clustered at the state level.

5.2.1 Test of Hypothesis 4

In our first set of tests, we investigate the effect of wrongful discharge laws on establishments created by start-up firms. Hypothesis 4(a) predicts a positive effect for the same. The results of these tests are reported in Columns 1 and 2 of Table 9. Column 1 reports the results of the baseline specification where we only include state and year fixed effects. In Column 2, we include the state characteristics — the logarithm of a state's nominal GSP in a given year (*ln(GSP)*), the logarithm of a state's population in a given year (*ln(Population)*), and the logarithm of the number of degree-granting institutions of higher education (colleges) in a state in a given year (*ln(College)*) — as in our tests for innovation.[22]

In both specifications, 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: the adoption of the good faith clause in a state led to an increase in the entry of establishments by 10.1% in that state when compared to the control group of states which did not adopt this particular wrongful discharge law (using the specification of Column 2). The other two exceptions do not matter statistically.

We also examine the effect on establishments created by all firms, i.e. not only by startup firms. The results are displayed in Columns 3 and 4 of Table 9. In Column 3, we run our basic specification with only state and year fixed effects; Column 4 shows the results for the regression that includes state, year and age group fixed effects, as well as our usual set of time-varying state controls. 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. The economic magnitude is quite large: the adoption of the good faith clause in a state led to an increase in the entry of establishments by 5.7% in that state when compared to the control group of states which did not adopt this particular wrongful discharge law (using the specification of Column 4).

In Columns 5 and 6, we explore the concomitant effect on employment due to the creation of new establishments. Column 5 again represents the baseline specification with state and year fixed

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

effects, while Column 6 additionally includes the time-varying state-level controls along with firm age group fixed effects. The effect of good faith on job creation due to start-up firms is consistently positive across all the specifications, although it is not statistically significant. The passage of the good faith clause resulted in a (statistically insignificant) increase in job creation from establishment start-ups by 3.7% (using the results from Column 6) vis-à-vis states that did not adopt this unjust dismissal law.

In sum, we find strong support for part (a) of Hypothesis 4. With respect to part (b) of Hypothesis 4, we find a statistically weak effect that is consistent with this hypothesis.

5.2.2 Test of Hypothesis 5

We now examine Hypothesis 5 which relates the passage of wrongful discharge laws to the closures of existing firms as well as the job losses resulting from such shut-downs. Columns 7–10 of Table 9 document the results using these dependent variables. The specifications in this table are identical to those employed in the previous tests. Across all the specifications, we find a consistently positive effect of the good faith exception on the closure of establishments as well as on job destruction from the exit of such establishments; the effects are statistically significant in three out of the four specifications. The economic magnitudes of these effects are large too — the adoption of the good faith exception in a state led to a 6.7% rise in establishment shut-downs and a 7.4% reduction in employment due to such shut-downs when compared to the control group of states which did not adopt this particular wrongful discharge law (based on coefficient estimates from Columns 8 and 10, respectively). The impact of the other two wrongful discharge laws is statistically negligible.

Overall, our results show that not only do wrongful discharge laws foster innovation, they also hasten the process of creative destruction. This effect is achieved by enhancing the creation of new establishments and new jobs, as well as by hastening the closure of mature establishments which also results in job losses in such establishments.[23]

6 Related Literature

Existing theoretical arguments examining the effects of employment protection make conflicting predictions about the welfare implications of employment protection laws. Early studies argued that employment protection leads to inefficient allocation of resources 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. This is because job switching

[23] In Section 4.3.4, we explained why it could be that California and Massachusetts drive the entrepreneurship results. As argued therein, if our results hold when we exclude these two states from our sample, then such concerns would be alleviated. Indeed, when we re-run our basic specifications by excluding the observations from these two states, the results (available upon request) are qualitatively and quantitatively similar.

is likely to be efficient precisely when current income is low; however, in such states, risk-averse workers may be least willing to pay the job-switching costs. Similarly, MacLeod & Nakavachara (2007) argue that just-cause employment laws can provide workers with better incentives to make relationship-specific investments and can enhance employment, particularly in occupations that require high levels of skill.

Several empirical studies document the economic consequences of wrongful discharge laws. Dertouzos and Karoly (1992) find a 1-5% reduction in employment due to the passage of wrongful-discharge laws while Miles (2000) finds no impact. Autor (2003) investigates the effect of the implied-contract exception on growth in employment in the temporary help services (THS) industry. Consistent with the fact that the implied-contract exception does not apply to THS employment, which is temporary in nature, he finds that the adoption of the implied-contracts exception explains up to 20% of the growth of THS between 1973 and 1995.

Autor et al. (2004) lay emphasis on using unexpected changes in the law to assess its effect on outcome variables. Therefore, Autor et al. (2006) employ a coding that attributes a law change to the month in which a precedent-setting court decision occurs. They find a negative effect of about 0.8-1.7% on state employment rates due to the passage of the implied-contract exception; they also document that the sum of job creation and destruction are significantly reduced by the passage of the implied-contract and good-faith exceptions. Kugler and Saint-Paul (2004) investigate the impact of the wrongful discharge laws through the lens of adverse selection in the labor market. They find that the implied-contract and good-faith exceptions reduced the re-employment likelihood of unemployed workers vis-à-vis employed workers.

Autor et al. (2007) study whether wrongful discharge laws 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. Schanzenbach (2003) finds that the adoption of the implied contract exception increased job tenure, while returns to tenure as well as wages did not increase. Bird and Knopf (2009), in a study focussing on the banking industry, investigate whether the adoption of wrongful discharge laws between 1977 and 1999 had an effect on firm performance. They find that the implied-contracts exception increased labor expenses, and had a negative impact on profitability.

In contrast to the preceding empirical studies that highlight the negative effects of wrongful discharge laws, MacLeod & Nakavachara (2007) find that the passage of wrongful discharge laws increased employment, particularly in occupations that required a high level of skill. Furthermore, Autor et al. (2007) document that the adoption of the good faith exception led to sizeable increases in manufacturing employment. Our study resembles MacLeod & Nakavachara (2007) in documenting the ex-ante incentive benefits of wrongful discharge laws.

In the context of a conglomerate firm, Seru (2007) studies divisional managers' incentives to pursue innovative projects when corporate headquarters cannot commit to not share the surplus generated by a particular innovating division with other divisions in the conglomerate. Seru (2007) argues that this lack of commitment may arise because corporate headquarters may not be able to resist ex-post the temptation to transfer surplus when a more lucrative investment opportunity arises in another division. Since the possibility of sharing surplus ex-post blunts divisional manager incentives ex-ante, conglomerate firms end up stifling innovation when compared to focused firms. His empirical analysis confirms this thesis. Though the settings differ, our paper resembles Seru (2007) in examining how an agent's incentives for innovative effort are affected by the principal (firm)'s inability to commit ex-ante.

In less directly related work, Lerner, Sorensen and Stromberg (2008) examine the effect of private equity investments on innovation. They find evidence that is inconsistent with claims that private equity firms generate profits by sacrificing long-run investments. Instead, they document that private equity investments appear to lead to a beneficial refocusing of the firms' innovative portfolios. This finding is consistent with a greater long-term and illiquid nature of private equity ownership compared to dispersed public ownership, features that serve as a commitment device to management to facilitate long-term projects and R&D.

7 Conclusion

In the corporate sector, some of the most successful innovators like 3M and Google have a culture that encourages employees to take risks and that tolerates failure (Hindo, 2007). 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 simple model and 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 value-maximizing innovative as well as entrepreneurial pursuits. We provide this evidence by studying the effects of the staggered passage of wrongful discharge laws 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 novel establishment-level measures of entrepreneurship and job creation and destruction.

This evidence complements the findings in Acharya, Baghai, and Subramanian (2010), who show in a cross-country setting that stringent dismissal laws lead to greater innovation. Acharya and Subramanian (2009) focus on another aspect of the legal environment – the creditor or debtor friendliness of the bankruptcy code. They find that debtor-friendly codes, by giving firms a "fresh start" when they falter, promote more innovative pursuits. Given the corroborating results of these papers, we conclude that laws 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 (creditor right laws, labor laws, protection of intellectual property rights, etc.) on innovation and economic growth.

Appendix A: Proofs

Steps for deriving the expressions for employee's expected payoff U_j and firm's expected payoff V_j:

$$\begin{aligned}
U_j &= \underbrace{\left(1-\frac{\xi-e_j}{\sigma_j}\right)\cdot\left(q_j^F+q_j^S\alpha_j\right)}_{\text{Project is successful}} + \underbrace{\left(\frac{\xi-e_j}{\sigma_j}\right)\mu\cdot q_j^F}_{\text{Project fails but firm does not fire employee}} \\
&\quad \underbrace{-\frac{\xi-e_j}{\sigma_j}(1-\mu)\cdot\rho q_j^F}_{\text{Employee's dis-utility}} - \underbrace{\frac{e_j^2}{2}}_{\text{Cost of effort}} \qquad \text{(A-1)} \\
V_j &= \underbrace{\left(1-\frac{\xi-e_j}{\sigma_j}\right)\cdot\left[\left(1-q_j^S\right)\alpha_j-q_j^F\right]}_{\text{Project is successful}} + \underbrace{\left(\frac{\xi-e_j}{\sigma_j}\right)\mu\cdot\left(\beta-q_j^F\right)}_{\text{Project fails but firm does not fire employee}} \\
&\quad + \underbrace{\left(\frac{\xi-e_j}{\sigma_j}\right)\int_\mu^1(\gamma+\delta-\theta)\,d\delta}_{\text{Project fails and firm replaces original employee}} \qquad \text{(A-2)}
\end{aligned}$$

where μ denotes the probability of retaining the original employee. Note that the last term in V_j captures the fact that the original employee is replaced only if $\delta > \mu$ (using Lemma 1) and cash flows under the new employee equals $\gamma+\delta-\theta$. Also, note that U_j incorporates the fact that the employee gets no wage if she is fired.

Proof of Lemma 2: The optimal project choice is given by

$$\begin{aligned}
&\max_j V_j\left(e_j^*, q_j^*\right) \qquad \text{(A-3)}\\
&s.t.\ U_j\left(e_j^*, q_j^*\right) \geq 0\\
&e_j^*\left(q_j\right) = \arg\max_{e_j} U_j\left(e_j; q_j\right)\\
&q_j^* = \arg\max_{q_j} V_j\left[q_j\left(e_j^*\right)\right]
\end{aligned}$$

where the employee's reservation utility in equilibrium equals 0. Since the labor market is competitive, the IR constraint is satisfied with equality. Therefore, $U_j = 0$. Since $V_j = W_j - U_j$, the above problem reduces to

$$\begin{aligned}
&\max_{(q,j)} W_j\left(e_j^*, q_j^*\right) \qquad \text{(A-4)}\\
&e_j^*\left(q_j\right) = \arg\max_{e_j} U_j\left(e_j; q_j\right)\\
&q_j^* = \arg\max_{q_j} V_j\left[q_j\left(e_j^*\right)\right]
\end{aligned}$$

$\diamondsuit$

Steps for deriving the expressions for q_j^{F*}, q_j^{S*} and e_j^* when $\mu > 0$ and $\rho > 0$: Simplifying equation $(A-1)$ we get

$$U_j = q_j^F + q_j^S \alpha_j - \left(\frac{\xi - e_j}{\sigma_j}\right)\left[q_j^F (1-\mu)(1+\rho) + q_j^S \alpha_j\right] - \frac{e_j^2}{2} \tag{A-5}$$

Given project j and the compensation contract $\left(q_j^S, q_j^F\right)$, the choice of investment e_j^*, which maximizes U_j, is given by the unique solution:

$$e_j^*(q_j) = \frac{\left[q_j^S \alpha_j + q_j^F (1-\mu)(1+\rho)\right]}{\sigma_j} \tag{A-6}$$

Simplifying equation $(A-2)$ we get

$$V_j = \left(1 - \frac{\xi - e_j}{\sigma_j}\right) \cdot \left[\left(1 - q_j^S\right)\alpha_j - q_j^F\right] + \left(\frac{\xi - e_j}{\sigma_j}\right)\left[\mu\left(\beta - q_j^F\right) + (1-\mu)\left\{\gamma - \theta + 0.5(1+\mu)\right\}\right] \tag{A-7}$$

Differentiating w.r.t. q_j^S and q_j^F and setting the derivatives equal to zero, we get

$$\frac{dV_j^*}{dq_j^S} = \underbrace{-\left(1 - \frac{\xi - e_j^*}{\sigma_j}\right)\alpha_j}_{\text{Cost of increasing } q_j^S\text{: lower payoff to firm}} + \underbrace{\frac{Q_j}{\sigma_j}\frac{de_j^*}{dq_j^S}}_{\substack{+ \\ \text{Benefit of increasing } q_j^S\text{: Greater effort by employee}}} \tag{A-8}$$

$$\frac{dV_j^*}{dq_j^F} = \underbrace{-\left\{1 - \frac{\xi - e_j^*}{\sigma_j}(1-\mu)\right\}}_{\text{Cost of increasing } q_j^F\text{: lower payoff to firm}} + \underbrace{\frac{Q_j}{\sigma_j}\frac{de_j^*}{dq_j^F}}_{\substack{+ \\ \text{Benefit of increasing } q_j^F\text{: Greater effort by employee}}} \tag{A-9}$$

where for notational simplicity, we define

$$Q_j = \left(1 - q_j^S\right)\alpha_j - (1-\mu)\,q_j^F - \mu\beta - (1-\mu)\left\{\gamma - \theta + 0.5(1+\mu)\right\} \tag{A-10}$$

Also, using equation $(A-6)$ we get

$$\frac{de_j^*}{dq_j^S} = \frac{\alpha_j}{\sigma_j}; \frac{de_j^*}{dq_j^F} = \frac{(1-\mu)(1+\rho)}{\sigma_j} \tag{A-11}$$

Finally, using equation $(A-8)$ and $(A-11)$ we get

$$\frac{\xi - e_j^*}{\sigma_j} = 1 - \frac{\mu}{\rho(1-\mu)} \tag{A-12}$$

Since $\mu = \beta - \gamma + \theta < \frac{\rho}{\rho+1}$ using (8), it follows that the equilibrium probabilities of project success and failure are non-negative. Substituting equation $(A-12)$ together with equation $(A-6)$ and solving we get

$$q_j^{F*} = \frac{\sigma_j \xi - \alpha_j + \mu\beta}{\rho(1-\mu)} + \left[\frac{2\mu}{\rho^2(1-\mu)^2} - \frac{1}{(1-\mu)\rho}\right]\sigma_j^2 + \frac{\gamma - \theta + 0.5(1+\mu)}{\rho} \tag{A-13}$$

$$\alpha_j q_j^{S*} = \sigma_j \xi - \left[1 - \frac{\mu}{\rho(1-\mu)}\right]\sigma_j^2 - (1-\mu)(1+\rho) q_j^{F*} \tag{A-14}$$

$\diamondsuit$

Proof of Proposition 1: Part (a): Using equation $(A-8)$ and $(A-11)$ with $\rho = 0$, it is easy to show that $\frac{1}{\alpha_j}\frac{dV_j^*}{dq_j^S} - \frac{1}{1-\mu}\frac{dV_j^*}{dq_j^F} = \frac{\mu}{1-\mu}$. Since $\mu > 0$, both $\frac{dV_j^*}{dq_j^S}$ and $\frac{dV_j^*}{dq_j^F}$ cannot equal zero simultaneously. Therefore, both q_j^S and q_j^F cannot have interior solutions. Now using equations $(A-5)$ and $(A-7)$, we get

$$W_j^*(\rho = 0) = U_j^*(\rho = 0) + V_j^*(\rho = 0) = \tag{A-15}$$

$$\left(1 - \frac{\xi - e_j^*}{\sigma_j}\right)\alpha_j + \left(\frac{\xi - e_j}{\sigma_j}\right)\left[\mu\left(\beta - q_j^F\right) + (1-\mu)\{\gamma - \theta + 0.5(1+\mu)\}\right] - \frac{\left(e_j^*\right)^2}{2} \tag{A-16}$$

so that

$$\frac{dW_j^*(\rho = 0)}{dq_j^S} = \frac{\left(1 - q_j^S\right)\alpha_j - \mu\beta - (1-\mu)\{\gamma - \theta + 0.5(1+\mu)\} - q_j^F(1-\mu)}{\sigma_j}\frac{\alpha_j}{\sigma_j}$$

When $q_j^S = 1$, $\frac{dW_j^*(\rho=0)}{dq_j^S} < 0$. Therefore, the total surplus can be improved by decreasing q_j^S. Furthermore, since $q_j^S = 1$ implies that the firm does not get any of the cash flow when the project is successful, the firm finds it individually rational as well to choose $q_j^S < 1$. Therefore, $\frac{dV_j^*(\rho=0)}{dq_j^S} \leq 0$. Using equation $(A-8)$ this implies $\frac{Q_j}{\sigma_j^2} \leq 1 - \frac{\xi - e_j^*}{\sigma_j}$, which in turn implies $\frac{dV_j^*(\rho=0)}{dq_j^F} \leq -\mu < 0$. Therefore, $q_j^{F*} = 0$. Using equation $(A-6)$ it follows that $\frac{de_j^*}{d\mu} = 0$.

Parts (b) and (c): Using (9), it follows that $\theta = 0 \Rightarrow \mu = 0$ and $\theta > 0 \Rightarrow \mu > 0$. Using equation $(A-8)$ with $\mu = 0$, we get

$$\frac{1}{1+\rho}\frac{dV_j^*(\theta = 0)}{dq_j^F} - \frac{1}{\alpha_j}\frac{dV_j^*(\theta = 0)}{dq_j^S} = \frac{\rho}{1+\rho}\left(1 - \frac{\xi - e_j^*}{\sigma_j}\right) \tag{A-17}$$

Since $\rho > 0$, it implies that both $\frac{dV_j^*(\theta=0)}{dq_j^F}$ and $\frac{dV_j^*(\theta=0)}{dq_j^S}$ can equal zero only if the probability of success in equilibrium, which equals $\left(1 - \frac{\xi - e_j^*}{\sigma_j}\right)$, is zero always. Since the firm would like to choose the compensation contracts such that the probability of success is positive, both q_j^S and q_j^F cannot have interior solutions. Now, using equations $(A-5)$ and $(A-7)$ with $\mu = 0$ we get

$$W_j(\theta = 0) = \left(1 - \frac{\xi - e_j}{\sigma_j}\right)\alpha_j + \left(\frac{\xi - e_j}{\sigma_j}\right)\left[\gamma + 0.5(1+\mu) - \rho q_j^F\right] - \frac{e_j^2}{2} \tag{A-18}$$

so that

$$\frac{dW_j(\theta = 0)}{dq_j^S} = \left[\frac{\left(1 - q_j^S\right)\alpha_j - q_j^F - \gamma - 0.5}{\sigma_j}\right]\frac{\alpha_j}{\sigma_j}$$

Thus, $\frac{dW_j(\theta=0)}{dq_j^S} < 0$ if $q_j^S = 1$. Therefore, the total surplus can be improved by decreasing q_j^S from $q_j^S = 1$. Furthermore, since $q_j^S = 1$ implies that the firm does not get any of the cash flow when the project is successful, this implies that the firm would choose $q_j^S < 1$. Similarly, since $\alpha_j > 2\gamma > \gamma + \beta + 0.5 > \gamma + q_j^F + 0.5$ using (3), it follows that $\frac{dW_j}{dq_j^S} > 0$ if $q_j^S = 0$. Therefore, the total surplus can be improved by increasing q_j^S from $q_j^S = 0$ (to increase the employee's effort). Therefore, $q_j^S > 0$. It follows that q_j^S has an interior solution. Using $\frac{dV_j^*\left(q_j^{S*}\right)}{dq_j^S} = 0$ together with equation $(A-6)$ and solving we get:

$$q_j^{S*}(\mu = 0) = \frac{\xi + k}{2k} - \frac{\sigma_j}{2k} - \frac{\beta(2+\rho) + \gamma + 0.5}{2k\sigma_j} \tag{A-19}$$

From equation $(A-17)$, it follows using $\frac{dV_j^*\left(q_j^{S*}\right)}{dq_j^S} = 0$ that $\frac{dV_j^*}{dq_j^F} > 0$, which implies that q_j^F has the boundary solution $q_j^{F*} = \beta$. As we have shown above (see "*Steps for deriving the expressions for* q_j^{F*}, q_j^{S*} *and* e_j^* *when* $\mu > 0$ *and* $\rho > 0$") q_j^S and q_j^F have interior solutions when $\mu > 0$ and $\rho > 0$. Therefore $q_j^F < \beta$ when $\theta > 0$ and $\rho > 0$.$\diamondsuit$

Proof of Proposition 2: Using equation $(A-12)$ we get

$$\frac{de_j^*}{d\sigma_j} = -\left[1 - \frac{\mu}{\rho(1-\mu)}\right] < 0 \text{ using } (8) \therefore \sigma_I > \sigma_R \Rightarrow e_I^* < e_R^* \tag{A-20}$$

$$\frac{d^2 e_j^*}{d\sigma_j d\mu} = \frac{1}{\rho(1-\mu)^2} > 0 \therefore \sigma_I > \sigma_R \Rightarrow \frac{d\left(e_I^* - e_R^*\right)}{d\mu} > 0 \tag{A-21}$$

$\diamondsuit$

Proof of Proposition 3: Using equations $(A-5)$ and $(A-7)$ together with equation (5), we get

$$W_j^* = \frac{\mu k \sigma_j}{\rho(1-\mu)} + \left(1 - \frac{\mu}{\rho(1-\mu)}\right)\left[\mu\beta + (1-\mu)\left\{\gamma + 0.5(1+\mu) - \rho q_j^{F*}\right\}\right] - \frac{\left(e_j^*\right)^2}{2} \tag{A-22}$$

Differentiating w.r.t. σ_j and simplifying we get

$$\frac{dW_j^*}{d\sigma_j} = \sigma_j + k - \frac{4\sigma_j\mu}{\rho(1-\mu)} + \frac{3\sigma_j\mu^2}{\rho^2(1-\mu)^2} \tag{A-23}$$

Now differentiating w.r.t. σ we get

$$\frac{d^2 W_j^*}{d\mu d\sigma_j} = \frac{2\sigma_j}{\rho\left(1-\mu\right)^2}\left[\frac{3\mu}{\rho\left(1-\mu\right)} - 2\right]$$

Define $\overline{\rho} = \frac{2(1-\mu)}{3\mu}$. Then $\rho < \overline{\rho} \Rightarrow \rho < \frac{2(1-\mu)}{3\mu} \Rightarrow \frac{d^2W_j^*}{d\theta d\sigma_j} = \frac{d^2W_j^*}{d\mu d\sigma_j} > 0$. Since θ increases monotonically with μ, it follows that $\frac{dW_R^*}{d\theta} < \frac{dW_I^*}{d\theta}$.$\diamondsuit$

Proof of Proposition 4: Define $\overline{\sigma} = 3k$. Then using equation $(A-23)$ we get $\left.\frac{dW_j^*}{d\sigma_j}\right|_{\mu=\frac{2\rho}{2\rho+3}} = k - \frac{\sigma_j}{3} < 0$ since $\sigma_j > \overline{\sigma}$ according to (6). Now using $(A-23)$ again, we get $\left.\frac{dW_j^*}{d\sigma_j}\right|_{\mu=\frac{\rho}{\rho+1}} = k > 0$. Since $\frac{d^2W_j^*}{d\mu d\sigma_j} > 0$ (as proved in Proposition 3) and $\frac{2\rho}{2\rho+3} < \frac{\rho}{\rho+1}$, it follows that $\frac{dW_j^*}{d\sigma_j}$ has a single crossing in the range $\mu \in \left[\frac{2\rho}{2\rho+3}, \frac{\rho}{\rho+1}\right]$. The result therefore follows using the fact that θ varies positively with μ.$\diamondsuit$

Appendix B – "Difference-in-Difference" Interpretation for Fixed Effect Panel Regressions

In this Appendix, we show that the fixed effects panel regressions employed in equation (19) estimate a "difference-in-difference" in a generalized multiple treatment groups, multiple time period setting.

We begin with the model specification used in equation (19); without loss of generality, we focus on the "Good Faith" clause only in order to make the exposition more tractable:

$$y_{ist} = \beta_i + \beta_t + \beta_1 * Good\_Faith_{st} + \beta \cdot X + \varepsilon_{ist} \tag{B-1}$$

During the sample period 1970-1999, suppose the wrongful discharge law index for state s, $Good\_Faith_{st}$, changes n times in years $t_1, ..., t_n$ where $1 < ... < n$ and t_l denotes the year in which the l^{th} change occurred for state s. Denote $m_l = [t_l + 1, t_{l+1}]$ as the time interval during which the l^{th} change has occurred but not the $(l+1)^{th}$. Let $Good\_Faith_s(m_l)$ denote the value of the good faith index during the period m_l. Thus, $Good\_Faith_{st} = Good\_Faith_s(m_l)$ for any $t \in m_l$.

Therefore,

$$\begin{aligned} y_{ist} &= \beta_i + \beta_t + \beta_1 \cdot Good\_Faith_s(m_l) + \varepsilon_{ist}, t \in m_l & \text{(B-2)} \\ y_{ist'} &= \beta_i + \beta_{t'} + \beta_1 \cdot Good\_Faith_s(m_{l+1}) + \varepsilon_{ist'}, t' \in m_{l+1} & \text{(B-3)} \end{aligned}$$

Subtracting $(B-2)$ from $(B-3)$, we obtain

$$y_{ist'} - y_{ist} = (\beta_{t'} - \beta_t) + \beta_1 \cdot \Delta Good\_Faith_{sl} + \varepsilon_{ist'} - \varepsilon_{ist} \tag{B-4}$$

where

$$\Delta Good\_Faith_{sl} = Good\_Faith_s(m_{l+1}) - Good\_Faith_s(m_l)$$

denotes the magnitude of the l^{th} change in the good faith index in state s.

Let s' denote a state that did not adopt a good faith exception over the time intervals m_l or m_{l+1} or equivalently the time period $[t_l + 1, t_{l+2}]$.

$$y_{is't} = \beta_i + \beta_t + \beta_1 \cdot Good\_Faith_{s'}(m_l) + \nu_{ist}, t \in m_l \tag{B-5}$$

$$y_{is't'} = \beta_i + \beta_{t'} + \beta_1 \cdot Good\_Faith_{s'}(m_{l+1}) + \nu_{ist'}, t' \in m_{l+1} \tag{B-6}$$

Because the good faith index is unchanged over the time period $[t_l + 1, t_{l+2}]$,

$$Good\_Faith_{s'}(m_l) = Good\_Faith_{s'}(m_{l+1}) \tag{B-7}$$

Subtracting $(B-5)$ from $(B-6)$ and using $(B-7)$, we obtain

$$y_{is't'} - y_{is't} = (\beta_{t'} - \beta_t) + \nu_{ist'} - \nu_{ist} \tag{B-8}$$

Subtracting $(B-8)$ from $(B-4)$, we obtain

$$[y_{ist'} - y_{ist}] - [y_{is't'} - y_{is't}] = \beta_1 \cdot \Delta Good\_Faith_{sl} + [(\varepsilon_{ist'} - \nu_{ist'}) - (\varepsilon_{ist} - \nu_{ist})]$$

Assuming that

$$E\left[\{(\varepsilon_{ist'} - \nu_{ist'}) - (\varepsilon_{ist} - \nu_{ist})\} \,|\Delta Good\_Faith_{sl}\right] = 0 \tag{B-9}$$

we get after taking expectations

$$\beta_1 \cdot \Delta Good\_Faith_{s,l} = \underbrace{E\left[y_{ist'} - y_{ist}\right]}_{\text{Before-after difference for Treatment}} - \underbrace{E\left[y_{is't'} - y_{is't}\right]}_{\text{Before-after difference for Control}}$$

Thus, the coefficient β_1 in $(B-1)$ estimates the "difference-in-difference" in a multiple treatment groups, multiple time periods setting.

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

The figure shows the adoption of *Wrongful-Discharge Laws* in U.S. states over the time-period 1970–1999. Specifically, for each year, we plot the number of U.S. states that have adopted a given unjust-dismissal provision. The wrongful discharge data coding is from Autor, Donohue, and Schwab (2006).

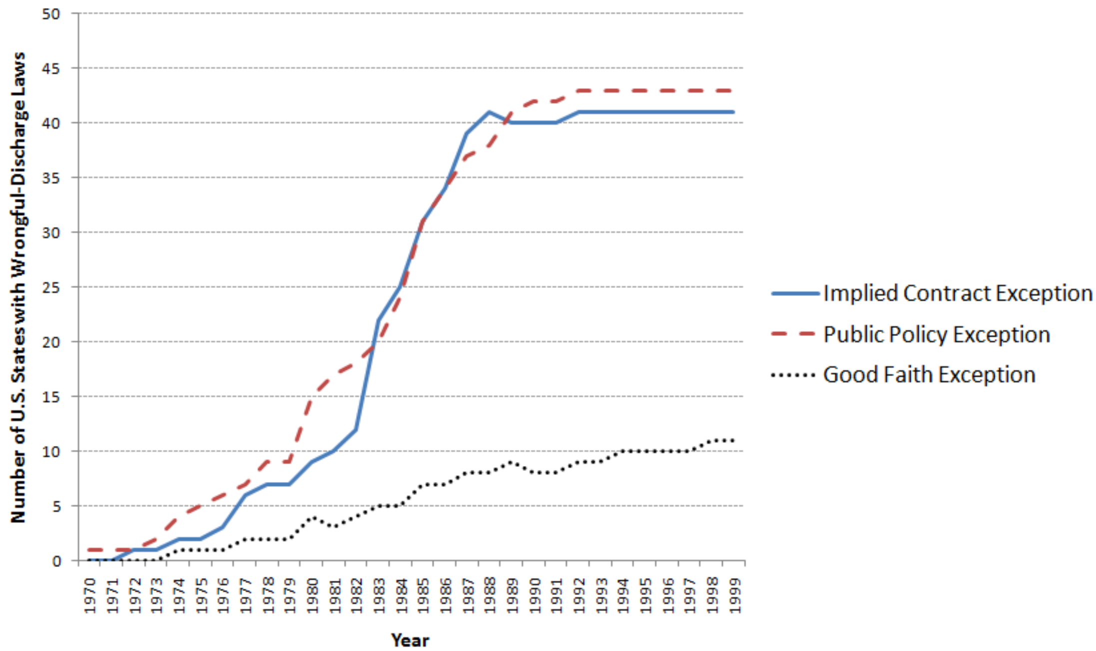

Figure 2: **Cross-Sectional and Time-Series Variation in the Wrongful Discharge Laws**

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, for each year, we plot the aggregate number of *Wrongful-Discharge Laws* adopted by a given state. The wrongful discharge data coding is from Autor, Donohue, and Schwab (2006).

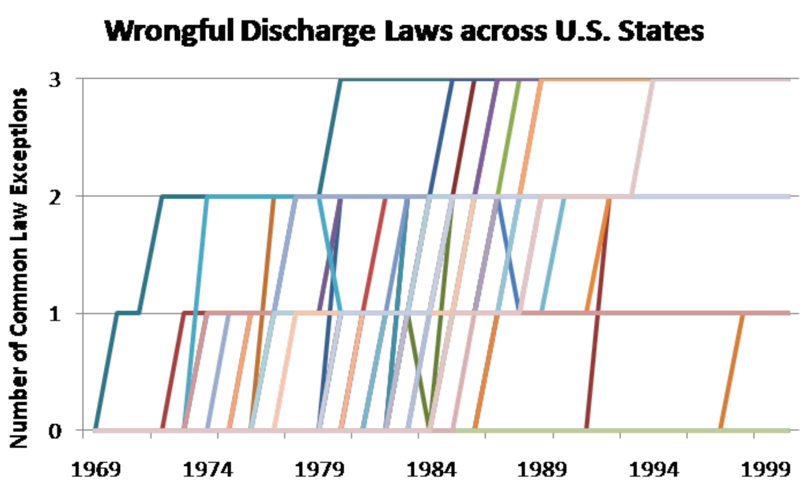

Figure 3: **Timing and Sequence of Events.**

The figure shows the timing and sequence of events for our model described in Section 3.

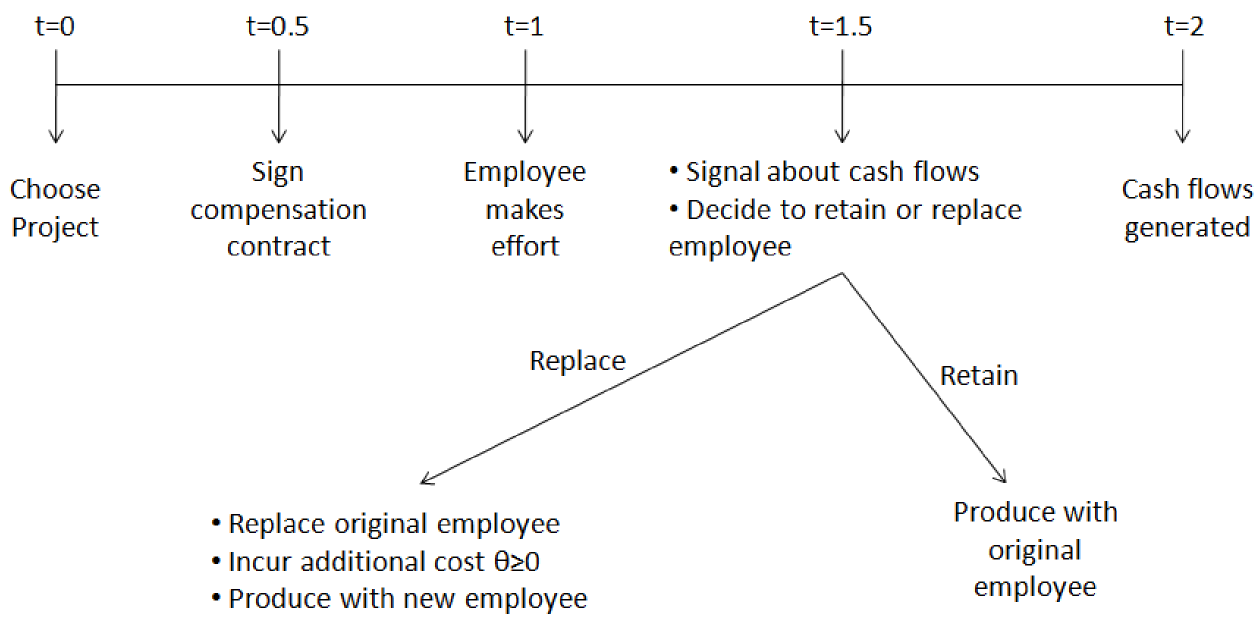

Figure 4: **Effect of the Passage of the Good-Faith Exception in California in 1980.**

This figure shows a visual difference-in-difference examining the effect of the passage of the good faith exception in California in 1980. On the y-axis, the graph plots the logarithm of the number of patents filed by firms in California over the years 1975-1991 vis-à-vis the same for the states that did not pass any wrongful discharge law during this period, which included Delaware, Florida, Georgia, Louisiana, Pennsylvania and Rhode Island; to enable comparison, the measure is normalized to equal 1 in 1980.

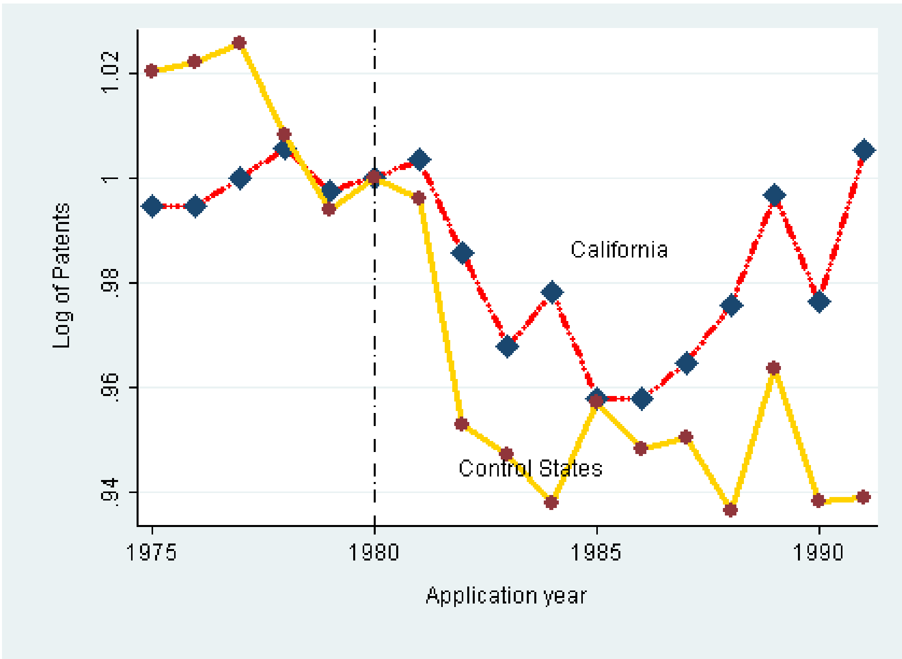

Table 1: **Summary Statistics – Innovation Sample.**

In this table, we give summary statistics for the variables used in the difference-in-difference regressions. The following **dependent variables** are employed in the difference-in-difference tests: $ln(Patents)$, $ln(Citations)$; $Ln(Patents/Employee)$, 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 $ln(Citations/R\&D)$, the last two variables being defined analogously.

The **explanatory variables** employed 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 sales. *Anti-Takeover Index* is the state-level index of anti-takeover statutes from Bebchuk and Cohen (2003). $ln(R\&D/Sales)$ is the log of the ratio of research and development expenditures to firm sales; missing values of research and development expenditures are set to zero. *Competition* is the fraction of total (2-digit) industry sales (excluding those of the firm itself) 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 1977–2000). $ln(GSP)$ is the logarithm of nominal GSP per state and year. $ln(Population)$ is the logarithm of a state's population in a given year. $ln(College)$ is the logarithm of the number of degree-granting institutions of higher education (colleges) in a given state and year.

Patent data is from the NBER Patents File (Hall, Jaffe and Trajtenberg, 2001). The wrongful discharge law data is based on the coding by Autor et al. (2006). Firm-level data is from Compustat. Data on state value added and population is from the U.S. Bureau of Economic Analysis. Data on the number of colleges is from the annual Statistical Abstracts from the U.S. Census Bureau. The sample spans 1970–1999.

	Dependent Variables					
	Obns.	*Mean*	*Median*	*Std. Devn.*	*Min.*	*Max.*
Number of patents	82,452	7.486	2	28.053	1	1,157
Number of citations	82,452	58.304	11	234.350	0	9,319
ln(Patents)	82,452	1.350	1.099	0.923	0.693	7.054
ln(Citations)	82,452	2.560	2.485	1.575	0	9.140
ln(Patents/Employee)	78,748	-1.183	-1.403	2.206	-6.776	7.601
ln(Patents/R&D)	69,674	-2.213	-2.157	2.250	-9.094	8.006
ln(Citations/Employee)	71,732	0.518	0.357	2.421	-6.743	10.609
ln(Citations/R&D)	63,357	-0.423	-0.364	2.549	-9.094	9.741
	Explanatory Variables					
	Observations	*Mean*	*Median*	*Standard Deviation*	*Minimum*	*Maximum*
Good Faith	82,452	0.179	0	0.383	0	1
Implied Contract	82,452	0.528	1	0.499	0	1
Public Policy	82,452	0.593	1	0.491	0	1
Market-to-Book	72,750	1.779	1.247	2.304	0.180	144.258
Size	80,395	6.543	6.914	2.457	-6.908	12.071
Anti-takeover Index	73,043	1.010	0	1.443	0	5
ln(R&D/Sales)	69,272	-3.425	-3.507	1.400	-10.248	7.555
Competition	75,896	0.071	0.031	0.104	0	0.961
$Competition^2$	75,896	0.016	0.001	0.050	0	0.923
Ratio of Value Added	55,496	0.090	0.082	0.051	0.000	0.481
ln(GSP)	55,496	11.985	11.995	1.031	8.144	14.124
ln(Population)	82,452	15.833	15.832	0.856	12.626	17.327
ln(College)	82,452	4.604	4.644	0.797	1.099	6.016

Table 2: **Difference-in-Difference Tests with Patents and Citations as Dependent Variables.**

The OLS regressions below implement the following model:
$y_{ist} = \beta_i + \beta_t + \beta_1 * Good\_Faith_{st} + \beta_2 * Implied\_Contract_{st} + \beta_3 * Public\_Policy_{st} + \beta \cdot X_{ist} + \varepsilon_{ist}$
where y_{ist} is a measure of innovation for firm i from state s in year t; in these regressions we employ $ln(Patents)$ and $ln(Citations)$ as our dependent variables. β_i and β_t denote respectively firm and application year fixed effects. β_1 – β_3 measure the difference-in-difference effects of the passage of the three unjust-dismissal provisions (*Good Faith*, *Implied Contract*, and *Public Policy*).
X_{ist} denotes the set of control variables. *Market-to-Book* ratio is the market value of assets to total book assets. *Size* is the natural logarithm of sales. *Anti-Takeover Index* is the state-level index of anti-takeover statutes from Bebchuk and Cohen (2003). $ln(R\&D/Sales)$ is the log of the ratio of research and development expenditures to firm sales. *Competition* is the fraction of total (2-digit) industry sales (excluding those of the firm itself) 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 gross state product (GSP) in a given sector and state divided by the total GSP in that state (data for 1977–2000). $ln(GSP)$ is the logarithm of nominal GSP per state and year. $ln(Population)$ is the logarithm of a state's population in a given year. $ln(College)$ is the logarith of the number of degree-granting institutions of higher education (colleges) in a given state and year. Patent data is from the NBER Patents File (Hall, Jaffe and Trajtenberg, 2001). The wrongful discharge law data is based on the coding by Autor et al. (2006). Firm-level data is from Compustat. Data on state value added and population is from the U.S. Bureau of Economic Analysis. Data on the number of colleges is from the annual Statistical Abstracts from the U.S. Census Bureau. The sample spans 1970–1999. 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)	(4) ln(Citations)
Good Faith	0.146*	0.250***	0.087*	0.160***
	(0.073)	(0.083)	(0.045)	(0.058)
Public Policy	0.074	0.119**	0.074**	0.127**
	(0.049)	(0.053)	(0.036)	(0.048)
Implied Contract	0.093**	0.155***	-0.004	0.030
	(0.038)	(0.044)	(0.033)	(0.043)
Market-to-Book			-0.002	-0.010**
			(0.002)	(0.004)
Size			0.097***	-0.030
			(0.023)	(0.022)
ln(R&D/Sales)			0.082***	0.060***
			(0.018)	(0.022)
Competition			4.270***	4.905***
			(0.574)	(0.832)
Competition^2			-4.511***	-4.915***
			(0.825)	(1.164)
Ratio of Value Added			1.264**	1.680**
			(0.539)	(0.671)
Anti-takeover Index			-0.005	0.003
			(0.010)	(0.010)
ln(College)			-0.054	-0.075
			(0.070)	(0.090)
ln(GSP)			-0.031	0.096
			(0.144)	(0.229)
ln(Population)			0.136	0.051
			(0.174)	(0.253)
Firm and Year Fixed Effects	Y	Y	Y	Y
Observations	82,452	82,452	38,019	38,019
R-squared	0.207	0.347	0.238	0.396

Table 3: **Difference-in-Difference Tests with Patents and Citations, Scaled by Employees (/by R&D Dollars), as Dependent Variables.**

The OLS regressions below implement the following model:
$y_{ist} = \beta_i + \beta_t + \beta_1 * Good\_Faith_{st} + \beta_2 * Implied\_Contract_{st} + \beta_3 * Public\_Policy_{st} + \beta \cdot X_{ist} + \varepsilon_{ist}$
where y_{ist} is a measure of innovation for firm i from state s in year t; in the regressions in Columns 1–4, we employ $Ln(Patents/Employee)$ and $Ln(Citations/Employee)$ as our first set of dependent variables; these are the log of the number of patents (resp. citations) per 1,000 firm employees. In Columns 5–8, we employ $Ln(Patents/R\&D)$ and $Ln(Citations/R\&D)$ as our dependent variables; these are the log of the number of patents (resp. citations) per million R&D dollars. β_i and β_t denote respectively firm and application year fixed effects. $\beta_1 - \beta_3$ measure the difference-in-difference effects of the passage of the three unjust-dismissal provisions (*Good Faith*, *Implied Contract*, and *Public Policy*).
X_{ist} denotes the set of control variables. *Market-to-Book* ratio is the market value of assets to total book assets. *Size* is the natural logarithm of sales. *Anti-Takeover Index* is the state-level index of anti-takeover statutes from Bebchuk and Cohen (2003). $ln(R\&D/Sales)$ is the log of the ratio of research and development expenditures to firm sales. *Competition* is the fraction of total (2-digit) industry sales (excluding those of the firm itself) 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 gross state product (GSP) in a given sector and state divided by the total GSP in that state (data for 1977–2000). $ln(GSP)$ is the logarithm of nominal GSP per state and year. $ln(Population)$ is the logarithm of a state's population in a given year. $ln(College)$ is the logarithm of the number of degree-granting institutions of higher education (colleges) in a given state and year.
Patent data is from the NBER Patents File (Hall, Jaffe and Trajtenberg, 2001). The wrongful discharge law data is based on the coding by Autor et al. (2006). Firm-level data is from Compustat. Data on state value added and population is from the U.S. Bureau of Economic Analysis. Data on the number of colleges is from the annual Statistical Abstracts from the U.S. Census Bureau. The sample spans 1970–1999. 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(Pat. /Emp.)	(2) ln(Cit. /Emp.)	(3) ln(Pat. /Emp.)	(4) ln(Cit. /Emp.)	(5) ln(Pat. /R&D)	(6) ln(Cit. /R&D)	(7) ln(Pat. /R&D)	(8) ln(Cit. /R&D)
Good Faith	0.173*	0.228**	0.118**	0.187***	0.184*	0.238**	0.113*	0.178**
	(0.095)	(0.093)	(0.056)	(0.068)	(0.098)	(0.095)	(0.060)	(0.075)
Public Policy	0.126**	0.162***	0.090*	0.098*	0.156**	0.192***	0.097**	0.107**
	(0.060)	(0.058)	(0.045)	(0.051)	(0.065)	(0.063)	(0.043)	(0.051)
Implied Contract	0.119**	0.150***	0.002	0.034	0.142**	0.180***	0.005	0.038
	(0.052)	(0.046)	(0.040)	(0.046)	(0.059)	(0.054)	(0.042)	(0.048)
Market-to-Book			0.002	0.000			-0.010*	-0.010
			(0.003)	(0.005)			(0.005)	(0.007)
Size			-0.642***	-0.769***			-0.587***	-0.703***
			(0.035)	(0.025)			(0.045)	(0.034)
ln(R&D/Sales)			-0.103***	-0.126***				
			(0.020)	(0.031)				
Competition			5.229***	5.261***			5.194***	5.199***
			(0.669)	(0.818)			(0.749)	(0.902)
Competition^2			-5.753***	-5.228***			-5.599***	-5.048***
			(0.954)	(1.185)			(1.101)	(1.329)
Ratio of Value Added			1.809***	1.968***			1.588**	1.721**
			(0.661)	(0.678)			(0.670)	(0.690)
Anti-takeover Index			-0.001	0.014			-0.011	-0.000
			(0.012)	(0.011)			(0.015)	(0.013)
ln(College)			-0.061	-0.066			-0.055	-0.058
			(0.086)	(0.108)			(0.087)	(0.110)
ln(GSP)			-0.013	0.075			-0.089	0.008
			(0.177)	(0.258)			(0.187)	(0.276)
ln(Population)			0.148	0.068			0.221	0.131
			(0.215)	(0.295)			(0.223)	(0.309)
Firm and Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Observations	78,748	71,732	37,820	34,021	69,674	63,357	38,019	34,198
R-squared	0.753	0.669	0.755	0.671	0.733	0.676	0.706	0.649

Table 4: **Relative Impact of Wrongful Discharge Laws on Aggregate Innovation in Different Industries based on their Innovation Intensity.**

The OLS regressions below implement the following model:
$y_{ist} = \beta_i + \beta_t + \beta_1 * Good\_Faith_{st} * High\_Intensity_{jt} + \beta_2 * Good\_Faith_{st} * Low\_Intensity_{jt} + \beta_3 * Implied\_Contract_{st} * High\_Intensity_{jt} + \beta_4 * Implied\_Contract_{st} * Low\_Intensity_{jt} + \beta_5 * Public\_Policy_{st} * High\_Intensity_{jt} + \beta_6 * Public\_Policy_{st} * Low\_Intensity_{jt} + \beta \cdot X_{ist} + \varepsilon_{ist}$
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. β_1, β_2, and β_3 measure the difference-in-difference effect of the passage of unjust-dismissal provisions (Good Faith, Implied Contract, and Public Policy, respectively) for high innovation intensity industries, while β_2, β_4, and β_6 measure the effect of the passage of unjust-dismissal provisions (Good Faith, Implied Contract, and Public Policy, respectively) for low innovation intensity industries. $High\_Intensity_{jt}$ takes the value of one, if the mean number of patents filed in a given 2-digit SIC industry in a given year exceeds the median value of these mean 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 the following additional control variables, which are included in the regressions but whose coefficients are not reported to conserve space: *Market-to-Book* ratio is the market value of assets to total book assets. *Size* is the natural logarithm of sales. *Anti-Takeover Index* is the state-level index of anti-takeover statutes from Bebchuk and Cohen (2003). $ln(R\&D/Sales)$ is the log of the ratio of research and development expenditures to firm sales. *Competition* is the fraction of total (2-digit) industry sales (excluding those of the firm itself) generated by competitors in a given state (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 gross state product (GSP) in a given sector and state divided by the total GSP in that state and year (data for 1977–2000). $ln(GSP)$ is the logarithm of nominal GSP per state and year. $ln(Population)$ is the logarithm of a state's population in a given year. $ln(College)$ is the number of degree-granting institutions of higher education (colleges) in a given state and year.
Patent data is from the NBER Patents File (Hall, Jaffe and Trajtenberg, 2001). The wrongful discharge law data is based on the coding by Autor et al. (2006). Firm-level data is from Compustat. Data on state value added and population is from the U.S. Bureau of Economic Analysis. Data on the number of colleges is from the annual Statistical Abstracts from the U.S. Census Bureau. The sample spans 1970–1999. 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 /Employees)	(4) ln(Citations /Employees)	(5) ln(Patents /R&D)	(6) ln(Citations /R&D)
Good Faith ∗ High_Intensity	0.099**	0.181***	0.132***	0.220***	0.129**	0.214***
	(0.041)	(0.052)	(0.049)	(0.062)	(0.050)	(0.063)
Good Faith ∗ Low_Intensity	0.056	0.107	0.082	0.106	0.078	0.104
	(0.070)	(0.092)	(0.086)	(0.101)	(0.086)	(0.102)
Public Policy ∗ High_Intensity	0.083**	0.139***	0.099*	0.113**	0.102**	0.118**
	(0.041)	(0.051)	(0.050)	(0.053)	(0.049)	(0.052)
Public Policy ∗ Low_Intensity	0.044	0.088	0.062	0.053	0.074	0.065
	(0.049)	(0.083)	(0.064)	(0.088)	(0.062)	(0.085)
Implied Contract ∗ High_Intensity	-0.020	0.009	-0.012	0.018	-0.016	0.013
	(0.040)	(0.055)	(0.049)	(0.055)	(0.048)	(0.055)
Implied Contract ∗ Low_Intensity	0.044	0.090	0.042	0.080	0.058	0.099
	(0.045)	(0.067)	(0.057)	(0.073)	(0.055)	(0.072)
High_Intensity	0.007	-0.017	-0.006	-0.059	0.020	-0.026
	(0.044)	(0.073)	(0.050)	(0.068)	(0.052)	(0.069)
Additional Control Variables	*Y*	*Y*	*Y*	*Y*	*Y*	*Y*
Firm and Year Fixed Effects	Y	Y	Y	Y	Y	Y
Observations	38,019	38,019	37,820	34,021	38,019	34,198
R-squared	0.239	0.396	0.755	0.671	0.730	0.667

Table 5: **Robustness: Difference-in-Difference Tests – Excluding California and Massachusetts.**

The OLS regressions below implement the following model:
$y_{ist} = \beta_i + \beta_t + \beta_1 * Good\_Faith_{st} + \beta_2 * Implied\_Contract_{st} + \beta_3 * Public\_Policy_{st} + \beta \cdot X_{ist} + \varepsilon_{ist}$
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. The sample excludes all firms whose headquarters are located in California or Massachusetts. $\beta_1 - \beta_3$ measure the difference-in-difference effects of the passage of the three unjust-dismissal provisions (*Good Faith*, *Implied Contract*, and *Public Policy*).
X_{ist} denotes the set of control variables. *Market-to-Book* ratio is the market value of assets to total book assets. *Size* is the natural logarithm of sales. *Anti-Takeover Index* is the state-level index of anti-takeover statutes from Bebchuk and Cohen (2003). *ln(R&D/Sales)* is the log of the ratio of research and development expenditures to firm sales. *Competition* is the fraction of total (2-digit) industry sales (excluding those of the firm itself) generated by competitors in a given state (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 gross state product (GSP) in a given sector and state divided by the total GSP in that state and year (data for 1977–2000). $ln(GSP)$ is the logarithm of nominal GSP per state and year. $ln(Population)$ is the logarithm of a state's population in a given year. $ln(College)$ is the number of degree-granting institutions of higher education (colleges) in a given state and year.
Patent data is from the NBER Patents File (Hall, Jaffe and Trajtenberg, 2001). The wrongful discharge law data is based on the coding by Autor et al. (2006). Firm-level data is from Compustat. Data on state value added and population is from the U.S. Bureau of Economic Analysis. Data on the number of colleges is from the annual Statistical Abstracts from the U.S. Census Bureau. The sample spans 1970–1999. 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 /Employees)	(4) ln(Citations /Employees)	(5) ln(Patents /R&D)	(6) ln(Citations /R&D)
Good Faith	0.147**	0.180**	0.174**	0.227**	0.172**	0.224**
	(0.064)	(0.082)	(0.077)	(0.098)	(0.075)	(0.095)
Public Policy	0.096**	0.147***	0.118**	0.122**	0.122***	0.127**
	(0.037)	(0.052)	(0.046)	(0.057)	(0.045)	(0.056)
Implied Contract	-0.024	0.006	-0.025	0.002	-0.023	0.005
	(0.030)	(0.043)	(0.037)	(0.046)	(0.037)	(0.046)
Market-to-Book	-0.003	-0.014**	-0.002	-0.004	-0.004	-0.004
	(0.004)	(0.006)	(0.004)	(0.007)	(0.005)	(0.008)
Size	0.091***	-0.020	-0.671***	-0.768***	-0.894***	-0.983***
	(0.015)	(0.027)	(0.020)	(0.028)	(0.020)	(0.034)
ln(R&D/Sales)	0.068***	0.054**	-0.086***	-0.091**	-0.916***	-0.945***
	(0.016)	(0.025)	(0.026)	(0.035)	(0.020)	(0.030)
Competition	4.658***	5.634***	5.637***	5.954***	5.643***	5.925***
	(0.717)	(0.967)	(0.837)	(0.973)	(0.868)	(0.997)
$Competition^2$	-4.939***	-5.805***	-6.184***	-6.093***	-6.127***	-5.950***
	(1.026)	(1.350)	(1.171)	(1.385)	(1.205)	(1.409)
Ratio of Value Added	1.043*	1.371**	1.576**	1.625**	1.378**	1.413**
	(0.527)	(0.655)	(0.656)	(0.654)	(0.643)	(0.641)
Anti-takeover Index	-0.015	-0.005	-0.013	0.004	-0.019*	-0.003
	(0.009)	(0.011)	(0.012)	(0.012)	(0.011)	(0.011)
ln(College)	-0.017	-0.050	-0.019	-0.038	-0.011	-0.030
	(0.062)	(0.089)	(0.076)	(0.107)	(0.076)	(0.107)
ln(GSP)	-0.028	0.035	0.011	0.027	-0.027	0.001
	(0.133)	(0.197)	(0.163)	(0.217)	(0.162)	(0.216)
ln(Population)	0.081	0.055	0.062	0.060	0.089	0.076
	(0.145)	(0.199)	(0.174)	(0.229)	(0.173)	(0.228)
Firm and Year Fixed Effects	Y	Y	Y	Y	Y	Y
Observations	30,389	30,389	30,240	27,136	30,389	27,271
R-squared	0.243	0.384	0.729	0.640	0.738	0.671

Table 6: **Robustness: Difference-in-Difference Tests – Creation of the Court of Appeals of the Federal Circuit (1982).**

The OLS regressions below implement the following model:
$y_{ist} = \beta_i + \beta_t + \beta_1 * Good\_Faith_{st} + \beta_2 * Implied\_Contract_{st} + \beta_3 * Public\_Policy_{st} + \beta \cdot X_{ist} + \varepsilon_{ist}$
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. Panel A shows the results for sub-period 1970–1982, while Panel B reports the results for 1983–1999. β_1 – β_3 measure the difference-in-difference effects of the passage of the three unjust-dismissal provisions (*Good Faith*, *Implied Contract*, and *Public Policy*).
X_{ist} denotes the set of the following additional control variables, which are included in the regressions but whose coefficients are not reported to conserve space: *Market-to-Book* ratio is the market value of assets to total book assets. *Size* is the natural logarithm of sales. *Anti-Takeover Index* is the state-level index of anti-takeover statutes from Bebchuk and Cohen (2003). *ln*(*R&D*/*Sales*) is the log of the ratio of research and development expenditures to firm sales. *Competition* is the fraction of total (2-digit) industry sales (excluding those of the firm itself) generated by competitors in a given state (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 gross state product (GSP) in a given sector and state divided by the total GSP in that state and year (data for 1977–2000). *ln*(*GSP*) is the logarithm of nominal GSP per state and year. *ln*(*Population*) is the logarithm of a state's population in a given year. *ln*(*College*) is the number of degree-granting institutions of higher education (colleges) in a given state and year.
Patent data is from the NBER Patents File (Hall, Jaffe and Trajtenberg, 2001). The wrongful discharge law data is based on the coding by Autor et al. (2006). Firm-level data is from Compustat. Data on state value added and population is from the U.S. Bureau of Economic Analysis. Data on the number of colleges is from the annual Statistical Abstracts from the U.S. Census Bureau. The sample spans 1970–1999. 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: Sample Period 1970–1982						
	(1)	(2)	(3)	(4)	(5)	(6)
	ln(Pat.)	ln(Cit.)	ln(Pat. /Employ.)	ln(Cit. /Employ.)	ln(Pat. /R&D)	ln(Cit. /R&D)
Good Faith	0.072*	0.220***	0.111**	0.243***	0.110**	0.242***
	(0.042)	(0.060)	(0.051)	(0.067)	(0.051)	(0.067)
Public Policy	0.135**	0.198***	0.165**	0.182**	0.166**	0.184***
	(0.059)	(0.062)	(0.070)	(0.068)	(0.069)	(0.067)
Implied Contract	-0.031	0.012	-0.039	0.009	-0.041	0.008
	(0.064)	(0.096)	(0.077)	(0.112)	(0.076)	(0.111)
	(0.218)	(0.366)	(0.270)	(0.386)	(0.271)	(0.387)
Additional Control Variables	*Y*	*Y*	*Y*	*Y*	*Y*	*Y*
Firm and Year Fixed Effects	Y	Y	Y	Y	Y	Y
Observations	7202	7202	7182	7004	7202	7024
R-squared	0.263	0.259	0.662	0.574	0.696	0.590
PANEL B: Sample Period 1983–1999						
	(1)	(2)	(3)	(4)	(5)	(6)
	ln(Pat.)	ln(Cit.)	ln(Pat. /Employ.)	ln(Cit. /Employ.)	ln(Pat. /R&D)	ln(Cit. /R&D)
Good Faith	0.093*	0.157***	0.125**	0.185**	0.120**	0.180**
	(0.047)	(0.058)	(0.058)	(0.071)	(0.057)	(0.071)
Public Policy	0.060	0.111**	0.074	0.073	0.081	0.082
	(0.040)	(0.055)	(0.050)	(0.058)	(0.049)	(0.058)
Implied Contract	-0.010	0.019	0.001	0.027	-0.003	0.024
	(0.036)	(0.049)	(0.045)	(0.052)	(0.044)	(0.051)
Additional Control Variables	*Y*	*Y*	*Y*	*Y*	*Y*	*Y*
Firm and Year Fixed Effects	Y	Y	Y	Y	Y	Y
Observations	30817	30817	30638	27017	30817	27174
R-squared	0.245	0.422	0.768	0.695	0.736	0.679

Table 7: **Robustness: Difference-in-Difference Tests – Division / Subsidiary Level Tests and Sample Selection.**

The OLS regressions below implement the following model:
$y_{j\rightarrow i,st} = \beta_j + \beta_t + \beta_1 * Good\_Faith_{st} + \beta_2 * Implied\_Contract_{st} + \beta_3 * Public\_Policy_{st} + \varepsilon_{jst}$
where $y_{j\rightarrow i,st}$ is a measure of innovation done by division/subsidiary j (of firm i) in state s in year t. β_j and β_t denote respectively division/subsidiary and application year fixed effects. β_1 – β_3 measure the difference-in-difference effects of the passage of the three unjust-dismissal provisions (*Good Faith*, *Implied Contract*, and *Public Policy*). Columns 1&2 show the results for the NBER patent data sample matched to the Compustat dataset, while Columns 2&3 report the results for the full NBER patent data sample.
Patent data is from the NBER Patents File (Hall, Jaffe and Trajtenberg, 2001). The wrongful discharge law data is based on the coding by Autor et al. (2006). The sample spans 1970–1999. Robust standard errors (clustered at the state level) are given in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
Sample:	*NBER Patent Data – Compustat matched sample*		*full NBER Patent Data Sample*	
	ln(Patents)	ln(Citations)	ln(Patents)	ln(Citations)
Good Faith	0.115**	0.197***	0.069*	0.120**
	(0.051)	(0.062)	(0.037)	(0.045)
Implied Contract	0.086**	0.141***	0.059**	0.096***
	(0.035)	(0.039)	(0.023)	(0.028)
Public Policy	0.061	0.105**	0.052*	0.084**
	(0.044)	(0.049)	(0.029)	(0.034)
Division / Subsidiary Fixed Effects	Y	Y	Y	Y
Year dummies	Y	Y	Y	Y
Observations	107,172	107,172	354,433	354,433
R-squared	0.229	0.361	0.425	0.579

Table 8: **Summary Statistics – Entrepreneurship Sample.**

In this table, we give summary statistics for the variables used in the difference-in-difference regressions. The following **dependent variables** are employed: *Ln(Establishments Created by Start-Ups)*, the logarithm of the number of start-up firms; *Ln(Establishment Entries)*, the logarithm of the number of establishment entrants; *Ln(Establishment Exits)*, the log of the number of establishment closures; *Ln(Job Creation due to Start-Ups)*, the log of the number of new jobs resulting from the creation of new start-up firms; *Ln(Job Destruction due to Firm Deaths)*, the log of the number of employment losses resulting from the closure of establishments. The dependent variables are drawn from the Business Dynamics Statistics database from the U.S. Census Bureau.

The **explanatory variables** employed 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. The wrongful discharge law data is based on the coding by Autor et al. (2006).

Ln(GSP) is the logarithm of nominal gross state product per state and year; *Ln(Population)* is the logarithm of a state's population in a given year. The latter two variables are obtained from the U.S. Bureau of Economic Analysis. *Ln(College)* is the logarithm of the number of degree-granting institutions of higher education (colleges) in a given state and year. The educational data is from the annual Statistical Abstracts of the U.S. Census Bureau.

The sample spans 1977–2005.

Dependent Variables						
	Obns.	*Mean*	*Median*	*Std. Devn.*	*Min.*	*Max.*
Ln(Establishments Created by Start-Ups)	7,957	5.337	5.165	1.938	2.485	8.776
Ln(Establishment Entries)	71,519	3.478	3.258	1.402	1.386	6.373
Ln(Establishment Exits)	63,397	3.980	3.784	1.556	1.609	7.074
Ln(Job Creation due to Start-Ups)	71,519	6.130	5.943	1.479	3.784	9.145
Ln(Job Destruction due to Firm Deaths)	62,548	6.815	6.817	1.131	4.718	8.899
Explanatory Variables						
	Obns.	*Mean*	*Median*	*Std. Devn.*	*Min.*	*Max.*
Good Faith	125,316	0.166	0	0.372	0	1
Implied Contract	125,316	0.710	1	0.454	0	1
Public Policy	125,316	0.751	1	0.432	0	1
Ln(GSP)	101,367	0.075	0.006	0.330	0	3.931
Ln(Population)	91,307	5.126	3.812	5.330	0.412	33.999
Ln(College)	91,307	0.076	0.058	0.072	0.006	0.419

Table 9: **Difference-in-Difference Tests: Entrepreneurship.**

The OLS regressions below implement the following model:

$y_{klst} = \beta_l + \beta_s + \beta_t + \beta_1 * Good\_Faith_{st} + \beta_2 * Implied\_Contract_{st} + \beta_3 * Public\_Policy_{st} + \beta \cdot X_{klst} + \varepsilon_{klst}$

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 and β_t denote respectively firm age, state and year fixed effects. $Good\_Faith_{st}$, $Implied\_Contract_{st}$, and $Public\_Policy_{st}$ measure whether a given wrongful discharge law is in place in a given state and year. β_1, β_2 and β_3 measure the difference-in-difference effect of the passage of each of the three wrongful discharge laws (good-faith, implied-contract, public-policy exceptions respectively) on our dependent variable of interest.

X_{klst} denotes the set of the following time-varying control variables: *Ln(GSP)* is the logarithm of nominal gross state product per state and year; *Ln(Population)* is the logarithm of a state's population in a given year. The latter two variables are obtained from the U.S. Bureau of Economic Analysis. *Ln(College)* is the logarithm of the number of degree-granting institutions of higher education (colleges) in a given state and year. The educational data is from the annual Statistical Abstracts of the U.S. Census Bureau.

The sample spans 1977–2005. 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)	(9)	(10)
	ln(Establishments Created by Start-Ups)		ln(Establishment Entries)		ln(Job Creation due to Start-Ups)		ln(Establishment Exits)		ln(Job Destruction due to Firm Deaths)	
Good Faith	0.094*	0.096*	0.073**	0.055*	0.045	0.036	0.129**	0.065	0.111**	0.071**
	(0.052)	(0.050)	(0.034)	(0.032)	(0.038)	(0.028)	(0.052)	(0.045)	(0.053)	(0.031)
Implied Contract	-0.032	-0.032	-0.027	-0.025	-0.043	-0.028	-0.003	-0.002	-0.006	0.001
	(0.047)	(0.049)	(0.019)	(0.017)	(0.028)	(0.017)	(0.024)	(0.019)	(0.027)	(0.019)
Public Policy	-0.010	-0.044	0.007	-0.006	0.020	-0.000	-0.016	-0.019	-0.033	-0.051*
	(0.045)	(0.050)	(0.023)	(0.018)	(0.029)	(0.018)	(0.030)	(0.024)	(0.034)	(0.027)
ln(GSP)		-0.004		0.018		0.067***		0.020		0.032
		(0.055)		(0.027)		(0.025)		(0.025)		(0.025)
ln(Population)		0.362		0.399***		0.553***		0.465***		0.578***
		(0.232)		(0.120)		(0.068)		(0.128)		(0.117)
ln(College)		-0.166*		-0.084**		-0.094**		-0.053		-0.078*
		(0.096)		(0.031)		(0.043)		(0.044)		(0.046)
State and year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Firm age group FE	N	N	N	Y	N	Y	N	Y	N	Y
Observations	7,957	6,182	71,519	51,568	71,519	51,568	63,397	45,176	62,548	44,385
Adjusted R-squared	0.050	0.041	0.134	0.439	0.202	0.715	0.116	0.187	0.418	0.599