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Dismissal Laws, Innovation and Economic Growth

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Keywords
labor laws, R&D, technological change, law and finance, entrepreneurship, growth

Comments

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Dismissal Laws, Innovation and Economic Growth*

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Abstract

I theoretically and empirically show that dismissal laws – laws that impose hurdles on firing of employees – spur innovation and thereby economic growth. Theoretically, dismissal laws make it costly for firms to arbitrarily discharge employees. This enables firms to commit to not punish short-run failures of employees. Because innovation is inherently risky and employment contracts are incomplete, dismissal laws enable such commitment. Specifically, absent such laws, firms cannot contractually commit so ex-ante. The commitment provided by dismissal laws encourages employees to exert greater effort in risky, but path-breaking, projects thereby fostering firm-level innovation. I provide empirical evidence supporting this thesis using the discontinuity provided by the passage of the federal Worker Adjustment and Retraining Notification Act. Using the fact that this Act only applied to firms with 100 or more employees, I undertake difference-in-difference and regression discontinuity tests to provide this evidence. Building on endogenous growth theory, which posits that economic growth stems from innovation, I also show that dismissal laws correlate positively with economic growth. However, other forms of labor laws correlate negatively with economic growth and swamp the positive effect of dismissal laws.

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

Keywords: Labor laws, R&D, Technological change, Law and finance, Entrepreneurship, Growth.

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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, three 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. For instance, strong labor market regulation is often blamed to be one of the reasons for Europe's economic under-performance compared to the US (see a recent study by McKinsey Global Institute, 1997). Indeed, once a situation to terminate an employment contract arises, tying down an employer's hands from doing so can 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, while flexible labor market conditions in the U.S. are anecdotally contrasted to the rigidities in several European countries, in Acharya, Baghai and Subramanian (2013), my coauthors and I show that *dismissal laws foster innovation even within European countries*. Moreover, we show that while dismissal laws foster innovation other forms of labor laws do not. This nuance is important because laws that impose hurdles on dismissal capture only one particular form of restriction on the employer-employee relationship. Labor laws, however, affect many other aspects of the employer-employee relationship and, therefore, exhibit considerable variety. For example, one important category of labor laws impacts workers' ability to unionize, while another one governs workers' rights to engage in militant action in the form of strikes. While dismissal laws at the country level have an ex ante positive incentive effect on innovation, other forms of labor laws do not generate such ex ante positive incentive effects on innovation. We provide this evidence by contrasting country-level changes in dismissal laws from 1970 to 2002 in Europe with that in the United States.

Third, the image of a flexible U.S. labor market does not reflect substantive legal changes in the U.S. states 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 Acharya, Baghai and Subramanian (2014), my coauthors and I develop a theoretical model where dismissal laws help to limit an employer's ability to hold up the innovating employee. In an incomplete contract setting, we show theoretically that dismissal laws foster innovation by spurring innovative effort by employees. Such effort encourages firms to choose ex ante risky, yet value-enhancing, innovative activities. We then exploit the *natural experiment* offered by the passage of dismissal laws to examine their effect on innovation and entrepreneurship. Since the motivation behind the passage of these laws were unrelated to either innovation or entrepreneurship, they offer a clean empirical setting. 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.

In this chapter, I build on this work to examine a significant legal change in dismissal laws at the federal level in the U.S. — the passage of the Worker Adjustment and Retraining Notification (WARN) Act in 1989. Using a theoretical model and empirical analysis that exploits a unique feature of the Act, I show that this change fostered innovation among firms. Using other dismissal law changes at the country level, as in Acharya, Baghai and Subramanian (2013), I then show that dismissal laws correlate positively with economic growth. By appealing to endogenous growth theory and the careful identification of the effects on innovation, I infer that dismissal laws foster innovation and thereby economic growth.

I develop a theoretical model to capture the higher costs imposed on firms by dismissal laws. Dismissal laws impose direct and indirect costs on firms in dismissing their 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. If the employee sues the firm upon dismissal, dismissal laws require the firm to prove in a court of law that the dismissal was not unjust. Therefore, in the presence of dismissal laws, firms also incur indirect costs in collecting systematic records of the employee's performance and thereby produce verifiable information about the employee's effort. Note that dismissal laws *do not* make firing a worker impossible; rather, they require the firm to provide a valid and *verifiable* reason for the dismissal. The model is thus different from the one in Acharya, Baghai and Subramanian (2014), where we focus on how wrongful discharge laws reduce hold up by employers by enabling them to commit that they would not act in bad faith with their employees.

I model an all-equity firm that 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 the testable empirical predictions.

A key friction in the model is that contracts are incomplete as in Hart (1995). Specifically, I 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. 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 dismissal laws leads to more innovation.

To investigate these hypotheses, I exploit the discontinuity introduced by the fact that the WARN Act was applicable *only to firms with 100 or more employees* to undertake within-country tests of the effect of changes in dismissal laws. First, I confirm that WARN did indeed bind by studying its effects on employment. Then, I compare U.S. firms that were affected by the law change (firms with 100 or more employees) to U.S. firms that were not (firms with less than 100 employees). I use data on patents issued by the USPTO to U.S. and foreign firms and citations to these patents as constructed by Hall, Jaffe and Trajtenberg (2001). I find that compared to firms that were unaffected by the passage of WARN, those affected file more patents post WARN; in addition, they file patents that are more widely cited.

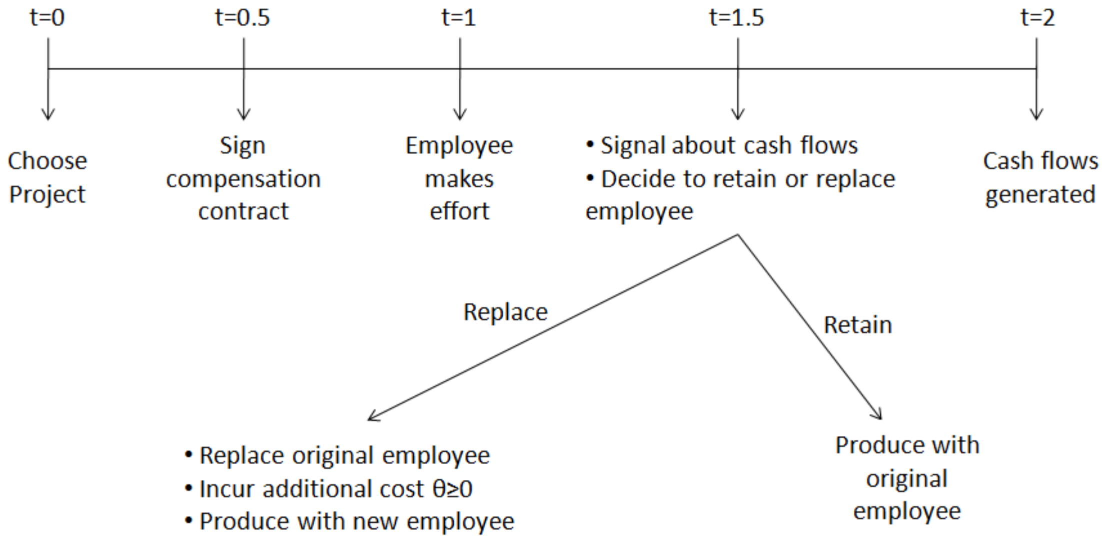
Having tested for the positive effect of labor laws on innovation, I inquire what such an effect implies for country-level *economic growth*. While the endogenous growth theory (see Aghion and Howitt (1992)) implies that this positive effect of labor laws on innovation should translate into a similar positive effect on economic growth, other theories suggest that stringent labor laws, which grant excessive bargaining power to organized labor, blunt investment incentives and thereby country-level economic growth (see Stern (2001) for example). Indeed, existing empirical evidence finds support for this inimical effect of labor laws on economic growth (see Besley and Burgess (2004)). Motivated by these conflicting predictions, I examine the effect of labor law changes on growth in real value added for each ISIC industry in a country. Consistent with the evidence in Besley and Burgess (2004), I find after controlling for country, industry, and year fixed effects, as well as other country level variables, that the overall effect of labor laws on economic growth is negative. However, when I disaggregate the labor laws into their sub-components, I find that laws governing dismissal of employees have a large, *positive* effect on growth in real value added; the other labor law components have either negative or insignificant effects on economic growth. Using difference-in-difference tests that exploit changes in dismissal laws in the US and France, I find further support for this positive effect.

Taken together, these tests enable us to conclude that innovation is fostered by stringent labor laws, especially by laws governing dismissal of employees and in those sectors of the economy that are more innovation-intensive. Furthermore, while the overall effect of stringent labor laws is to dampen economic growth, laws that govern dismissal of employees are an exception since they encourage economic growth through greater firm-level innovation.

2 Theoretical Model

To derive sharp empirical predictions, I develop a model in which a firm chooses either of two projects; these projects differ only in their degree of innovation. Denote the *routine* project by R while I denote the *innovative* project by I. To fix ideas, consider a pharmaceutical company deciding to invest in either of the following two projects: (1) inventing and launching a new drug; or (2) manufacturing and launching a generic substitute for an existing drug. Launching a generic substitute involves uncertainties due to customer demand and competition. In contrast, inventing a new drug entails additional uncertainties associated with the process of exploration and discovery, whether such a drug could be administered to humans, and whether it would receive FDA approval. Thus, inventing and launching a new drug, which corresponds to the more innovative project I in the model, entails significantly more risk than launching a generic substitute for an existing drug, which corresponds to the less innovative project R in the model.

Figure 2 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



Timing and sequence of events

verifiable.

After deciding on a project, at date 0.5, the firm hires an employee to work on this project; 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 explained 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. 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, 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. 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 is normalized to zero. 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), 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, 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.

Assume the labor market to be competitive with employees earning their reservation utility in equilibrium, which is normalized to zero. Finally, the common discount rate equals zero.

2.1 Incompleteness of contracts

A key friction in the model is that contracts are incomplete as in Hart (1995). Specifically, 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. I 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, 2011). 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 investment is assumed 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.

2.2 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 the 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, assume that each project, if successful, generates a return that is proportional to its risk:

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

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

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

2.3 Risk Preferences

While the firm is assumed to be risk-neutral, the employee is averse to the risk of being fired. To ensure tractability, the employee's utility is modeled 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 I denote by ρ $(\rho > 0)$; and (ii) the probability of her getting fired.[1]

[1] 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.

2.4 Dismissal Laws

As in MacLeod and Nakavachara (2007), I model the passage of 'Dismissal 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.[2] If the employee sues the firm upon dismissal, dismissal laws require the firm to prove in a court of law that the dismissal was not unjust. Therefore, in the presence of Dismissal Laws, firms also incur indirect costs to acquire verifiable information about the employee's effort. Note that dismissal 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.

I model this effect of dismissal 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 dismissal laws do not make dismissals impossible in equilibrium, assume:

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

2.5 Analysis

The model is solved by backward induction. Consider the firm's decision at date 1.5 whether or not to replace the original employee. First, consider 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

[2] 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).

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 I 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, dismissal 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, I 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.*

2.6 Results

Given these steps for solving the model, I 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 dismissal 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 dismissal 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. Dismissal 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 dismissal 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 dismissal 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 dismissal 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 dismissal laws 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 dismissal 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, dismissal 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 dismissal laws 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 dismissal laws.

This result generates the empirical prediction that the passage of dismissal 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 dismissal laws would manifest more in the innovation-intensive industries than in the 'brick-and-mortar' industries.

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.

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 dismissal laws are not stringent* $\left(\theta \leq \widehat{\theta}\right)$ *and 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 dismissal 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 dismissal laws are less stringent. Thus, the effect of dismissal laws in enabling commitment by the firm translates into a positive effect on firm value as well.

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

Hypothesis 1: Passage of dismissal laws leads to greater innovation.

Hypothesis 2: Passage of dismissal laws leads to a larger increase in employee effort in the innovative projects when compared to the routine projects.

3 Effect of dismissal laws on innovation

I present tests of the main hypothesis using within-country variation in dismissal law changes in the U.S. These tests exploit a *discontinuity* introduced by the passage of the federal U.S. Worker Adjustment and Retraining Notification (WARN) Act. These tests complement the settings used in Acharya, Baghai and Subramanian (2013, 2014). A key advantage of these tests is that they remove any concerns about country-level unobserved factors driving the results.

3.1 An Overview of the WARN Act

The WARN Act is a federal law (P.L. 100-379) that was enacted by the U.S. Congress on August 4, 1988, and became effective on February 4, 1989.[3] The WARN Act requires employers to give written notice 60 days before the date of a mass layoff or plant closing to affected workers, to the local government's chief elected official where the employment site is located and to the State Rapid Response Dislocated Worker Unit. Subject to the law are private employers with 100 or more full-time employees, or with 100 or more employees who work at least a combined 4,000 hours a week. Only layoffs classified as "mass layoffs" or "plant closings," or layoffs of 500 or more full-time workers at a single site of employment, are covered.[4] In the case of non-compliance, employees, their representatives, and units of local government can bring individual or class action suits in federal district courts against employers. Employers who violate the WARN Act are liable for damages in the form of back pay and benefits to affected employees.

[3] The details on the WARN Act reported in this section are drawn from the following two sources, unless otherwise noted: United States Department of Labor – Employment & Training Administration ($http://www.doleta.gov/layoff/warn.cfm$); and Levine (2007).

[4] A "plant closing" is defined as a closure of a facility within a single site of employment involving layoffs of at least 50 full-time workers. In the case of a "mass layoff," an employer lays off either between 50 and 499 full-time workers at a single site of employment, or 33% of the number of full-time workers at a single site of employment. For further details about the WARN Act, see Levine (2007).

The requirement of prior notification to local government together with penalties for non-compliance imply that the WARN passage increases the hurdles faced by employers when dismissing employees. This effect is in line with the effect of dismissal laws as discussed in the theoretical motivation. Therefore, I expect WARN to have the predicted effect on innovation.

Before examining the effect of WARN on innovation, a key question that arises is whether the WARN Act indeed binds for innovative firms. I provide evidence that the WARN Act applies to U.S. firms irrespective of their industry, and that its passage had a significant impact on firm employment. To show the diversity of companies affected by the WARN Act, I examine the WARN Act notices received by the Employment Development Department in California in 2009. These included the following companies[5]: AT&T company; Circuit City Stores, Inc.; Comcast Cable; San Francisco Chronicle; Sun Microsystems, Inc.; The Boeing Company; Walt Disney World Co.; Virgin Mobile USA; NEC Electronics America, Inc.; American Airlines, Inc.; Siemens; The McGraw-Hill Companies; FOX Interactive Media, Inc.; Henkel Corporation; Hilton Hotels Corporation; HSBC; National Semiconductor Corporation; Palm, Inc.; SAP America, Inc.; Seagate Technology LLC; Symantec; Yahoo! Inc.; JPMorgan Chase & Co.; Valeant Pharmaceuticals International; Adobe Systems Incorporated; Stanford University; Genentech, Inc.; and many others. Clearly, this list encompasses a broad range of firms, and also those that are known for their strength as innovators.

The range of firms issuing WARN Act notices illustrates that the threat of dismissal is a very clear and present danger for researchers. The following passage from a January 2009 Wall Street Journal article[6] is meant to emphasize this point further: "Pfizer Inc. is laying off as many as 800 researchers in a tacit admission that its laboratories have failed to live up to the tens of billions of dollars it has poured into them in recent years. [...] While the new cuts will only dent Pfizer's overall work force of 83,400, they strike at the company's lifeblood: the labs charged with discovering lucrative new drugs."

3.2 Do employment protection laws affect white-collar employees?

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

The leading case involving employment protection in the case of a *scientist* who followed

[5] Source: *http://www.edd.ca.gov/Jobs_and_Training/warn/eddwarnlwia09.pdf*

[6] "Corporate News: Pfizer Plans Layoffs in Research – Drug Maker Has Little in Pipeline to Show for Its $7.5 Billion R&D Budget," *The Wall Street Journal*, 14 January 2009.

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

Another famous case involves Lorenz v. Martin Marietta Corp. (823 P.2d 100; Colo. 1992). Paul M. Lorenz was a mechanical engineer, who specialized in fracture mechanics of metals. Martin Marietta Corporation, which was a supplier of external tanks to NASA's space shuttles, wrongfully terminated Lorenz's employment allegedly in violation of the public policy exception. Lorenz "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. Lorenz 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 affi rmed 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 violation in this case of employment.

3.3 Data

To construct proxies for innovation, I use data on patents filed with the U.S. Patent Offi ce (USPTO) and the citations to these patents, compiled in the NBER Patents File (Hall, Jaffe and Trajtenberg, 2001). Patents have long been used as an indicator of innovative activity in both micro- and macro-economic 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, 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 its innovation. In addition, patents measure only successful innovations. To that extent, the results are subject to the same criticisms as previous studies that use patents to measure innovation

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

(e.g., Griliches, 1990; Kortum and Lerner, 1999).

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. I match the NBER patents file to the Compustat data. Each assignee in the NBER dataset is given a unique and time-invariant identifier. I match the U.S. assignee names in the NBER patent dataset to the names of divisions and subsidiaries belonging to a corporate family from the Directory of Corporate Affiliations. I then match the name of the corporate parent to Compustat, which I use to obtain firm-level accounting data.

I date the 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 I use the application year as the relevant year for the analysis, the patents appear in the database only after they are granted. Hence, I use the patents actually granted (rather than the patent applications) for the analysis.

3.4 Proxies for Innovation

I use four different proxies for innovation. The first proxy is a simple count of the number of patents that were filed in a particular year in a specific patent class. As the second metric of innovative activity, I use the cumulative citations received by a firm's patents in a specific year. 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.[8] 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 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. These two proxies enable me to test *Hypothesis 1.*

As the third and fourth proxies for innovation, I employ the number of patents per employee as well as the number of citations per employee. These proxies enable me to capture employee effort in innovation and thereby test *Hypothesis 2.*

[8]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.

3.5 Test Design

I exploit the passage of the U.S. WARN Act as a quasi-natural experiment to investigate the impact of the strengthening of dismissal laws on innovation by U.S. firms. The key to implementing this test is that only employers with *more than 100 employees* are affected by the law (the "treatment group"), while firms with less than 100 employees are not (the "control group"). Figure 1 shows the linear fit of the number of patents and citations across time for the treated (firms with 100 or more employees) and control (firms with less than 100 employees) before and after 1989. The presence of a break for the treated firms and the absence of the same for the control group of firms in 1989 is quite clear from this figure. Tests formalizing this visual effect enable us to shut out any unobserved heterogeneity that may affect multiple-country examinations.

I measure the effect of the strengthening of dismissal laws via WARN on the treatment firms vis-à-vis the control firms using the following specification:

$$y_{it} = \beta_i + \beta_t + \beta_1 * Over100_{i,1987} * After1988_t + \beta X + \epsilon_{it} \tag{19}$$

where y is a proxy for innovation by firm i in year t, $After1988_t$ is a dummy taking the value of one after the passage of the WARN Act (i.e. for the years 1989-1994), and $Over100_{i,1987}$ is a dummy taking the value of one if a firm has $\geq$ 100 employees in 1987 and zero otherwise.[9] Using the firm size in 1987 – a year before the passage of the WARN Act – enables me to account for possible endogeneity in the firm size with respect to the WARN Act. β_i and β_t are firm and year fixed effects, respectively. X is a set of control variables. Since $After1988_t$ and $Over100_{i,1987}$ vary based on the year and the firm respectively, the year fixed effects and the firm fixed effects respectively subsume their individual effects. The sample covers twelve years around the passage of the WARN Act (from 1983-1994). I cluster all standard errors at the firm level. β_1 measures the difference-in-difference effect on innovation of the strengthening of dismissal laws via the WARN Act.

In addition to controlling for the time-invariant heterogeneity of firms via firm dummies and for general macro-economic factors via year dummies, I also control for firm size to account for the possibility that larger firms might innovate more on average. Furthermore,

[9] The number of employees obtained from Compustat (data item *emp*) is the number of all employees of consolidated subsidiaries, both domestic and foreign; this also includes U.S. employees working at a foreign facility of a U.S. employer, who *do* count towards the 100 employee threshold. However, foreign workers at foreign sites of U.S. firms do not count towards the threshold, but are included in the number of employees obtained from Compustat. We might therefore include some companies within the treatment group sample even though they are not affected by the WARN Act. However, this is of limited concern in our tests since we only consider patents filed by inventors who are not only working for U.S. firms, but also residing in the U.S.

I include Tobin's Q to control for investment opportunities, as these might also have an impact on a firm's innovation policies. Finally, 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, I employ a control for the external takeover pressure a firm faces.

I approximate Tobin's Q via the *Market-to-Book* ratio, which is the market value of assets to total book assets. Market value of assets is total assets (Compustat data 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). *Size* is the natural logarithm of sales (sale). *Anti-Takeover Index* is the state-level index of anti-takeover statutes from Bebchuk and Cohen (2003). The five anti-takeover statutes considered are Control Share acquisition, Fair-price, Business Combination, Poison Pill Endorsement, and Constituencies statutes. The resulting index is a simple count of the number of state anti-takeover statutes in place in a given state and year, and ranges from 0 to 5. In order to eliminate the impact of outliers, I winsorize the variables *Market-to-Book* and *Size* at 1% and 99%. Table 1 describes the summary statistics for the main variables used in the tests.

3.6 Impact of WARN Act on Employment: Difference-in-difference tests

I first examine whether the WARN Act was binding for firms by investigating the effect of its passage on employment fluctuations.

Table 2 documents the impact of the passage of the WARN Act on employment fluctuations. I run regressions as described in equation (19), but with the year-to-year employment change of firm i between year t and $t-1$ ($\Delta Emp_{t,t-1}$), as well as between year $t+1$ and t ($\Delta Emp_{t+1,t}$), as dependent variables. Thus, the coefficient β_1 captures the effect of increased employment protection through the passage of the WARN Act on annual net employment flows. As can be seen from columns 1-4 of Table 2, the WARN Act had a negative and, in most specifications, significant impact on employment fluctuations.

In order to ascertain that the WARN Act had an effect on innovative as well as less-innovative firms, I split the sample into two parts. First, I define innovation intensity, similar to the cross-country setup, as the median number of patents applied for by firms in industry j in year $(t-1)$. As I am using the Compustat-matched sample in the WARN tests, the industry classification here is based on two-digit SIC codes. I then perform separate tests for firm-years with innovation intensity below or equal to the median intensity for a given year. Table 3 shows the results of these tests. Columns 1 and 2 show the results of tests for firm-years with innovation intensity below the median intensity for a given year while columns 3 and 4 show the same for firm-years with innovation intensity above the median intensity. As can be seen from the results, the WARN Act reduced employment fluctuations in both high and low patenting intensity firms alike.

3.7 Impact of WARN Act on Innovation: Difference-in-difference tests

I now investigate the impact on innovation by carrying out difference-in-difference tests using the number of employees in a firm in 1987 to categorize them into the control and treatment groups. Table 4 shows the results from the difference-in-difference tests focussing on the impact of WARN on firm level innovation. Columns 1–2 implement equation 19 without control variables, while columns 3–4 include the control variables described above. In line with Hypothesis 1, I find that the strengthening of dismissal laws via the WARN Act had a positive and significant impact on U.S. firm-level innovation. To be specific, in column 3 of Table 4 (specification with control variables) I estimate that the passage of the WARN Act increases innovation as measured by patents by exp(0.217)-1=24% in the treatment group (firms with ≥ 100 employees) vis-à-vis the control group (firms with < 100 employees). The effect is of similar magnitude when innovation is measured by the number of citations (29%). These results are thus consistent with Hypothesis 1.

3.8 Impact of WARN Act on Innovative Effort: Difference-in-difference tests

As I discussed in Section 2.6, the positive effect of stringent dismissal laws on innovation results due to the positive effect that stringent dismissal laws have on employee effort (Hypothesis 2). Therefore, I investigate whether the passage of WARN had an effect on employee effort in innovative projects. For this purpose, I normalize the proxies for aggregate level of innovation using the number of employees in a firm. Table 5 report the results using $ln(patents/employees)$ and $ln(citations/employees)$ as the dependent variables. Similar to the strong results obtained using the aggregate measures of innovation, here I find that both patents and citations per 1000 employees increase significantly post the passage of WARN. Thus, the evidence in Tables 4 and 5 is consistent with WARN resulting in (i) an increase in employee effort in innovative projects; and (ii) an increase in aggregate measures of innovation.

3.9 Regression-Discontinuity Tests

To fully exploit the discontinuity due to the WARN Act and thereby provide the cleanest evidence of the hypotheses, I focus on firms in the range [90,110]. Since the number of firms in the [99,101] range is quite limited, we employ the expanded window [90,110]. Figure 2, which shows the before-after difference in the number of patents following the WARN Act as a function of the number of firm employees in 1987, depicts this discontinuous effect very clearly. To ascertain that results are not spurious, as placebo tests, I also test for any effects on innovation by using cutoffs of 50 and 150 employees and a sample of firms with employees in the range [40, 60] and [140, 160] respectively. I proceed by first showing that WARN indeed had a dampening effect on employee dismissals in affected firms. I then estimate the effect of WARN on innovation.

3.9.1 Test design: WARN Act and employee layoffs

To test whether the WARN Act indeed imposed a binding constraint for innovative firms, I define employee layoffs to have occurred in firm i in year t if the number of employees in that year is lower than that in the previous year. I then estimate the following linear probability model for the twelve years surrounding the passage of the WARN Act (1983-1994):

$$Ind(Emp_{i,t} < Emp_{i,t-1}) = \beta_t + \beta_1 \cdot Over100_{i,1987} * After1988_t + \beta_2 \cdot Over100_{i,1987} + \epsilon_{it} \quad (20)$$

where $Ind(Emp_{i,t} < Emp_{i,t-1})$ is a binary variable taking on a value of one in case of a net employment reduction in firm i from year $t-1$ to year t. The other variables are as defined in equation (19). Since employee layoffs due to the WARN Act do not exhibit much within-firm variation, I do not include firm-fixed effects in this specification. However, to control for average differences in employee layoffs across years, I include the year fixed effects β_t.

Column 1 in Panel A of Table 6 reports the results of the tests of equation (20) for firms having employees in the range [90,110] in 1987. I find that the passage of WARN *decreased* the likelihood of layoffs in the affected firms. Compared to the control set of firms in the range [90,99], the before-after difference in the likelihood of employee layoffs decreased by 25% for the treated firms in the range [100,110]. Columns 2-5 in Panel A of Table 6 show the results for the effect of WARN on innovation. First, in Columns 2-3 of Panel A, I report the results of tests for the proxies of aggregate innovation using the log of the number of patents and citations respectively as the dependent variables. In line with Hypothesis 1, I find that the strengthening of dismissal laws via the WARN Act had a positive and significant impact on U.S. firm-level innovation.

I test Hypothesis 2 in Columns 4-5 of Panel A by using *ln(patents/ employees)* and *ln(citations/ employees)* as the dependent variables. Here as well, I find that both patents and citations per employee increase after the passage of WARN for the "treatment" group of firms; however, the increase is only statistically significant for the citations-based measure.

Panels B and C of Table 6 show the results for the placebo tests using only firms with employment in the range [40, 60] and [140, 160] respectively in 1987. In each of these panels, Column 1 shows the effect on employee layoffs, while Columns 2-3 show the results for the log of the number of patents and citations, respectively. Finally, Columns 4-5 report the results using log of the number of patents and citations per employee respectively. In both these panels, I can infer that there was no differential effect at the corresponding placebo cutoffs. This provides reassurance that the positive effect of WARN on innovation documented in Panel A is not spurious.

3.9.2 Robustness Tests for the Effect of the WARN Act on Innovation

I present additional robustness tests for the effect of the WARN Act on innovation in Table 7. In these tests, I examine the piecewise linear effect of the passage of the WARN Act on innovation across firms with different numbers of employees. I employ the whole sample of firms in these tests. In Columns 1 and 2, I confirm what I observed in Figure 2: consistent with the 100 employee threshold imposed by the WARN Act, I find that the positive break in innovation occurs for firms with more than 100 employees when compared to firms with fewer than 100 employees. These tests also further underscore that the effect occurs at the level of hundred employees and not below.

Inference from a regression-discontinuity design can be invalid if the assignment variable – in the setting the number of employees per firm – can be precisely manipulated. One could argue that to avail themselves of the positive innovation incentive effects that the credible commitment to a more stable employment policy in the form of stronger dismissal laws brings, firms may choose their employment figures so as to fall within the scope of application of WARN. However, inference is valid as long as there is not *exact* manipulation. As Lee and Lemieux (2010, p.283) point out: "If individuals – even while having some influence – are unable to *precisely* manipulate the assignment variable, *a consequence* of this is that the variation in treatment near the threshold is randomized as though from a randomized experiment." I argue that this is the case in the tests for three reasons. First, employers cannot unilaterally decide on the number of employees - employees are free to quit anytime, and there are well-documented search frictions in the labor market which can prevent employers from going on a hiring spree. Second, I use the employee count in 1987, one year before the passage of WARN, to classify firms into treatment and control group, which reduces the possibility of such manipulation driving the results. To the extent that some of the firms that I classify as control firms increase employment so as to fall under WARN and then innovate more, this actually biases against finding the hypothesized result.

Finally, it is likely that firms below 100 employees would switch to the treatment group after WARN only if it helps them to create greater incentives for innovation. Thus, if it were the case that such endogenous switching from control to treatment group is accounting for the results, in Columns 3 & 4 of Table 7, I would observe the greatest and lowest magnitudes respectively in the $(100 \leq Emp < 105)_{i,1987}$ and $(125 \leq Emp)_{i,1987}$ ranges with the coefficient for the $(105 \leq Emp < 125)_{i,1987}$ range between these two extremes. This is because the effect of endogenous switching is likely to be largest in the $[100, 105)$ group and be lowest in the ≥ 125 group. However, in Columns 3-4 I do not find such differences in the coefficients. In fact, I find that the F-test for the equality of the coefficients corresponding to each range cannot be rejected at the 95% level. In sum, I am able to alleviate concerns that the results are driven by the endogenous switching of firms from control to treatment groups or vice-versa.

3.10 Benefits of Tests Using the WARN Act

The above tests based on WARN offer several advantages. First, since the sample for the WARN tests ended in 1994, they enable us to conclude that the results on the positive effect of dismissal laws on innovation are not driven by any spurious effects that patent reforms motivated by the General Agreement on Tariffs and Trade (GATT) may have had.[10]

Second, the tests based on the WARN Act mitigate effects of any other contemporaneous factors that may confound the results. This strength of the WARN based tests stems from a combination of three factors. First and foremost, since the firms are separated into treatment and control groups based on the number of employees, any unobserved factor that affects all firms uniformly (i.e. irrespective of employment figures) cannot be driving the results. Nevertheless, as a second line of defense, I have used firm-fixed effects to account for time-invariant effects of unobserved factors, in general, and firm size, in particular. Second, I have performed regression-discontinuity tests to focus on firms just above and below the employment cut-off relevant for WARN.

Third, in the difference-in-difference tests, I have included firm size to account for any *time-varying* correlation of any unobserved factors with firm size. Therefore, laws or policy

[10] Under the GATT changes, an unexpired issued patent or a patent application pending on June 8, 1995, has a term of protection that is the longer of 17 years from the date of issuance of the patent or 20 years from the filing date of the patent application. For applications filed on or after June 8, 1995, the patent life is now twenty years, measured from the earliest patent application. However, since our sample for the WARN tests ended in 1994, our results are not driven by GATT related changes.

changes or any other unobserved factors that may influence innovation cannot affect the results unless they resemble WARN in discriminating based on the size of the *workforce*.

Fourth, related to the above, the WARN tests also alleviate concerns that the results may be affected by the coinciding of the post WARN period with the recession in the early 1990s. To the extent that this recession slowed down the average pace of innovation, the application year fixed effects should capture this effect.

Fifth, since firms of similar sizes should have felt the effect of the recession similarly, the regression-discontinuity specification provides confirmation that the results are not affected by the recession in the 1990s.

Finally, the WARN Act was not intended to specifically encourage innovation or economic growth.[11] Therefore, the tests above can reasonably be interpreted as a truly causal effect of the WARN Act passage on innovation.

4 Effect of Dismissal Laws on Economic Growth

The endogenous growth theory (see Aghion and Howitt (1992)) posits that firm level innovation accounts for economic growth at the country level. Given their positive effect on innovation, do dismissal laws have a similar positive effect on economic growth? Moreover, does the effect of other forms of labor laws on economic growth resemble that of dismissal laws?

To investigate this question, I use the labor law index developed by Deakin et al. (2007), which is employed in Acharya, Baghai and Subramanian (2013). I refer the reader to Acharya, Baghai and Subramanian (2013) for a detailed description of the index. I cannot use the WARN Act for this investigation for two reasons. Firstly, the WARN Act was a law change at the federal level and therefore, economic growth cannot be contrasted within the U.S. Second, the WARN Act only affected the laws pertaining to dismissal and not other forms of labor laws. Therefore, WARN does not allow me to investigate if the effect of other forms of labor laws on economic growth resembles that of dismissal laws.

Using the Deakin et al. (2007) index, I examine how changes in labor laws affect industry level growth rates in real value added. I start with a log-linear specification for the effect in levels of labor laws on real-value added:

$$\ln Y_{ict} = \beta_i t + \beta_c t + \gamma_t + \boldsymbol{\beta}_1 * LaborLaws_{c,t} + \beta X + \eta_{ict} \tag{21}$$

where Y_{ict} denotes the real value added in ISIC industry i in country c in year t. γ_t de-

[11] Brügemann (2007) examines various articles in the business press that document the events preceding and following the WARN Act. He does not find any evidence arguing that the Act was aimed at improving a specific aspect of the U.S. economy.

notes year fixed effects while $\beta_i t$ and $\beta_c t$ denote a time-trending, industry-specific and time-trending, country-specific effects that allow for time-varying country-level and industry-level factors to affect output in a given industry in a given country. To alleviate endogeneity concerns in the above estimation, I employ the first-difference transformation on (21) and obtain the following specification:

$$y_{ict} = \beta_i + \beta_c + \beta_t + \boldsymbol{\beta}_1 * \Delta LaborLaws_{c,t} + \beta \cdot \Delta X + \varepsilon_{ict} \tag{22}$$

where $y_{ict} = \ln \frac{Y_{ict}}{Y_{ic,t-1}}$ denotes the continuously compounded growth in real value added in ISIC industry i in country c in year t, and $\beta_t = \gamma_t - \gamma_{t-1}, \varepsilon_{ict} = \eta_{ict} - \eta_{ic,t-1}$. The dependent variable here is similar to that employed in Rajan and Zingales (1998) (they use the annualized growth rate rather than the continuously compounded one). β_1 here measures the impact of changes in labor laws on the growth in real value added. The country fixed effects β_c and β_i control for country- and industry-specific unobserved factors affecting growth in real value added while the year-fixed effects control for inter-temporal differences in growth in real value added. Given these fixed effects, the assumption required to identify β_1 is that *time-varying* unobserved determinants of growth in real value added at the country and industry levels are uncorrelated with the labor law index.

I obtain data on nominal value added from the UNIDO Industrial Statistics database. I use CPI data from the US Bureau of Labor Statistics to deflate the value added data in order to obtain real values; as CPI data for India is not available from the aforementioned source, I obtain the CPI data for that country from the International Labour Organization's Labour Statistics database. the sample extends from 1970-2003.

I display the results of this test in Table 8. In all regressions, I include country and year fixed effects; standard errors are clustered at the industry (ISIC class) level to account for heteroscedasticity and autocorrelation. Several interesting features emerge. Most importantly, as can be seen from Panel A, columns 1 and 2, the overall impact of stringent labor laws on growth is significantly negative. Moreover, the impact of strong creditor rights on growth is also significantly negative, which is consistent with the findings in Acharya and Subramanian (2009). In the regressions in columns 1 and 2, I control for the logarithm of the level of imports and the level of exports that a given country has with the US in each year at each 3-digit ISIC industry level, in order to account for the effect of bilateral trade; furthermore, in column 2, I also control for industry level comparative advantage by including the ratio of value added in a 3-digit ISIC industry in a particular year to the total value added by that country in that year. Finally, in column 2, I also include the logarithm of real GDP per capita in order to control for a country's economic development. In terms of economic magnitudes, the coefficient estimates in column 1 and 2 indicate that an increase in the aggregate labor index by one would, ceteris paribus, result in a 2.5% decrease in output.[12]

Splitting the Deakin et al. (2007) labor index into its five sub-components allows us to paint a more nuanced picture of the impact of labor laws on growth. As can be seen from column 3 in Panel A, more stringent regulation of dismissal laws has a large positive and significant effect on industry level growth rates; the impact of the other labor law components on growth is insignificant. Quantitatively, the impact of regulation of dismissal on output / growth is substantial: The coefficient of 0.3 indicates that an increase in the dismissal index by one, implying a strengthening of dismissal laws, would, ceteris paribus, result in a 7.5% increase in output.

4.0.1 Difference-in-difference tests using single country changes

To make further progress on the causal effects of laws governing dismissal on economic growth, I examine the effects of large dismissal law changes on industry level growth rates using *difference-in-difference* tests that exploit single country changes.

The results can be seen in Table 9. The first test examines the impact of dismissal law changes in France in the early 1970s; the "control group" is the US. Results are reported in column 1 of Table 9. In the second natural experiment, where I exploit dismissal law changes in the US in 1989, the "control group" is Germany, which did not experience such a law change in the sample period. Results are presented in column 2 of Table 9. The results from the two natural experiments indicate that the effect of stringent dismissal laws on growth is indeed positive and significant.

In sum, after controlling for country, industry, and year fixed effects, as well as other country level variables, I find a negative effect of aggregate labor laws on economic growth. When I disaggregate the labor laws into their sub-components, I find that stringent regulation of dismissal laws has a large positive and significant effect on industry level growth rates; the impact of the other labor law components on growth is either negative or insignificant. Finally, using dismissal law changes in the US, UK, and France, I document that the impact of stringent dismissal laws on industry growth is similarly positive and significant.

5 Related Literature

This chapter contributes to the literature that examines the effect of laws that govern the relationships between employees and their employers. Botero et al. (2004) find that

[12] The coefficient on the aggregate labor index is approximately -0.1, which means that a 10% increase in the index will result in a 1% decrease in output. Similarly, a 25% increase in the index, which implies a one unit change in the aggregate labor index (which takes on values between 0 and 4), would result in a 2.5% decrease in output.

heavier regulation of labor leads to adverse consequences for labor market participation and unemployment and conclude that government interventions in the labor market are driven primarily by political economic considerations and not by any reasons of efficiency. Atanassov and Kim (2007) examine the interaction between labor laws and investor protection laws and find that rigid employment laws lead to higher likelihood of value-reducing major asset sales, particularly when investor protection is weak. They find that assets are sold to forestall layoffs, even if these asset sales hurt performance. Besley and Burgess (2004) conclude from their study of manufacturing performance in Indian states that pro-worker labor laws are associated with lower levels of investment, productivity, and output. Bassanini, Nunziata and Venn (2009) also conclude that mandatory dismissal regulations have a depressing effect on productivity growth in industries where layoff restrictions are more likely to be binding, based on data for OECD countries from 1982 to 2003.

In contrast to these studies which document the negative effects of labor laws, this study finds that stringent dismissal laws spur employees to exert innovative effort and thereby encourage innovation and economic growth. The study complements the work of Acharya, Baghai and Subramanian (2013, 2014) by focussing on a federal law change in the U.S. and examining concomitant effects on economic growth. As explained in the introduction, the model developed in this study differs from that in Acharya, Baghai and Subramanian (2014). While the model in that study focuses on the effect of wrongful discharge laws in enabling firms to commit to their employees ex-ante that they would not act in bad faith ex-post, the model in this study focuses on the costs that dismissal laws impose on firms when they tried to fire their employees. Also, this study differs from that in Acharya, Baghai and Subramanian (2013) by focusing on innovation at the firm level rather than at the industry (i.e. patent class) level.

In other related studies, Menezes-Filho and Van Reenen (2003) focus on a specific aspect of labor laws — the extent to which unions are allowed to operate — and survey the existing literature for their effects on innovation. They note that while U.S. studies find a negative impact of unions on innovation, European studies do not support these findings. the study pools together five representative countries that span three different legal "origins" and account for over 70% of patents filed in the U.S. While Menezes-Filho and Van Reenen (2003) focus on laws governing unions, I examine all dimensions of labor laws and pay particular attention to laws governing dismissal of employees.

Also related to the study is the work by MacLeod and Nakavachara (2007). They present a model which builds on the literature of relationship specific investment in order to capture the effect that employment law has on the incentives of the firm to select and monitor workers carefully. Using current population survey data from 1983–1994, they investigate the impact of the adoption of so-called "Dismissal Laws" by U.S. state courts on employment. In most states these dismissal laws take the form of non-statutory common law exceptions from the employment-at-will doctrine which began to be recognized by many U.S. state courts from the 1970's onwards. Macleod and Nakavachara (2007) present evidence that these dismissal laws enhance employment in industries requiring high relationship specific-investment and reduce employment in low relationship-specific investment sectors.

6 Policy Implications for Asian Economies

This study provides important implications for the Asian economies. These implications generally stem from the fact that most Asian economies, except for Japan, lag behind the leading innovators such as United States and Germany. It is quite pertinent in this context that Japan, with its policies of life-time employment that economically capture stringent dismissal laws in their essence, remains the most innovative among Asian economies (Mariguchi and Ono, 2004; Ono, 2010). As our theoretical model posits, innovative projects are inherently risky. So, the insurance effect that stringent dismissal laws or life-time employment policies provide leads employees to increase their investment disproportionately more, when compared to employment at will, in the innovative project than in the routine project. Therefore, country-level policies that discriminate between brick-and-mortar sectors and the innovative sectors in the nature of employment protection can be extremely useful in fostering incentives for innovation. Thus, our study suggests that countries intending to foster innovation may benefit from focussing on "innovation promotion zones," where the labor regulation is adapted such that dismissal of employees is difficult. These zones would contrast to the "export promotion zones," where the labor regulation is minimal to encourage manufacturing exports. Such seggregation is important to distinguish the innovative sectors of the economy from the brick-and-mortar sectors, where labor regulation should be minimal to reduce the inefficiencies that are created from stringent dismissal laws.

Policymakers must be careful to not interpret our study as advocating stringent dismissal laws for all sectors of the economy. As we have shown theoretically, the incentive for employees to invest more when dismissal laws are stringent manifests primarily in the innovative sectors. The inefficiencies created by labor regulation can only get exacerbated by uniformly making dismissal more stringent across all sectors.

7 Conclusion

In this study, I presented empirical evidence that there is a positive relationship between the ease with which employees can be dismissed by firms and their innovation; such innovation also seems to correlate with country-level economic growth.

To aid identification, the effect on innovation of the dismissal law I examined might have been purely an unintended consequence of these laws. However, the robustness and strength of the results begs the question whether such laws might in fact be necessary to promote innovation. Can firm-level contracts not suffice to provide employees the incentives to innovate? One possibility is that innovation may have externalities and thus institutions supporting innovation might be desirable to get socially efficient investments in innovation (Romer, 1986; Grossman and Helpman, 1991; and Aghion and Howitt, 1992). Another possibility is that firm-level contracts lack the force of commitment that laws offer. Since the outcomes of innovation are unpredictable, they are difficult to contract ex ante (Aghion and Tirole, 1994), which renders private contracts to motivate innovation susceptible to renegotiation. Such possibility of renegotiating contracts dilutes their ex-ante incentive effects. Since laws are considerably more difficult for private parties to renegotiate than firm-level contracts, legal protection of employees in the form of stringent dismissal laws can introduce the time-consistency in firm behavior absent with only private contracts.

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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

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

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

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

$\diamondsuit$

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

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

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:

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

Simplifying equation $(A-2)$ I get

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

Differentiating w.r.t. q_j^S and q_j^F and setting the derivatives equal to zero, I 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, I 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 $(A-6)$ I 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 $(A-11)$ I 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 I 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 $(A-7)$, I get

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

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

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 $\mu=0$, I 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 $\mu=0$ I 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 I 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 I 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 $(A-12)$ I get

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

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

$\diamondsuit$

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

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

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

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

Now differentiating w.r.t. σ I get

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

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 $(A-23)$ I 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, I 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.$\diamondsuit$

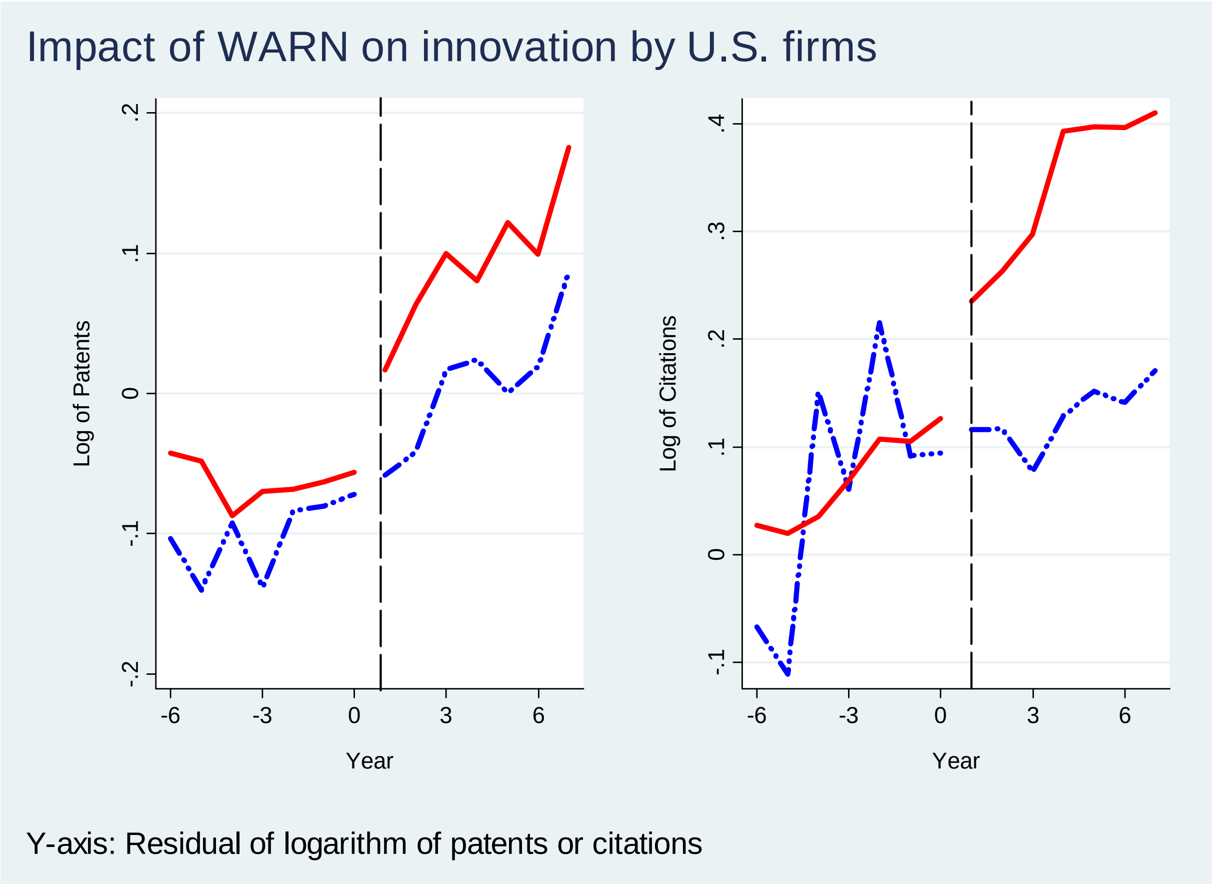

Figure 1: Effect of passage of WARN Act on innovation in U.S.

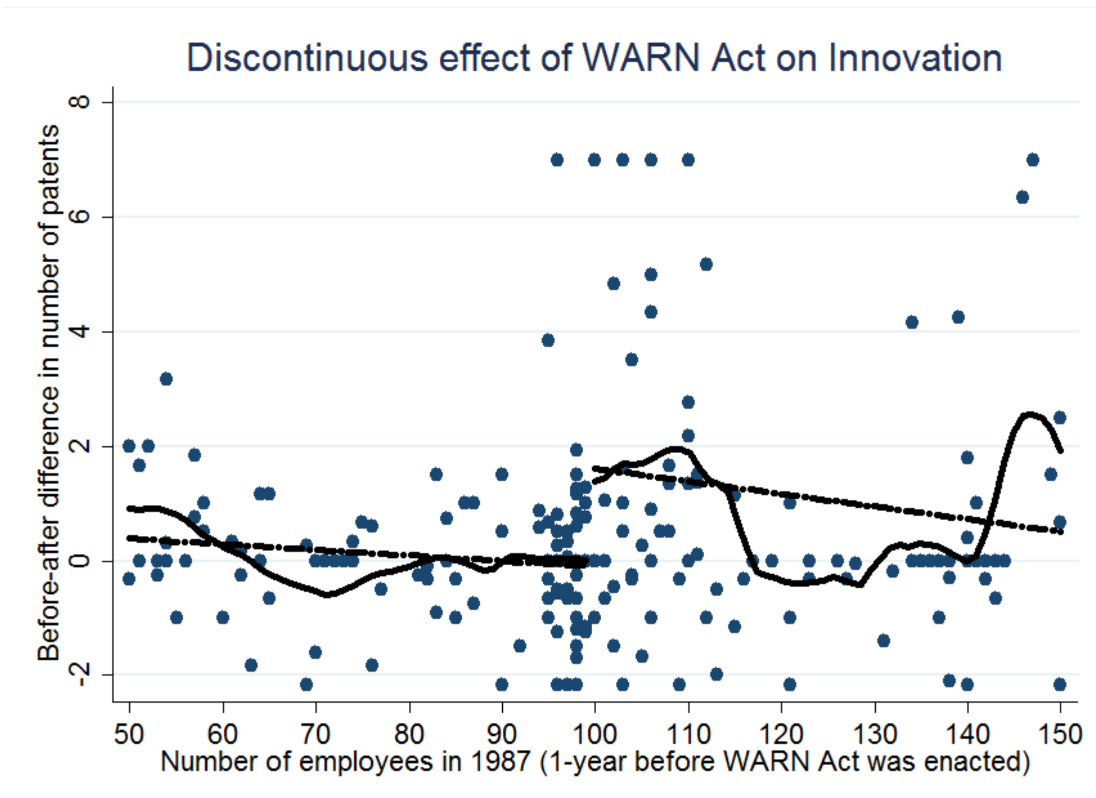

Figure 2: Discontinuous effect based on employee size of WARN Act on innovation

Table 1: Summary Statistics.

The table gives summary statistics for the following variables: number of patents, number of employees, firm size, and the firm's market-to-book ratio. Patent data is from the NBER Patents File (Hall, Jaffe and Trajtenberg, 2001).

Variable	Observations	Mean	Median	Standard Deviation
Number of patents	12822	17.1	2	61
Number of citations	12822	173.7	24	706.8
Number of employees	9397	16147.2	2552	45634.6
Firm size - Sales ($millions)	10900	2630.8	309.3	8452.4
Market-to-book ratio	10900	2.1	1.3	4.3

Table 2:
Impact of WARN Act on US firm-level employment – Difference-in-difference tests

The OLS regressions below implement the following model:
$\Delta Emp_{t,t-1} = \beta_i + \beta_t + \beta_1 * Over100_{i,1987} * After1988_t + \beta X + \epsilon_{it}$
where $\Delta Emp_{t,t-1}$ is the year-to-year employment change of firm i between year t and $t-1$ ($\Delta Emp_{t+1,t}$ is the corresponding employment change between year $t+1$ and t), and β_i and β_t are firm and year fixed effects, respectively. The sample covers twelve years around the passage of the WARN Act (from 1983-1994). $After1988_t$ is a dummy taking the value of one after the passage of the WARN Act (i.e. the years 1989-1994). $Over100_{i,1987}$ is a dummy taking the value of one if a firm has $\geq$ 100 employees in 1987, and zero otherwise. β_1 measures the difference-in-difference effect on innovation of the strengthening of dismissal laws via the WARN Act. X is a 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). Patent data is from the NBER Patents File (Hall, Jaffe and Trajtenberg, 2001). Firm-level data is from Compustat. Robust standard errors (clustered at the firm level) are given in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
Dependent variable is	$\Delta Emp_{t,t-1}$	$\Delta Emp_{t+1,t}$	$\Delta Emp_{t,t-1}$	$\Delta Emp_{t+1,t}$
$Over100_{i,1987} * After1988_t$	-0.328**	-0.543***	-0.234	-0.765***
	(0.16)	(0.15)	(0.21)	(0.19)
Size			0.930***	-0.395***
			(0.20)	(0.14)
Market-to-Book			0.139***	0.140***
			(0.042)	(0.040)
Anti-Takeover Index			-0.004	0.135
			(0.096)	(0.17)
Constant	-0.063	0.611***	-5.772***	1.013
	(0.22)	(0.18)	(1.24)	(0.70)
Observations	9,025	9,397	7,968	8,142
R-squared	0.19	0.18	0.19	0.17
Firm dummies	Y	Y	Y	Y
Application year dummies	Y	Y	Y	Y

Table 3: Impact of WARN Act on US firm-level employment for innovative and non-innovative industries – Difference-in-difference tests

The OLS regressions below implement the following model:
$\Delta Emp_{t,t-1} = \beta_i + \beta_t + \beta_1 * Over100_{i,1987} * After1988_t + \beta X + \epsilon_{it}$
where $\Delta Emp_{t,t-1}$ is the year-to-year employment change of firm i between year t and $t-1$ ($\Delta Emp_{t+1,t}$ is the corresponding employment change between year $t+1$ and t), and β_i and β_t are firm and year fixed effects, respectively. The sample covers twelve years around the passage of the WARN Act (from 1983-1994). $After1988_t$ is a dummy taking the value of one after the passage of the WARN Act (i.e. the years 1989-1994). $Over100_{i,1987}$ is a dummy taking the value of one if a firm has ≥ 100 employees in 1987, and zero otherwise. β_1 measures the difference-in-difference effect on innovation of the strengthening of dismissal laws via the WARN Act. X is a 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). Patent data is from the NBER Patents File (Hall, Jaffe and Trajtenberg, 2001). Firm-level data is from Compustat.
In columns 1–4, we split the sample into two parts according to innovation intensity. We define innovation intensity in industry j as the median number of patents applied for by firms in two-digit SIC industry j in year $(t-1)$. Columns 1 & 2 present the results from tests for firm-years with innovation intensity below or equal to the median intensity for a given year, while columns 3 & 4 show the results for firm-years with innovation intensity above the median intensity for a given year.
Robust standard errors (clustered at the firm level) are given in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
	Low Innovation Intensity	Low Innovation Intensity	High Innovation Intensity	High Innovation Intensity
Dependent variable is	$\Delta Emp_{t,t-1}$	$\Delta Emp_{t+1,t}$	$\Delta Emp_{t,t-1}$	$\Delta Emp_{t+1,t}$
$Over100_{i,1987} * After1988_t$	-0.221	-0.550***	-0.982*	-1.742***
	(0.27)	(0.19)	(0.57)	(0.60)
Size	0.973***	-0.227	0.988**	-1.052***
	(0.25)	(0.15)	(0.39)	(0.35)
Market-to-Book	0.123**	0.145***	0.187**	0.215**
	(0.053)	(0.051)	(0.073)	(0.087)
Anti-Takeover Index	-0.037	0.088	0.007	0.281
	(0.11)	(0.25)	(0.22)	(0.24)
Constant	-4.251***	0.828	-6.432**	4.218
	(1.05)	(0.67)	(2.77)	(2.67)
Observations	5,510	5,609	2,458	2,517
R-squared	0.29	0.27	0.18	0.16
Firm dummies	Y	Y	Y	Y
Application year dummies	Y	Y	Y	Y

Table 4:
Impact of WARN Act on US firm-level innovation – Difference-in-difference tests

The OLS regressions below implement the following model:
$y_{it} = \beta_i + \beta_t + \beta_1 * Over100_{i,1987} * After1988_t + \beta_2 * Over100_{i,1987} + \beta_3 * After1988_t + \beta X + \epsilon_{it}$
where y is a proxy for firm-level and time-varying innovation (the natural logarithm of patents or citations, as well as the natural log of patents and citations per 1,000 employees), and β_i and β_t are firm and year fixed effects, respectively. The sample covers twelve years around the passage of the WARN Act (from 1983-1994). $After1988_t$ is a dummy taking the value of one after the passage of the WARN Act (i.e. the years 1989-1994); this coefficient is subsumed by the year dummies. $Over100_{i,1987}$ is a dummy taking the value of one if a firm has $\geq$ 100 employees in a given year, and zero otherwise. β_1 measures the difference-in-difference effect on innovation of the strengthening of dismissal laws via the WARN Act. X is a 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). Patent data is from the NBER Patents File (Hall, Jaffe and Trajtenberg, 2001). Firm-level data is from Compustat.
Robust standard errors (clustered at the firm level) are given in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable is Natural Logarithm of	(1) Patents	(2) Citations	(3) Patents	(4) Citations
$Over100_{i,1987} * After1988_t$	0.144**	0.281***	0.217***	0.252**
	(0.059)	(0.088)	(0.069)	(0.10)
$Over100_{i,1987}$	0.124**	-0.084	-0.196***	-0.234**
	(0.051)	(0.093)	(0.067)	(0.11)
Size			0.275***	0.221***
			(0.030)	(0.041)
Market-to-Book			0.001	0.016
			(0.009)	(0.013)
Anti-Takeover Index			-0.044***	-0.033
			(0.015)	(0.021)
Constant	1.094***	3.551***	0.071	2.591***
	(0.050)	(0.088)	(0.17)	(0.19)
Observations	12,822	12,545	10,900	10,684
R-squared	0.86	0.80	0.87	0.80
Firm dummies	Y	Y	Y	Y
Application year dummies	Y	Y	Y	Y

Table 5:
Impact of WARN Act on US firm-level innovation – Difference-in-difference tests

The OLS regressions below implement the following model:
$y_{it} = \beta_i + \beta_t + \beta_1 * Over100_{i,1987} * After1988_t + \beta_2 * Over100_{i,1987} + \beta_3 * After1988_t + \beta X + \epsilon_{it}$
where y is a proxy for firm-level and time-varying innovation (the natural logarithm of patents or citations, as well as the natural log of patents and citations per 1,000 employees), and β_i and β_t are firm and year fixed effects, respectively. The sample covers twelve years around the passage of the WARN Act (from 1983-1994). $After1988_t$ is a dummy taking the value of one after the passage of the WARN Act (i.e. the years 1989-1994); this coefficient is subsumed by the year dummies. $Over100_{i,1987}$ is a dummy taking the value of one if a firm has $\geq$ 100 employees in a given year, and zero otherwise. β_1 measures the difference-in-difference effect on innovation of the strengthening of dismissal laws via the WARN Act. X is a 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). Patent data is from the NBER Patents File (Hall, Jaffe and Trajtenberg, 2001). Firm-level data is from Compustat.
Robust standard errors (clustered at the firm level) are given in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable is Natural Logarithm of	(1) Patents per 1,000 employees	(2) Citations per 1,000 employees	(3) Patents per 1,000 employees	(4) Citations per 1,000 employees
$Over100_{i,1987} * After1988_t$	0.207***	0.355***	0.138**	0.177*
	(0.070)	(0.096)	(0.069)	(0.10)
$Over100_{i,1987}$	-0.893***	-1.100***	-0.525***	-0.545***
	(0.076)	(0.11)	(0.073)	(0.11)
Size			-0.324***	-0.383***
			(0.029)	(0.039)
Market-to-Book			-0.001	0.016
			(0.009)	(0.013)
Anti-Takeover Index			-0.038**	-0.028
			(0.016)	(0.021)
Constant	1.399***	3.870***	3.105***	4.959***
	(0.071)	(0.10)	(0.17)	(0.23)
Observations	12,821	12,544	10,899	10,683
R-squared	0.91	0.86	0.91	0.85
Firm dummies	Y	Y	Y	Y
Application year dummies	Y	Y	Y	Y

Table 6: Impact of WARN
Act on US firm-level Employment and innovation – Regression discontinuity tests.

The regressions below implement the following model:
$y_{it} = \beta_i + \beta_t + \beta_1 * Over100_{i,1987} * After1988_t + \beta X_{it} + \epsilon_{it}$
β_i and β_t are firm and year fixed effects, respectively. Across all three panels, the dependent variables are (the log of) patents and citations, as well as (the log of) patents and citations scaled by the number of employees. In addition, we also employ as dependent variable $Ind(Emp_{i,t} - Emp_{i,t-1} < 0)$, a binary variable taking on a value of one in case of a net employment reduction in firm i from year $t-1$ to year t. $Over100_{i,1987}$ is a dummy variable taking the value of one in each year if a given firm has ≥ 100 employees *in 1987*, and zero otherwise. $After1988_t$ is a dummy taking the value of one after the passage of the WARN Act (i.e. the years 1989-1994. The sample period is 1983–1994. Robust standard errors (clustered at the firm level) are given in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable is	$Ind(Emp_{i,t} < Emp_{i,t-1})$	Ln(Patents)	Ln(Citations)	Ln(Patents / Employees)	Ln(Citations / Employees)
Panel A: $90 \leq Employment_{i,1987} < 110$					
	(1)	(2)	(3)	(4)	(5)
$Over100_{i,1987} * After1988_t$	-0.293**	0.370**	0.606***	0.599	0.724*
	(0.114)	(0.146)	(0.217)	(0.444)	(0.432)
$Over100_{i,1987}$	0.283***				
	(0.083)				
Observations	435	916	916	765	765
Adjusted R-squared	0.027	0.828	0.693	0.649	0.681
Panel B: $40 \leq Employment_{i,1987} < 60$					
	(1)	(2)	(3)	(4)	(5)
$Over50_{i,1987} * After1988_t$	-0.076	0.176	0.633	-0.468*	0.191
	(0.209)	(0.152)	(0.598)	(0.254)	(0.476)
$Over50_{i,1987}$	-0.030				
	(0.147)				
Observations	115	259	259	230	230
Adjusted R-squared	0.039	0.188	0.348	0.633	0.492
Panel C: $140 \leq Employment_{i,1987} < 160$					
	(1)	(2)	(3)	(4)	(5)
$Over150_{i,1987} * After1988_t$	0.104	-0.115	0.201	-0.164	0.033
	(0.159)	(0.357)	(0.451)	(0.592)	(0.717)
$Over150_{i,1987}$	-0.124				
	(0.181)				
Observations	88	170	170	155	155
Adjusted R-squared	0.073	0.490	0.633	0.447	0.516
Firm FE	N	Y	Y	Y	Y
Application Year FE	Y	Y	Y	Y	Y

Table 7: Impact of WARN Act on US firm-level innovation – Robustness of regression discontinuity results

The regressions below implement the following model:
$y_{it} = \beta_i + \beta_t + \beta_1 * (X \leq Emp < Y)_{i,1987} * After1988_t + \beta X_{it} + \epsilon_{it}$
β_i and β_t are firm and year fixed effects, respectively. The dependent variables are (the log of) patents and citations. $(X \leq Emp < Y)_{i,1987}$ is a dummy variable taking the value of one in each year if a given firm has between X and Y employees *in 1987*, and zero otherwise; as, for a given firm, this variable does not vary over time, its effect is subsumed in the firm dummies. $After1988_t$ is a dummy taking the value of one after the passage of the WARN Act (i.e. the years 1989-1994); this coefficient is subsumed by the year dummies. Patent data is from the NBER Patents File (Hall, Jaffe and Trajtenberg, 2001). Firm-level data is from Compustat. The sample period is 1983–1994. Robust standard errors (clustered at the firm level) are given in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable is LN of	(1) Patents	(2) Citations	(3) Patents	(4) Citations
$(60 \leq Emp < 80)_{i,1987} * After1988_t$	-0.212*	-0.208		
	(0.118)	(0.230)		
$(80 \leq Emp < 100)_{i,1987} * After1988_t$	-0.154*	-0.137		
	(0.090)	(0.161)		
$(100 \leq Emp < 120)_{i,1987} * After1988_t$	0.179**	0.402**		
	(0.086)	(0.184)		
$(120 \leq Emp)_{i,1987} * After1988_t$	0.076	0.364***		
	(0.048)	(0.121)		
$(100 \leq Emp < 105)_{i,1987} * After1988_t$			0.230	0.441**
			(0.150)	(0.193)
$(105 \leq Emp < 125)_{i,1987} * After1988_t$			0.255***	0.437**
			(0.092)	(0.196)
$(125 \leq Emp)_{i,1987} * After1988_t$			0.166***	0.448***
			(0.047)	(0.082)
Observations	13,067	13,067	13,067	13,067
Adjusted R-squared	0.851	0.736	0.851	0.736
Firm FE	Y	Y	Y	Y
Application Year FE	Y	Y	Y	Y

Table 8: Effect of Labor Laws on Industry Level Growth.

The OLS regressions below implement the following model:
$\Delta y_{ict} = \beta_i + \beta_c + \beta_t + \boldsymbol{\beta}_1 * \Delta LaborLaws_{c,t} + \beta \cdot \Delta X + \varepsilon_{ict}$
where y_{ict} is the natural logarithm of real value added in ISIC industry i in country c in year t. Δ is the first difference operator. $\beta_i, \beta_c, \beta_t$ denote ISIC class, country, and year fixed effects. β_1 measures the impact of labor laws on output/growth. The sample period is 1970–2003. "F.D." denotes that the first difference of a variable was employed in the regression. Data on nominal value added are obtained from the UNIDO Industrial Statistics database. CPI data from the US Bureau of Labor Statistics was used to deflate the value added data in order to obtain real values; as CPI data for India was not available from the US Bureau of Labor Statistics, the CPI data for that country was obtained from the International Labour Organization's Labour Statistics database. The labor law index data is from Deakin et al. (2007). The *Creditor Rights Index* is from Djankov, McLiesh, and Shleifer (2007). *Log Imports* is the log of a country's imports from the US in a given 3-digit ISIC industry in a given year; *Log Exports* is the log of a country's exports to the US in a given 3-digit ISIC industry in a given year (export and import data are from Nicita and Olarreaga, 2006). *Ratio of Value Added* is the ratio of value added in the 3-digit ISIC in a year to the total value added by that country in that year (from UNIDO). *Log of per capita GDP* is the logarithm of real GDP per capita. Standard errors are robust to heteroscedasticity and autocorrelation. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable is First Difference in	(1) ln(Real Value Added)	(2) ln(Real Value Added)	(3) ln(Real Value Added)
Labor Index (F.D.)	-0.096*	-0.101**	
	(0.041)	(0.032)	
Creditor Rights Index (F.D.)	-0.076***	-0.080***	
	(0.013)	(0.007)	
Log Imports (F.D.)	-0.000	-0.000	
	(0.001)	(0.000)	
Log Exports (F.D.)	0.000	0.001	
	(0.001)	(0.000)	
Ratio of Value Added (F.D.)		6.575***	
		(1.63)	
Log of per capita GDP (F.D.)		1.449***	
		(0.28)	
Regulation of dismissal (F.D.)			0.299***
			(0.056)
Regulation of working time (F.D.)			-0.120
			(0.14)
Alternative employment contracts (F.D.)			-0.149
			(0.086)
Employee representation (F.D.)			-0.117
			(0.15)
Industrial action (F.D.)			0.353
			(0.32)
Constant	-0.069**	-0.114***	0.066
	(0.022)	(0.029)	(0.051)
Country, Year, and ISIC class dummies	Y	Y	Y
Observations	751	751	1446
R-squared	0.38	0.71	0.28

Table 9: Effect of Labor Laws on Industry Level Growth: Two-country Tests.

The OLS regressions below implement the following model:
$\Delta y_{ict} = \beta_i + \beta_c + \beta_t + \boldsymbol{\beta}_1 * \Delta LaborLaws_{c,t} + \beta \cdot \Delta X + \varepsilon_{ict}$
where y_{ict} is the natural logarithm of real value added in ISIC industry i in country c in year t. Δ is the first difference operator. $\beta_i, \beta_c, \beta_t$ denote ISIC class, country, and year fixed effects. β_1 measures the impact of labor laws on output/growth. The sample period is 1970–2003. "F.D." denotes that the first difference of a variable was employed in the regression. Data on nominal value added are obtained from the UNIDO Industrial Statistics database. CPI data from the US Bureau of Labor Statistics was used to deflate the value added data in order to obtain real values; as CPI data for India was not available from the US Bureau of Labor Statistics, the CPI data for that country was obtained from the International Labour Organization's Labour Statistics database. The labor law index data is from Deakin et al. (2007). The *Creditor Rights Index* is from Djankov, McLiesh, and Shleifer (2007). *Log Imports* is the log of a country's imports from the US in a given 3-digit ISIC industry in a given year; *Log Exports* is the log of a country's exports to the US in a given 3-digit ISIC industry in a given year (export and import data are from Nicita and Olarreaga, 2006). *Ratio of Value Added* is the ratio of value added in the 3-digit ISIC in a year to the total value added by that country in that year (from UNIDO). *Log of per capita GDP* is the logarithm of real GDP per capita. Standard errors are robust to heteroscedasticity and autocorrelation. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)
	France & US;France dismissal law change in early 1970s; data from 1970-1988	Germany & US; US dismissal law change in 1989; data from 1970-1995
Dependent Variable is First Difference in	ln(Real Value Added)	ln(Real Value Added)
Regulation of dismissal (F.D.)	0.640***	0.328*
	(0.074)	(0.15)
Constant	0.077***	0.105***
	(0.015)	(0.014)
Country, Year, and ISIC class dummies	Y	Y
Observations	330	434
R-squared	0.35	0.31