

Wrongful Discharge Laws and Innovation: Appendix

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Appendix A: General Model

In our basic model, we assumed that innovation generated from the innovation project I can only be firm-specific. Here, we extend our model to the case when innovation can be both generic and firm-specific. The key feature of the firm-specific (generic) innovation is that it generates more value if commercialized inside the firm (outside the firm with a venture capitalist, VC). We assume that the innovation is firm-specific with probability κ and generic with probability $(1 - \kappa)$. Thus, if project I is implemented, the unconditional probability of a firm-specific innovation is κe_I and that of a generic innovation is $(1 - \kappa)e_I$. The parameter κ thus captures the exogenous technological characteristics that determine the extent to which the employees' effort increases the likelihood of a firm-specific innovation.

To derive the outside options *endogenously*, we model the following extensive-form game that E and F play after knowing whether the innovation was successful or not and, if successful, whether the innovation is firm-specific or generic. Figure A-1 shows the timing and sequence of events. E first decides whether to start a new firm and commercialize the innovation with the help of an investor or to continue with F and implement the innovation within the firm. If E decides to start a new firm, then F sues him for violating the non-compete clause in his employment contract. The probability of F successfully prosecuting E depends on the legal regime governing mobility of human capital in the state. We assume that with probability λ , the court rules that E cannot implement the innovation outside the firm ($\lambda = 0$ corresponds to no limitations on the mobility of human capital).

If E decides to leave F , F hires a new employee (E') to replace E and implements the innovation with E' . If E decides to stay with F , F decides whether to retain E or fire him and replace him with E' . If F fires E when the project is successful, then E sues F for “wrongful discharge.” As in the basic model, the probability that E wins a wrongful discharge case is μ ; the penalties that a firm has to pay for wrongful discharge are C .

At date 2, project cash-flows are realized and are allocated based on the bargaining outcomes at date 1.5. For project j , $j \in \{I, R\}$, the project cash flow equals α_j if the project yields a successful innovation and E implements it within the firm (i.e. with F), γ_j if the project yields a successful innovation and E implements the innovation outside the firm (i.e. with the VC), and β_j if the

project fails to generate an innovation.

Since an established firm possesses all the necessary resources to implement an innovation, we assume that the cash-flows generated by a firm-specific innovation that is successfully implemented within an incumbent firm are greater than the cash-flows generated by a generic innovation that is implemented by a new firm, which in turn are greater than the cash-flows if the innovation fails:

$$\beta_j \leq \gamma_j \leq \alpha_j \tag{A-1}$$

To capture the effect that when the innovation is firm-specific (generic), the cash-flows from implementing it within (outside) the firm are greater, we assume that the cash-flows from implementing a firm-specific (generic) innovation outside (within) the firm equal zero. Finally, we assume that the firm's cash-flows from implementing a successful innovation with the new employee E' are lower than the cash-flows from implementing it with the original employee E and equal $b\alpha_j$ ($0 < b < 1$).

As in the main paper we assume that $\beta_R = R - 0.5a$, $\alpha_R = R + 0.5a$ for the routine project while for the innovative project $\beta_I = a$, $\alpha_I = A$. Moreover, the payoff from the routine project if E implements the innovation outside the firm (i.e. with the VC) is zero, $\gamma_R = 0$ while $\gamma_I = G$. As in the main paper, we also the following simplified version of (A - 1) assume that:

$$0 < a < 1.5a < R < G + 0.5a < A - 0.5a \tag{A-2}$$

Finally:

$$c < b \tag{A-3}$$

A.1 Analysis

We first analyse the game that results if the firm chooses the innovative project I . We solve this game by backward induction. Consider first the extensive form game played at date 1.5. Let us denote E 's and F 's expected payoffs at date 1.5 as U and V respectively.

We will first analyze the case where the innovative project generates a successful innovation that is firm-specific.

If E chooses to remain in the firm, then F chooses either to retain or fire E . If F fires E , E

sues F for wrongful discharge. If E wins, the court orders F to pay damages equal to cA . Since F produces with E' in this case, the aggregate cash-flows from implementing the innovation equal bA . Since the labor market is competitive, F has all the bargaining power with E' and gets the payoff $(b - c)A$ while E 's payoff equals cA . If E loses the lawsuit, then E 's and F 's payoffs are respectively 0 and bA . Thus, E 's and F 's expected payoffs if F fires E equal μcA and $(b - \mu c)A$ respectively. These are the values of E 's and F 's outside options when they bargain in the case when F decides to retain E . Since the total cash-flows when F retains E equal A , 50 : 50 Nash bargaining yields the payoffs for E and F as $U = [0.5(1 - b) + \mu c]A$ and $V = [0.5(1 - b) - \mu c]A$. In equilibrium, F retains E since F 's payoffs are greater in this case than when it fires him.

If E starts a new firm when the innovation is firm-specific, his payoff is 0 while F recruits the new employee E' and generates cash-flows bA by employing him. As the labor market is competitive, F has all the bargaining power and gets the entire payoff bA in this case. Given the payoffs, it is easy to see that E chooses to stay with F and implements the innovation inside the firm. Figure A-2 summarizes these payoffs and the solution to the extensive form game at date 1.5.

Now consider the case when the project generates a successful generic innovation. In this case, if E decides to implement the innovation by creating a new firm, F sues E for violating the non-compete clauses in the employment agreement. Only if F loses the lawsuit can E proceed with implementing the innovation through the new firm. Since the payoff from implementing the innovation inside the incumbent firm is zero, F cannot be accused of wrongful discharge if it fires E in this case. Following steps that are similar to the above, we find that E decides to implement the innovation outside the firm and the payoffs to E and F are respectively $U = (1 - \lambda)G$ and $V = 0$. Figure A-3 summarises these payoffs and the solution to the extensive form game at date 1.5.

If the project does not generate a successful innovation, then the payoff from the project equals a . Following steps identical to those in the case of project success, we obtain payoffs for E and F as $U = [0.5(1 - b) + \mu c]a$ and $V = [0.5(1 - b) - \mu c]a$ respectively. Again, in equilibrium, F retains E since F 's payoffs are greater in this case than when F fires E .

Lemma A1 *When the innovation is a firm-specific one, the employee and the firm choose to implement the innovation within the firm. In contrast, when the innovation is a generic one, the employee chooses to start a new firm to implement the innovation.*

If the project does not generate a successful innovation, then the payoff from the project equals

0. Furthermore, even if F were to fire E , E cannot sue F for wrongful discharge. Since the payoff with or without E equals 0, F is indifferent between firing or retaining E .

Since the probability of a successful innovation is given by e_I and, in turn, the probabilities of firm-specific and generic innovations equal κe_I and $(1 - \kappa) e_I$, E 's expected payoff at date 1 equals

$$\bar{U}(e_I) = e_I \cdot [0.5(1 - b) + \mu c] A + (1 - e_I) \cdot [0.5(1 - b) + \mu c] a + (1 - \kappa) e_I \cdot (1 - \lambda)G - 0.5e_I^2 \quad (\text{A-4})$$

where $[0.5(1 - b) + \mu c] A$ denote E 's payoff when the innovation is successful, $[0.5(1 - b) + \mu c] a$ denote E 's payoff when the innovation fails, $(1 - \lambda)G$ captures E 's payoff from starting a new firm when the innovation is a generic one, e_I equals the probability of the project being successful and $0.5e_I^2$ equals E 's private cost of effort. Thus, the equilibrium level of effort, which is chosen by E to maximize $\bar{U}(e_I)$, is:

$$e_I^* = \kappa [0.5(1 - b) + \mu c] (A - a) + (1 - \kappa) (1 - \lambda)G \quad (\text{A-5})$$

Thus, as in Fulghieri and Sevilir (2011), an increase in the legal restrictions on the mobility of human capital λ dampens employee effort to innovate.

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

$$\begin{aligned} e_I^{FB} &= \arg \max_{e_I} [e_I \cdot A + (1 - e_I) \cdot a + (1 - \kappa) G e_I - 0.5e_I^2] \\ \Rightarrow e_I^{FB} &= \kappa (A - a) + (1 - \kappa) G \end{aligned} \quad (\text{A-6})$$

The game for the routine project is solved in an identical manner, which yields

$$e_R^* = [0.5(1 - b) + \mu c] \kappa a; e_R^{FB} = a \quad (\text{A-7})$$

A.2 Results

Proposition A1 *The equilibrium level of effort exerted by an employee when contracts are incomplete is lower than that in the first-best benchmark case when contracts are complete:*

$$e_I^* < e_I^{FB} \quad (\text{A-8})$$

The employee underinvests not only due to the hold-up by the firm when the innovation is firm-specific but also because of possible hold-up by the firm when the innovation is generic (and he wants to create a new firm to develop the innovation).

Proposition A2 *An increase in the stringency of WDL decreases the employee's underinvestment in the innovative project compared to the first-best level of investment.*

$$\frac{de_I^*}{d\mu} > \frac{de_I^{FB}}{d\mu} = 0 \quad (\text{A-9})$$

The intuition for this result is quite similar to Proposition (3) in the basic model.

Proposition A3 *An increase in the stringency of wrongful discharge provisions disproportionately increases the effort by the employee in the case of the innovative project relative to the increase in the effort in the routine project:*

$$\frac{de_I^*}{d\mu} > \frac{de_R^*}{d\mu} \quad (\text{A-10})$$

The intuition for this is analogous to Proposition (3) in the basic model.

Since the labor market is competitive, employees earn their reservation wage in equilibrium. Therefore, the firm chooses between innovative and routine project at date 0 to maximize the joint payoff from project j , which we denote by W_j . Lemma A2 formalizes this result.

Lemma A2 *The optimal project is chosen to maximize the aggregate payoff to firm and employee.*

We now examine the effect of WDL on the ex-ante expected surplus from pursuing an innovative project versus that from pursuing a routine project.

Proposition A4 *An increase in the stringency of wrongful discharge provisions increases the value*

of the innovative project disproportionately more than the value of the routine project.

$$\frac{d\bar{W}_I^*}{d\mu} > \frac{d\bar{W}_R^*}{d\mu} \quad (\text{A-11})$$

Proposition A5 *Given the parametric restriction that the payoff from the routine project is not very low, there exists a $\hat{\mu} \in (0, 1)$ such that the value from the routine project is higher than the value from the innovative project when WDL are not stringent ($\mu \leq \hat{\mu}$) and the reverse is true when such laws are stringent ($\mu > \hat{\mu}$)*

$$\mu \leq \hat{\mu} \Rightarrow \bar{W}_I^*(\mu) \leq \bar{W}_R^*(\mu) \quad (\text{A-12})$$

$$\mu > \hat{\mu} \Rightarrow \bar{W}_I^*(\mu) > \bar{W}_R^*(\mu) \quad (\text{A-13})$$

The intuition for both the above propositions follows directly from Proposition 3 and is similar to that provided for Proposition (4) and Proposition (5) in the main body of the paper.

To examine the effect of WDL on entrepreneurship, denote the expected probability of the employee creating a new firm with the VC as ν . Lemma A1 shows that the employee chooses to start a new firm when the innovative project generates a successful, generic innovation. Furthermore, the probability of a successful, generic innovation equals $(1 - \kappa) e_I$. Therefore, in equilibrium the expected probability of a new firm being created equals:

$$\nu = (1 - \kappa) e_I^* \quad (\text{A-14})$$

Proposition A6 *An increase in the stringency of wrongful discharge provisions increases the likelihood of the employee starting a new firm:*

$$\frac{d\nu}{d\mu} > 0 \quad (\text{A-15})$$

The intuition for this result follows directly from Proposition A2, which showed that an increase in the stringency of WDL increases the employee's effort. Since the firm invests in the employee to increase his human capital, any additional effort by the employee increases the likelihood of

both firm-specific as well as generic innovations. Since generic innovations are optimally developed outside the existing firm, an increase in the stringency of WDL increases the likelihood of new firm creation as well.

Appendix B: Proofs

Proof of Lemma A2: The optimal project choice is given by

$$\begin{aligned} \max_j \bar{V}_j(e_j^*) & \tag{B-1} \\ \text{s.t. } \bar{U}_j(e_j^*) & \geq 0 \\ e_j^* & = \arg \max_{e_j} \bar{U}_j(e_j) \end{aligned}$$

where the employee's reservation utility in equilibrium equals 0. Since the labor market is competitive, the IR constraint is satisfied with equality. Therefore, $\bar{U}_j = 0$. Since $\bar{V}_j = \bar{W}_j - \bar{U}_j$, the above problem reduces to

$$\begin{aligned} \max_j \bar{W}_j(e_j^*) & \tag{B-2} \\ \text{where } e_j^* & = \arg \max_{e_j} \bar{U}_j(e_j) \diamond \end{aligned}$$

Proof of Proposition A1: Using equations (A – 5) and (A – 6), we get

$$\begin{aligned} e_I^{FB} - e_I^* & = [0.5(1+b) - \mu c](A - a) + (1 - \kappa)G\lambda > 0 \text{ using (A – 3) and } 0 < \mu < 1, A > a \diamond \\ e_R^{FB} - e_R^* & = [0.5(1+b) - \mu c]\kappa a > 0 \text{ using (A – 3) and } 0 < \mu < 1. \diamond \end{aligned}$$

Proof of Propositions A2 and A3: Differentiating equation (A – 5) w.r.t. μ we get $\frac{de_I^*}{d\mu} = \kappa c(A - a) > 0$; $\frac{de_R^*}{d\mu} = \kappa ca > 0$. From (4), $A > 2a \Rightarrow \frac{de_I^*}{d\mu} > \frac{de_R^*}{d\mu}$. Since $e_j^{FB} = \text{constant } \forall j = I, R$ the results follow. \diamond

Proof of Proposition A4:

$$\begin{aligned}\overline{W}_I &= \kappa [e_I^* A + (1 - e_I^*) a] + (1 - \kappa) e_I^* G - 0.5 (e_I^*)^2 \\ \overline{W}_R &= \kappa [e_R^* (R - 0.5a) + (1 - e_R^*) (R + 0.5a)] - 0.5 (e_R^*)^2\end{aligned}\tag{B-3}$$

$$\begin{aligned}\frac{d\overline{W}_I}{d\mu} &= [\kappa (A - a) + (1 - \kappa) G - e_I^*] \frac{de_I^*}{d\mu} = \kappa c (A - a)^2 [\kappa \{0.5 (1 + b) - \mu c\} + (1 - \kappa) G \lambda] \\ &> 0 \text{ using } (A - 3) \text{ and } 0 < \mu < 1, A > a.\end{aligned}\tag{B-4}$$

$$\frac{d\overline{W}_R}{d\mu} = [\kappa (A - a) - e_R^*] \frac{de_R^*}{d\mu} = c \kappa^2 a^2 \{0.5 (1 + b) - \mu c\}\tag{B-5}$$

$$< \frac{d\overline{W}_I}{d\mu} \because a < A - a \text{ from } (A - 2) \text{ and } \lambda > 0, \kappa < 1. \diamond\tag{B-6}$$

Proof of Propositions A5: We make the following parametric restriction for Proposition 5. To allow for the fact that in some legal environments, choosing the routine project may be optimal, we assume that $R < \frac{3}{2}a + \frac{\kappa(3+b)(1-b)}{8} (A^2 - 2Aa)$. For the innovative project:

$$\begin{aligned}\overline{W}_I &= \kappa [e_I^* A + (1 - e_I^*) a] + (1 - \kappa) e_I^* G - 0.5 (e_I^*)^2 \\ &= \{0.25\kappa (A - a) (3 + b - 2\mu C) + 0.5 (1 - \kappa) (1 + \lambda) G\} \\ &\quad \{0.5\kappa (A - a) (1 - b + 2\mu C) + (1 - \kappa)(1 - \lambda) G\} + \kappa a\end{aligned}$$

By using the payoffs for the routine project, we get:

$$\begin{aligned}\overline{W}_R &= \kappa [e_R^* A + (1 - e_R^*) a] - 0.5 (e_R^*)^2 \\ &= \frac{\kappa^2 a^2}{8} (3 + b - 2\mu C) (1 - b + 2\mu C) + \kappa (R - 0.5a)\end{aligned}$$

Therefore

$$\begin{aligned}\overline{W}_I(\mu = 0) - \overline{W}_R(\mu = 0) &< \frac{\kappa^2}{8} (3 + b) (1 - b) (A^2 - 2Aa) - \kappa \left(R - \frac{3}{2}a \right) \\ &< 0 \text{ using the parametric restriction}\end{aligned}$$

where the second step follows from $G < A - a$ using (A - 2) and $\overline{W}_I(\mu = 0) - \overline{W}_R(\mu = 0)$ decreasing

in λ and increasing in κ and $0 < \kappa < 1$. Now

$$\begin{aligned} \overline{W}_I(\mu = 1) &> \frac{\kappa^2}{8} (3 + b - 2c) (1 - b + 2c) (A^2 - 2Aa) - \kappa \left(R - \frac{3}{2}a \right) \\ &> \frac{\kappa^2 c}{2} [1 + b - c] \text{ using the parametric restriction} \\ &> 0 \text{ using } (A - 3) \text{ and } A > 2a \diamond \end{aligned}$$

Appendix C: Additional Tests

C.1 Sample selection - general issues

We were able to merge 5,698 firms from the NBER patent data file to Compustat. These are firms that at some point in their life feature in Compustat. Roughly, we are able to merge about 1/3 of the relevant NBER patent data sample consisting of patent assignees located in the US to Compustat (reasons for limitations in the merge include the fact that the NBER patent dataset includes patents assigned to privately held firms, while Compustat doesn't). Not all the firms that we merge to Compustat have accounting data available for every year of the sample period (1971-1999). For example, only 4,942 firms that we merge to Compustat have data on book assets available in Compustat during parts of our sample period; this corresponds to 83,893 firm-year observations. Market-to-book is available for 75,658 firm-years. Real value-added is available for 67,838 firm-years (gross state product data by state and BEA sector is available from 1977-1999 from the BEA). The intersection set of all the firm-year observations for the time-period 1977-1999, conditioning on availability of all the control variables, is 48,433 observations, which is the number of observations for the regressions with the full set of control variables in Table 2.

In Table C-1, we show that small changes in significance and coefficient estimates between Columns 1 & 2 and 3 & 4 in Table 2 are not due to the reduction in sample size but are resulting from the necessary inclusion of control variables. While Columns 1 & 2 in Table C-1 exactly reproduce Columns 1 & 2 in Table 2, estimates in Columns 3 & 4 don't include control variables but condition on the availability of the control variables used in other specifications. Hence, these regressions have the same number of observations as Columns 3 & 4 in Table 2 (48,433 and 44,718 observations, respectively). The results from this comparison show that the coefficient estimates, in

particular those of the good-faith exception, are very similar in significance and magnitude across these specifications, and are not much affected by the change in sample size.

C.1.1 Division/ Subsidiary level tests and Sample Selection

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

$$y_{d \rightarrow i, s, t} = \beta_d + \beta_t + \beta_1 * GF_{st} + \beta_2 * PP_{st} + \beta_3 * IC_{st} + \varepsilon_{dst}$$

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

The results of these tests are described in Columns 1 and 2 of Table C-2. We can see that the conclusions drawn from our earlier tests are unaffected here: the impact of WDL remains positive and significant, with the good-faith clause having quantitatively the largest effect.

Also, in the earlier tests, we used the link of the NBER patent data to Compustat. This enabled us to use firm-level variables like *Size*, *Market-to-Book* and $\ln(R\&D/Sales)$ in the regressions. However, the Compustat-NBER patent data merge came at a cost: Not all U.S. firms (assignees) from the NBER patent data set could be matched to Compustat, resulting in a smaller sample that was possibly selected in systematic ways.

In order to show that our results are not driven by sample-selection, we repeat the main tests with the *full* NBER patent data sample for all corporate U.S. assignees. We therefore run regressions specified in equation (16) but for the full sample. The results of these tests are reported in Columns 3 and 4 of Table C-2. We can see that the conclusions drawn from our earlier tests are unaffected:

In the full NBER patent data sample, the impact of WDL remains positive and significant, with the good-faith exception having the largest effect.

C.2 Trend in Innovation after Good Faith Passage

Identification in difference-in-difference settings is based on a before-after comparison in levels between the treatment and control groups; the counterfactual trend behavior of treatment and control groups should be the same (Angrist and Pischke, 2008, pp.165). Figure 4 and Table 4 in the main paper suggest that this requirement is satisfied in our setting. Nonetheless, to check purely for a difference in trend due to the good faith exception (rather than a difference in trend over and above the difference in levels), we run regressions where we interact the dummy for the good faith exception with a linear time trend and exclude the level of the good faith exception. The results are reported in Table C-3. Consistent with the observation in figure 4, we find that the trend for innovation is greater after the adoption of the good faith exception.

C.3 Additional tests to examine the endogeneity of the Good-Faith Exception

In all our specifications, we included interactions between region dummies and year dummies to account for time-varying geographical differences in innovation as well as in the enactment of WDL. The regions were based on definitions by the U.S. Census Bureau. These dummies enabled us to control for the fact that the passage of the good-faith exception was more common in the Western U.S. region than in other areas of the U.S. Within the Western U.S. region, the passage of the good-faith exception was more common to the Northwest region. To address this point, we *sub-divide the West* into Northwest and Southwest regions and include interactions between the year dummies and dummies for these five regions.¹

Table C-4 shows results from tests that include geographical trends at the level of these *five* U.S. regions. Crucially, even after controlling for regional trends that distinguish between the Northern and Southern part of the West, we find that the passage of WDL – specifically the good-faith exception – leads to greater innovation.

¹*Northwest:* Alaska, Washington, Oregon, Montana, Idaho, Wyoming; *Southwest:* California, Nevada, Utah, Colorado, Arizona, New Mexico, Hawaii.

C.4 Effect of industry-level differences in employee turnover

Our model shows that WDL reduce the underinvestment stemming from the likelihood of hold-up by the employer. In industries where employee turnover is more pronounced, the employee would be more wary of hold-up by the employer, which would lead the employee to underinvest more when compared to an industry where employee turnover is low. Thus, when compared to industries where employee turnover is low, WDL would be *relatively* more effective in enhancing innovation in industries where employee turnover is high.

To test this prediction, we generate a time-varying classification of the Fama-French 48 industries into those where employee turnover is low and those where it is high. For this purpose, we first construct a time-varying, firm-level measure of employment variability: for each firm i and year t , we calculate the coefficient of variation of employment by dividing the standard deviation of the number of employees of firm i up to year t (starting with the firm’s first record in Compustat) by the mean number of employees in firm i up to year t . Each year, we then separate firms into industries with high and low employment variability: *High_EmpVar* takes the value of one, if the median firm’s employment variability in a given Fama-French industry in a given year exceeds the median firm’s employment variability across all industries in that year. *Low_EmpVar* is defined as $(1 - High_EmpVar)$.

Table C-5 shows the results of these tests. In this table, we separate the effect of the passage of the good-faith exception into one for industries with high employment variability, and one for industries with low employment variability. We find that the positive effect of the good-faith exception only manifests in industries with high employment variability, while there is no effect in industries with low employment variability.²

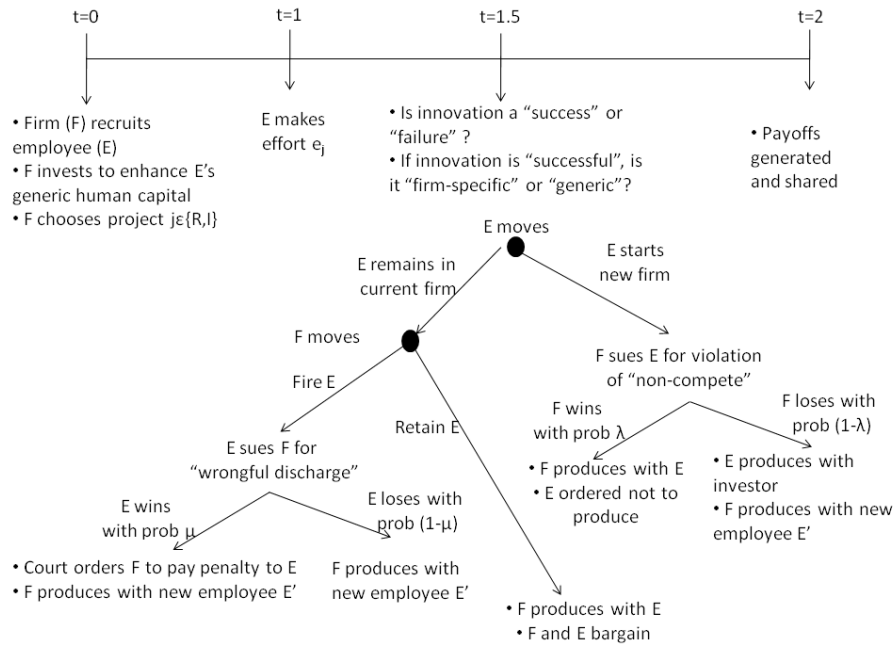
References

- [1] Agrawal, A. and D. Matsa, 2011, “Labor Unemployment Risk and Corporate Financing Decisions,” Working paper, New York University Stern School of Business.
- [2] Angrist, J. and J.-S. Pischke, 2008, “Mostly Harmless Econometrics: An Empiricist’s Companion,” Princeton University Press.
- [3] Autor, D., J. Donohue III, and S. Schwab, 2006, “The Costs of Wrongful-Discharge Laws,” *The Review of Economics and Statistics* 88(2), 211–231.

²The difference between high and low employment variability industries is significant in Columns 1–6 at the 10% level or higher.

Figure A-1: **Timing of Detailed Model.**

This figure illustrates the timing of events in our extended model (taking into account both generic and specific innovations) from Appendix A.



- [4] Fulghieri, P. and M. Sevilir, 2011, "Mergers, Spin-offs, and Employee Incentives," *Review of Financial Studies* forthcoming.
- [5] Hall, B. H., A. Jaffe and M. Trajtenberg. 2001. "The NBER Patent Citations Data File: Lessons, Insights and Methodological Tools," NBER working paper.

Figure A-2: **Payoffs when the innovation is firm-specific.**

This figure is based on the extended model from Appendix A and summarizes the payoffs in the case when the innovative project generates a successful firm-specific innovation.

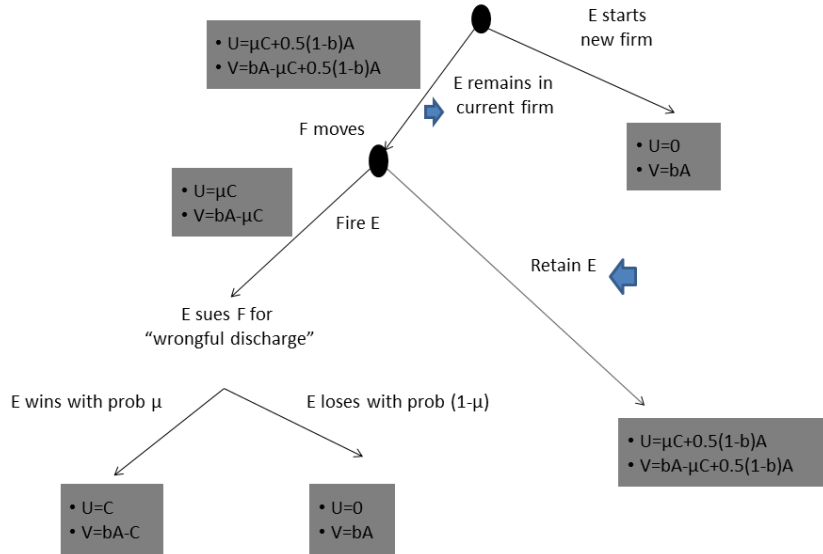


Figure A-3: **Payoffs when the innovation is generic.**

This figure is based on the extended model from Appendix A and summarizes the payoffs in the case when the innovative project generates a successful generic innovation.

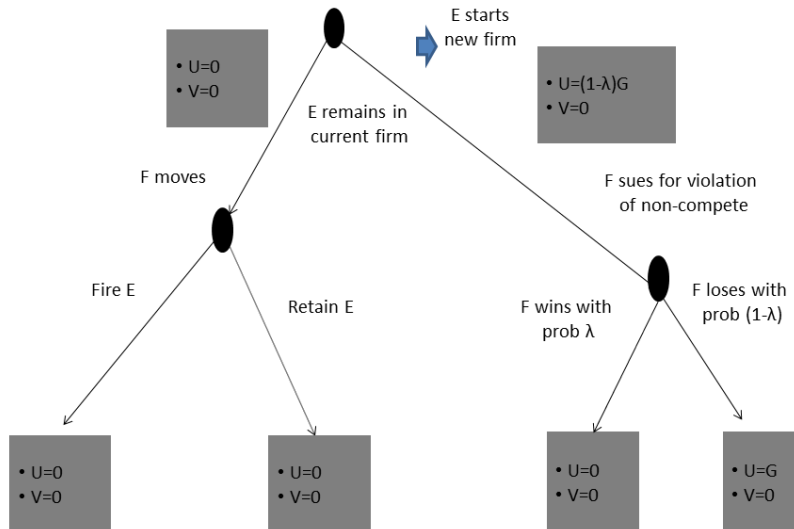


Table C-1: **Additional Tests on Sample Selection.**

The OLS regressions below implement the following model:

$$y_{ist} = \beta_i + \beta_t + \beta_1 * GF_{st} + \beta_2 * PP_{st} + \beta_3 * IC_{st} + \varepsilon_{ist}$$

where y_{ist} is a measure of innovation for firm i from state s in year t ; in these regressions we employ $\ln(Patents)$ and $\ln(Citations)$ as our dependent variables. β_i and β_t denote respectively firm and application year fixed effects. $\beta_1 - \beta_3$ measure the difference-in-difference effects of the passage of the three wrongful discharge provisions (*Good Faith*, *Public Policy*, and *Implied Contract*). The regressions reported in Columns 3 & 4 condition on the availability of the set of control variables used in this paper (without actually including said controls): *Market-to-Book*, *Size*, *Size*², $\ln(R\&D/Sales)$, *Competition*, *Competition*², *Ratio of Value Added*, $\ln(Real\ State\ GDP)$, $\ln(Colleges)$, $\ln(Enrollment)$, $\ln(Population)$, and *UI*.

Patent data is from the NBER Patents File (Hall, Jaffe and Trajtenberg, 2001). The wrongful discharge law data is based on the coding by Autor et al. (2006). The sample in columns 1 & 2 spans 1971–1999, while the sample period in columns 3 & 4 is 1977–1999. Robust standard errors (clustered at the state level) are given in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
	ln(Patents)	ln(Citations)	ln(Patents)	ln(Citations)
Good Faith	0.124** (0.051)	0.180*** (0.054)	0.144** (0.062)	0.210*** (0.066)
Public Policy	0.082 (0.056)	0.108** (0.052)	0.082 (0.060)	0.115** (0.053)
Implied Contract	0.095** (0.044)	0.142*** (0.041)	0.088 (0.054)	0.136*** (0.050)
Firm and Year dummies	Y	Y	Y	Y
Observations	104,504	96,849	48,433	44,718
Adjusted R-squared	0.157	0.218	0.139	0.220

Table C-2: **Robustness: Difference-in-Difference Tests – Division / Subsidiary Level Tests and Sample Selection.**

The OLS regressions below implement the following model:

$$y_{d \rightarrow i, s, t} = \beta_d + \beta_t + \beta_1 * GF_{st} + \beta_2 * PP_{st} + \beta_3 * IC_{st} + \varepsilon_{dst}$$

where $y_{d \rightarrow i, s, t}$ is a measure of innovation done by division/subsidiary d (of firm i) in state s in year t . β_d and β_t denote respectively division/subsidiary and application year fixed effects. $\beta_1 - \beta_3$ measure the difference-in-difference effects of the passage of the three wrongful discharge provisions (*Good Faith*, *Public Policy*, and *Implied Contract*). Columns 1 & 2 show the results for the NBER patent data sample matched to the Compustat dataset, while Columns 3 & 4 report the results for the full NBER patent data sample consisting of corporate US patent assignees.

Patent data is from the NBER Patents File (Hall, Jaffe and Trajtenberg, 2001). The wrongful discharge law data is based on the coding by Autor et al. (2006). The sample spans 1971–1999. Robust standard errors (clustered at the state level) are given in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Sample:	(1)	(2)	(3)	(4)
	ln(Patents)	ln(Citations)	ln(Patents)	ln(Citations)
	NBER Patent Data - Compustat matched sample		full NBER Patent Data Sample	
Good Faith	0.140** (0.062)	0.185*** (0.064)	0.083* (0.047)	0.114** (0.054)
Public Policy	0.086 (0.055)	0.118** (0.053)	0.064* (0.037)	0.087** (0.036)
Implied Contract	0.107** (0.045)	0.149*** (0.044)	0.067** (0.033)	0.098*** (0.033)
Assignee (Subsidiary) FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Observations	104,504	96,849	325,072	287,492
Adjusted R-squared	0.170	0.232	0.094	0.276

Table C-3: **Trend in Innovation After Good Faith Passage.**

The OLS regressions below implement the following model:

$$y_{i,s \rightarrow r,t} = \beta_i + \beta_r \times \beta_t + \beta_r + \beta_t + \beta_1 * GF_{st} * Trend_t + \beta_2 * PP_{st} + \beta_3 * IC_{st} + \beta \cdot X_{ist} + \varepsilon_{ist}$$

where $y_{i,s \rightarrow r,t}$ is a measure of innovation for firm i from state s (belonging to region r) in year t . β_i and β_t denote respectively firm and application year fixed effects. $Trend_t$ is a linear trend taking the value of zero for the year 1971, a value of one for 1972 etc. $\beta_r \times \beta_t$ captures general regional trends through the interaction of region dummies with year dummies (Columns 3&4); region dummies are based on four U.S. regions as defined by the U.S. census: Northeast, South, Midwest, and West. X_{ist} denotes the set of control variables. In the table below *Controls* denotes the following set of variables: $\ln(R\&D/Sales)$, *Market-to-Book*, *Size*, $Size^2$, *Competition*, $Competition^2$, *Ratio of Value Added*, $\ln(Real\ State\ GDP)$, $\ln(Colleges)$, $\ln(Enrollment)$, $\ln(Population)$, *UI*; for the description, see Table 1 in the main paper.

The sample spans 1971–1999 in Columns 1&2, 1977–1999 in Columns 3&4. Robust standard errors (clustered at the state level) are given in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
	ln(Patents)	ln(Citations)	ln(Patents)	ln(Citations)
Good Faith * Trend	0.008** (0.003)	0.010*** (0.003)	0.006* (0.003)	0.008** (0.004)
Public Policy	0.083 (0.056)	0.115** (0.052)	0.068** (0.032)	0.085* (0.043)
Implied Contract	0.094** (0.045)	0.140*** (0.041)	-0.025 (0.032)	-0.023 (0.036)
Controls	N	N	Y	Y
Firm and Year dummies	Y	Y	Y	Y
Region x Year dummies	N	N	Y	Y
Observations	104,504	96,849	48,433	44,718
Adjusted R-squared	0.157	0.218	0.178	0.244

Table C-4: **Effect of Wrongful Discharge Laws on Innovation after Accounting for Differences between North-Western and South-Western States of the West Region.**

The OLS regressions below implement the following model:

$$y_{i,s \rightarrow \bar{r},t} = \beta_i + \beta_{\bar{r}} \times \beta_t + \beta_{\bar{r}} + \beta_t + \beta_1 * GF_{st} + \beta_2 * PP_{st} + \beta_3 * IC_{st} + \beta \cdot X_{ist} + \varepsilon_{ist}$$

where $y_{i,s \rightarrow \bar{r},t}$ is a measure of innovation for firm i from state s (belonging to region \bar{r}) in year t . β_i and β_t denote respectively firm and application year fixed effects. $\beta_{\bar{r}}$ is a dummy variable for each U.S. region; we employ four U.S. regions as defined by the U.S. census: Northeast, South, Midwest, and West; the “West” region is additionally sub-divided into a Northern and Southern part. $\beta_{\bar{r}} \times \beta_t$ captures general regional trends through the interaction of region dummies with year dummies. $\beta_1 - \beta_3$ measure the difference-in-difference effects of the passage of the three wrongful discharge provisions (*Good Faith*, *Public Policy*, and *Implied Contract*). X_{ist} denotes the set of control variables. In the table below *Controls* denotes the following set of variables: $\ln(R\&D/Sales)$ (not included in Columns 5 & 6), *Market-to-Book*, *Size*, $Size^2$, *Competition*, $Competition^2$, *Ratio of Value Added*, $\ln(Real\ State\ GDP)$, $\ln(Colleges)$, $\ln(Enrollment)$, $\ln(Population)$, *UI*; for the description, see Table 1 in the main paper. The sample spans 1977–1999. Robust standard errors (clustered at the state level) are given in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	ln(Patents)	ln(Citations)	ln(Patents /Employees)	ln(Citations /Employees)	ln(Patents /R&D)	ln(Citations /R&D)	ln(Citations /Patent)
Good Faith	0.104* (0.053)	0.171** (0.065)	0.108** (0.053)	0.177*** (0.065)	0.110* (0.056)	0.176** (0.067)	0.057*** (0.018)
Public Policy	0.064** (0.032)	0.077* (0.041)	0.064* (0.032)	0.077* (0.041)	0.066* (0.034)	0.082* (0.043)	0.017 (0.020)
Implied Contract	-0.021 (0.032)	-0.019 (0.036)	-0.033 (0.032)	-0.030 (0.035)	-0.030 (0.035)	-0.029 (0.038)	0.007 (0.017)
Controls	Y	Y	Y	Y	Y	Y	Y
Firm and Year dummies	Y	Y	Y	Y	Y	Y	Y
Region (incl. N.- & S.-West) x Year dummies	Y	Y	Y	Y	Y	Y	Y
Observations	48,433	44,718	48,072	44,398	48,686	44,915	44,718
Adjusted R-squared	0.178	0.244	0.778	0.690	0.743	0.671	0.422

Table C-5: Relative Impact of Wrongful Discharge Laws on Innovation in Different Industries based on their Employment Variability.

The OLS regressions below implement the following model:

$$y_{i \rightarrow j, s \rightarrow r, t} = \beta_i + \beta_r \times \beta_t + \beta_r + \beta_t + \beta_1 * GF_{st} * High_EmpVar_{jt} + \beta_2 * GF_{st} * Low_EmpVar_{jt} + \beta_3 * PP_{st} + \beta_4 * IC_{st} + \beta_5 * High_EmpVar_{jt} + \beta * X_{ist} + \varepsilon_{ist}$$

where $y_{i \rightarrow j, s \rightarrow r, t}$ is a measure of innovation for firm i (belonging to industry j) from state s (belonging to region r) in year t . β_i and β_t denote respectively firm and application year fixed effects. $\beta_r \times \beta_t$ captures general regional trends through the interaction of region dummies with year dummies; region dummies are based on four U.S. regions as defined by the U.S. census: Northeast, South, Midwest, and West. β_1 measures the difference-in-difference effect of the passage of the good-faith exception for industries with high employment variability, while β_2 measures the effect of the passage of the good-faith exception for low employment variability industries. $High_EmpVar_{jt}$ takes the value of one, if the median firm's employment variability in a given Fama-French 48 industry in a given year exceeds the median firm's employment variability across all industries in that year; Low_EmpVar_{jt} is given by $(1 - High_EmpVar_{jt})$. In the table below *Controls* denotes the following set of variables: $\ln(R\&D/Sales)$ (not included in Columns 5 & 6), *Market-to-Book*, *Size*, *Size*², *Competition*, *Competition*², *Ratio of Value Added*, $\ln(\text{Real State GDP})$, $\ln(\text{Colleges})$, $\ln(\text{Enrollment})$, $\ln(\text{Population})$, *UI*; for the description, see Table 1 in the main paper. The sample spans 1977–1999. Robust standard errors (clustered at the state level) are given in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	(1) ln(Patents)	(2) ln(Citations)	(3) ln(Patents /Employees)	(4) ln(Citations /Employees)	(5) ln(Patents /R&D)	(6) ln(Citations /R&D)	(7) ln(Citations /Patent)
Good Faith * High_EmpVar	0.151** (0.063)	0.213*** (0.077)	0.155** (0.063)	0.217*** (0.076)	0.163** (0.065)	0.224*** (0.079)	0.055** (0.021)
Good Faith * Low_EmpVar	0.051 (0.057)	0.098 (0.068)	0.047 (0.058)	0.097 (0.068)	0.047 (0.062)	0.095 (0.073)	0.039* (0.021)
High_EmpVar	-0.012 (0.026)	-0.016 (0.029)	-0.053* (0.029)	-0.059* (0.030)	-0.041 (0.028)	-0.050* (0.029)	-0.007 (0.018)
Public Policy	0.065** (0.032)	0.079* (0.041)	0.065* (0.032)	0.079* (0.041)	0.067* (0.034)	0.084* (0.043)	0.017 (0.020)
Implied Contract	-0.025 (0.032)	-0.020 (0.035)	-0.035 (0.032)	-0.029 (0.035)	-0.033 (0.035)	-0.031 (0.038)	0.010 (0.017)
Controls	Y	Y	Y	Y	Y	Y	Y
Firm and Year dummies	Y	Y	Y	Y	Y	Y	Y
Region x Year dummies	Y	Y	Y	Y	Y	Y	Y
Observations	48,433	44,718	48,072	44,398	48,686	44,915	44,718
Adjusted R-squared	0.179	0.244	0.778	0.690	0.743	0.671	0.422