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No. 7171

LABOR LAWS AND INNOVATION

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FINANCIAL ECONOMICS



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Discussion Paper No. 7171
February 2009

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ABSTRACT

Labor Laws and Innovation

Can stringent labor laws be efficient? Possibly, if they provide firms with a commitment device to not punish short-run failures and thereby incentivize the pursuit of value-maximizing innovative activities. In this paper, we provide empirical evidence that strong labor laws indeed appear to have an *ex ante positive* incentive effect by encouraging the innovative pursuits of firms and their employees. Using patents and citations as proxies for innovation and a time-varying index of labor laws, we find that innovation is fostered by stringent labor laws, especially by laws governing dismissal of employees. We provide this evidence using levels-on-levels, changes-on-changes, and finally difference-in-difference regressions that exploit staggered country-level law changes. We also find that stringent labor laws disproportionately influence innovation in those sectors of the economy that are more innovation intensive. Finally, we find that while the overall effect of stringent labor laws is to dampen economic growth, laws that govern dismissal of employees are an exception: dismissal laws promote economic growth, consistent with the evidence that they encourage firm-level innovation.

JEL Classification: F30, G31, J5, J8 and K31

Keywords: entrepreneurship, growth, labor laws, law and finance, r&d and technological change

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Submitted 27 January 2009

First draft: November 18, 2008
This draft: January 24, 2009

1 Introduction

Do legal institutions of an economy affect the pattern of its real investments, and, in turn, its economic growth? In this paper, we focus on one specific aspect of this overarching theme: Does the legal framework that governs the relationships between employees and their employers affect the extent of innovation in an economy?

While the inefficiencies and rigidities associated with stringent labor laws — laws that prevent employers from seamlessly negotiating and/or terminating labor contracts with employees — are much celebrated in the academic literature¹ and the media, this discussion is generally centered around the *ex post* effects of labor laws.² In particular, it is not difficult to see that once the situation to renegotiate or terminate an employment contract has arisen, tying down an employer’s hands from doing so can lead to *ex post* inefficient outcomes. Much less studied, however, is the *ex ante* incentive effect of such strong labor laws. Might stringent labor laws be desirable as they provide firms a commitment device to not punish short-run failures and thereby incentivize their employees to undertake activities that are value-maximizing in the long-run? Indeed, if strong labor laws were always inefficient, their prevalence in many countries around the world would be hard to justify based on grounds of economic efficiency, and perhaps could be rationalized only by appealing to political economy considerations. Similarly, but for their *ex ante* effects in encouraging research, academic employment contracts guaranteeing life-time employment would be hard to rationalize. In this paper, we provide empirical evidence that strong labor laws indeed appear to have an *ex ante positive* incentive effect by encouraging firms and their employees to engage in more successful, and more significant, innovative pursuits.

To provide evidence supporting this *ex ante* positive effect of labor laws on innovation, we use data on patents issued by the USPTO to US and foreign firms and citations to these patents as constructed by Hall, Jaffe and Trajtenberg (2001). The “industry” level classification we employ pertains to the patent classes in this data. We measure innovation for an industry in a given year by the number of patents applied for (and subsequently granted), the number of all subsequent citations to these patents, and the number of firms filing for patents in that year and industry.

We use the index of labor laws constructed by Deakin et al. (2007). They construct this index by analyzing in detail the evolution of differences in employment protection legislation

¹Botero et al. (2004), for example, claim that heavier regulation of labor leads to adverse consequences for labor market participation and unemployment.

²For example, strong labor market regulation is often blamed to be one of the reasons for Europe’s economic under-performance compared to the US. For a recent study articulating this theme, see the study of France and Germany by the McKinsey Global Institute (1997).

in five countries — US, UK, France, Germany, and India. They analyze *forty* dimensions of labor laws and group them into five components that correspond to the regulation of: (i) alternative forms of labor contracting; (ii) working time; (iii) dismissal; (iv) employee representation; and (v) industrial action.³ This index offers the advantage that it takes into account not just the formal or positive law but also the self-regulatory mechanisms that play a functionally similar role to laws in certain countries. While employing the Deakin et al. index forces us to limit our study to only the five countries mentioned above, these countries account for 72% of the patents filed with the USPTO during our sample period. The aggregate measure of the stringency of employment protection used in our paper is the simple sum of the five components; higher values represent stricter labor laws, i.e. more employment protection.⁴

Employing this data, we test the following hypotheses:

HYPOTHESIS 1: Stronger labor laws lead to greater innovation.

HYPOTHESIS 2: Stronger laws governing dismissal of employees influence innovation more than other aspects of labor laws.

Since the ex ante incentives of ex post stringent labor laws should matter more in the innovative sectors of the economy, we also test whether

HYPOTHESIS 3: Stronger labor laws lead to relatively more innovation in the innovation intensive industries than in the traditional industries.

Our empirical investigation of these hypotheses proceeds in several steps. First, to examine the overall effect of labor laws in a country on its innovation, we employ fixed effects regressions of the level of innovation on the level of the labor index, where we include fixed

³More specifically, the five sub-indices are as follows: (i) *Alternative Employment Contracts* measures the cost to employers of using alternatives to the “standard” employment contracts (e.g., part-time employment, fixed-term contracts, agency work). (ii) *Regulation of Working Time* measures the extent to which the law protect employees’ working conditions by, for example, stipulating limits to annual leave holiday entitlements and daily working duration, and compensation for overtime and weekend working. (iii) *Regulation of Dismissal* measures the cost to employers for dismissals incurred through, for example, procedural constraints on dismissals, remedies for unfair dismissals, and dismissal notification process. (iv) *Employee Representation* measures the bargaining power of employees and the ability of employees to co-determine through the rights to board nomination or through the consultation process. (v) *Industrial Action* measures the strength of legal protection for employees engaging in industrial action (among others, strikes and lockouts). Further detail is provided in the Appendix.

⁴An alternative to the Deakin et al. (2007) index is the index developed by Botero et al. (2004), which covers many more countries but does not have any time-series variability. A second alternative is the EPL measure constructed by Nicoletti and Scarpetta (2001) for a set of OECD countries for the years 1990-1998. However, this index neither offers the cross-sectional comprehensiveness of the index constructed by Botero et al. (2004), nor the full extent of the longitudinal advantages of the index developed by Deakin et al. (2007).

effects for country, industry (i.e. patent class) and application year. In these tests, we find that more stringent employment protection positively influences the innovative activity in a country. This effect is statistically and economically significant: an increase in the labor index by one, *ceteris paribus*, increases the number of annual patents and subsequent citations in a patent class by 14.6% and 20.3% respectively.

In estimating this effect, we also control for (i) a country’s creditor rights using the Djankov et al. (2007) index, its rule of law, efficiency of judicial system, and anti-director’s index as in La Porta et al. (1998); (ii) a country’s bilateral trade with the US in each of its industries using its exports and imports with the US in different years, which is necessitated by our use of US patents to proxy innovation in these countries; (iii) a measure of the country’s comparative advantage in an industry using the ratio of value-added of an industry in a country in a given year to the total value-added for the country that year; and (iv) the GDP per capita of the country.

However, inferring a causal relationship between country level labor laws and innovation presents the challenge that country level labor laws are expected to be largely collinear with other country level unobserved factors. Since Deakin et al. trace the evolution of labor laws in the five countries from 1970-2006, their index exhibits substantial time-series variation, which we exploit in this study. In our second set of tests, therefore, we employ regressions containing country and application year fixed effects to examine the effect of *changes* in labor laws in these five countries on *changes* in innovation. We find that in these countries, changes that make labor laws more stringent increase innovation. By carefully studying the motivation behind these labor law changes, we alleviate the concern that the changes in the labor law were effected explicitly to boost innovation or that other country level changes coinciding with the changes in labor laws were correlated with changes in innovation.

In our third set of tests, we shed light on our hypothesis that labor laws that affect the ex-post likelihood of an employee being *dismissed from employment* matter more for innovation than other categories of labor laws. We first line up all the five components of the labor index and find that the “regulation of dismissal” component is the only one which has a consistently positive and significant effect on innovation. Motivated by this finding, we replace the aggregate labor index with the “regulation of dismissal” component and find similarly strong results: The coefficient of “regulation of dismissal” is positive and statistically significant, implying that tougher dismissal laws are positively associated with innovation.

Furthermore, we exploit the staggered changes in laws governing dismissal in our sample of countries to conduct *difference-in-difference* tests. We examine the before-after effect on innovation of the strengthening of laws governing dismissal in France over the period 1970-

1988 vis-à-vis the US, which did not change any labor laws over the same time period. We find that this before-after difference in innovation for French firms was 20% higher over this time period than the before-after difference over the same time period for the US firms. We also examine the effects of strengthening of laws governing dismissal in the UK in the 1970s and in the US in 1989 (in the latter case through the passage of the Worker Adjustment and Retraining Notification Act (WARN)) and obtain similar results.

We also investigate inter-industry differences in the effect of labor laws on innovation to examine the hypothesis that the effect of labor laws should be *disproportionately* higher in industries that exhibit a greater propensity to innovate than in other industries. To conduct these tests, we follow Acharya and Subramanian (2008) in ranking patent classes by their patenting intensity in the US. The main coefficient of interest in these regressions is that on the interaction of the proxy for patenting intensity with the Labor Law index. After including fixed effects for country, patent class and application year, we find that the coefficient on the interaction term is significantly positive, implying that the effect of labor laws is disproportionately higher in industries that have a greater propensity to innovate than in other industries.

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.

Finally, we inquire what these predictions imply 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, we 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), we 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 we disaggregate the labor laws into their sub-components, we 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, UK, and France, we find further support for this positive effect. Thus, we conclude that 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.

Our evidence provides direct support for the theoretical conclusions of Manso (2008). Manso considers the optimal compensation scheme that motivates innovation and shows theoretically that the optimal scheme exhibits substantial tolerance (or even reward) for failure and reward for long-term success. The intuition of Manso’s model fits naturally with the ex-ante incentive effect of strong labor laws on innovation we document. Innovative pursuits are likely to be of higher value in the long run but riskier in the short run. If the firm cannot commit to not firing its employees (for example, folding up its R&D units) when exploration of a new idea turns out to be unsuccessful, then it may find it too costly upfront to encourage innovation. Since innovation is generally perceived to have externalities (Romer, 1986; Grossman and Helpman, 1991; and Aghion and Howitt, 1992), such commitment may have to take the form of legal protection of employees in their contracts with employers.⁵ Pursuing a somewhat related idea, Acharya and Subramanian (2007) study theoretically and empirically the role of strong creditor rights in deterring innovation and growth. Our empirical evidence complements theirs by focusing on another aspect of the legal environment – the stringency of labor laws. It is an interesting, open question as to whether creditor rights and labor laws interact in their effects, whether they are substitutes or complements, and indeed, which of the two matters more for innovation.

2 Related Literature

Our paper is related to the literature on law and finance, which analyzes the impact of legal institutions on various aspects of corporate policy and economic outcomes, such as the nature of external financing of enterprises (La Porta, Lopez-de-Silanes, Shleifer and Vishny, 1997, 1998), the ownership structure of firms (La Porta, Lopez-de-Silanes and Shleifer, 1999), and the mix between market- and bank-dominated finance (Allen and Gale, 2000). Specifically, this paper contributes to the literature that examines the effect of laws that govern the relationships between employees and their employers. Botero et al. (2004) examine the extent of labor market intervention by governments and the motivation for the same. They

⁵It is worth pointing out that the optimal contract in Manso (2008) that promotes innovation is inherently *time-inconsistent*, and thus also naturally explains why strong labor laws would be perceived to be rigid and inefficient in states where they actually bind. Cremer (1995) makes a similar point but with the somewhat reverse intuition that in certain settings committing not to punish ex post might conflict with the provision of efficient ex ante incentives. Acharya, John and Sundaram (2000) argue, in a different context, that a certain amount of “resetting” of executive stock options – apparently an act of forbearance on part of firms toward their management – may be efficient for continuation outcomes even though it induces moral hazard ex ante.

conclude that these interventions are driven primarily by political economic considerations and not by any reasons of efficiency.

Directly related to our study is the one by Menezes-Filho and Van Reenen (2003), who 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 tend to find a negative impact of unions on innovation, European studies do not generally support these findings. Our study pools together five representative countries that span three different legal “origins” and finds that innovation is fostered by stringent labor laws, especially by stringent laws governing dismissal of employees.

In their ex post effects, the existing literature highlights that stronger labor laws may play a dual role. First, they redistribute resources from employers (or their ultimate ‘principals’, such as shareholders) to employees. In line with this argument, Botero et al. (2004), for example, claim that heavier regulation of labor leads to adverse consequences for labor market participation and unemployment. However, stronger labor laws may also have an ex-post efficiency aspect to them. They provide insurance to employees against risks associated with loss of income and employment (Simon, 1951). Furthermore, they reduce transaction costs derived from the incompleteness of the employment contract (Williamson, Wachter and Harris, 1975).

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. In contrast to this negative effect of labor laws on asset restructuring and firm performance, our study finds that stringent labor laws incentivize a firm and its employees to pursue value-enhancing innovative activities ex ante.

In less directly related work, Besley and Burgess (2004) study the role of labor market regulation in explaining the manufacturing performance in Indian states from 1958-1992. They conclude that regulating in a pro-worker direction is associated with lower levels of investment, productivity, and output in registered manufacturing. Scarpetta and Tressel (2004) investigate the empirical determinants of industry-level multifactor productivity growth for a sample of 17 industries in 18 OECD countries from 1984-1998. They find that employment protection legislation has a strong and negative impact on productivity in countries with an intermediate degree of corporatism, i.e. where sectoral wage bargaining is carried out predominantly without coordination.

Our work is closely related to the literature on endogenous growth pioneered by Romer (1986), Grossman and Helpman (1991), and Aghion and Howitt (1992). This literature

posits that investment in R&D and human capital is the central source of technical progress and an essential ingredient of growth. This theory stresses the need for government and private sector institutions to nurture competition and innovation and provide incentives for individuals to be inventive. We contribute to this literature by providing empirical evidence that laws that provide ex post job security to employees in the form of stringent laws governing dismissal indeed have a positive ex-ante effect on innovation.

3 Empirical Strategy

We investigate the effect of laws that govern the employer-employee relationship on the extent of innovation in a country. Inferring a causal relationship between country-level labor laws and innovation presents the challenge that country-level labor laws are expected to be largely collinear with other country-level unobserved factors. However, since the labor law indices developed by Deakin et al. (2007) (hereafter “the labor law index”) exhibit substantial variation in the time-series, we are able to design an empirical strategy to infer the causal relationship. Our analysis proceeds in several steps. First, to examine the overall effect of labor laws in a country on its innovation, we employ fixed effects regressions of the level of (as well as changes in) labor laws on the level of (respectively changes in) innovation. Second, to throw light on our hypothesis that labor laws that affect the ex post likelihood of an employee being dismissed from employment matter more for innovation than other categories of labor laws, we examine the effect of one specific component of labor laws — the regulation of dismissal. In these sets of tests, we conduct fixed effect “level on level” regressions as well as difference-in-difference tests, where we examine the before-after effect of a change in the laws regulating dismissal in the affected country (the “treatment group”) vis-a-vis the before-after effect in a country where such a change was not effected (the “control group”). In our final set of tests, we investigate inter-industry differences in the effect of labor laws on innovation to examine the hypothesis that the effect of labor laws should be *disproportionately* higher in industries that exhibit a greater propensity to innovate than in other industries.

We now explain these tests in greater detail.

3.1 Overall Effect of Labor Laws on Innovation

To start with, we employ a fixed effects specification where we control for unobserved factors at the country, time and industry (i.e. patent class) levels:

$$y_{ict} = \beta_i + \beta_c + \beta_t + \beta_1 * LaborLaws_{c,t} + \beta \cdot X + \varepsilon_{ict} \quad (1)$$

where y_{ict} is the natural logarithm of a measure of innovation for the USPTO patent class i from country c applied for in year t . $\beta_i, \beta_c, \beta_t$ denote respectively patent class, country and application year fixed effects. $LaborLaws_{c,t}$ denotes the stringency of labor laws based on the index value for country c in year t . X denotes the set of control variables. The application year fixed effects enable us to also control for the problem stemming from the truncation of citations, i.e., citations to patents applied for in later years would on average be lower than citations to patents applied for in earlier years. Similarly, the patent class fixed effects also enable us to control for time-invariant differences in patenting and citation practices across industries. In addition to these fixed effects, we employ standard errors that are robust to heteroscedasticity and autocorrelation at the patent class level.

Given the fixed effects, the assumption required to identify β_1 is that *time-varying* unobserved determinants of innovation at the country and patent class levels are uncorrelated with the labor law index. However, the labor law index may pick up *time-varying* omitted variables at the country level, or industries could be systematically different across countries that vary in the labor law index. This may show up as an effect of our variable of interest, which leads us to our second test where we examine the aggregate effect of country-level *changes* in labor laws on *changes* in innovation:

$$\Delta y_{ict} = \beta_c + \beta_t + \beta_1 * \Delta LaborLaws_{c,t} + \beta \cdot \Delta X + \varepsilon_{ict} \quad (2)$$

Since the *changes* in labor laws exhibit variation within a country, we include country fixed effects to control for country specific unobserved factors that may be influence these *changes*. Further, we include year fixed effects to control for any inter-temporal differences in *changes* in innovation.

The assumption required to identify the coefficient β_1 in (2) is that *time-varying* unobserved determinants of *changes* in innovation at the country level are uncorrelated with *changes* in the labor law index. Since a primary concern in a cross-country study such as ours is the effect of country level omitted variables on the laws in the country, the above regression employing changes addresses such endogeneity concerns. A potential concern could still be that the changes in the labor law were effected with the explicit intention of encour-

aging innovation or that the changes in labor law were correlated with country-level factors at that time that influence innovation as well. In Section 5.4, we argue based on Deakin et al. (2007) that such reverse causality or residual endogeneity concerns were absent in our context.

3.2 Effect of Laws Regulating Dismissal on Innovation

Our next set of tests is designed to shed light on the hypothesis that labor laws that affect the ex-post likelihood of an employee being dismissed from employment matter more for innovation than other categories of labor laws. For this purpose, we exploit the Deakin et al. (2007) classification of the universe of labor laws in a country into five different categories of laws that affect — (i) alternative employment contracts; (ii) regulation of work time; (iii) regulation of dismissal; (iv) employee representation; and (v) industrial action. Laws affecting “regulation of dismissal” include *inter alia* a legally mandated notice period for all dismissals, the procedural and substantive constraints on dismissal, and the method to be employed for notifying the dismissal. For example, would an oral statement notifying the dismissal suffice or does the employer need to seek the permission of a state body or third body prior to any individual dismissal or simply notify such authorities? To examine the relative significance of the laws regulating dismissal vis-a-vis other categories of laws, first, we replace the labor index in (1) with the five components of the labor index. Next, we focus on the “regulation of dismissal” component of the labor index by replacing the labor index in (1) with this particular component. Finally, to cleanly infer the effect of changes in the laws affecting regulation of dismissal, we undertake *difference-in-difference* tests. In our sample, the US, UK and France changed their laws regulating dismissal at different points in time (elaborated below). These “natural experiments” offer us the opportunity to estimate the causal effect of the labor law change through a difference-in-difference test.

Figures 2 and 3 illustrate the motivation for these difference-in-difference tests; the graphs show the aggregate labor law indices and dismissal law indices for the five countries in our sample over the period from 1970 to 2006. While all other labor law dimensions experienced changes spread over the entire sample period, laws affecting dismissal underwent changes primarily in three different instances: in the UK and France in the early 1970s and in the US in 1989. To intuitively understand the difference-in-difference tests, consider the effect on innovation due to the change in laws governing dismissal in the UK in the 1970s. A naive estimate of the effect of these law changes would be to simply compute the difference in innovation before (year 1970, for example) and after (1976 and beyond) the labor law change. However, this estimate would also be affected by time-trends that coincide with

the labor law change as well as other economy wide factors. To control for such factors, we also estimate this difference in innovation for the US, which did not undergo any change in labor laws between 1970 and 1988. The difference estimated for the US provides an answer to the counter-factual question: “what would have been the difference in innovation in the UK if the change in dismissal laws *had not occurred?*”. The difference between these two differences, therefore, captures the causal effect of the labor law change on innovation. We repeat these difference-in-difference tests for the other two “natural experiments” as well: (i) France versus US for the time period 1970-1988 to investigate the effect of the change in dismissal laws in France; and (ii) US versus Germany for the time period 1985-2002 to investigate the effect of the change in dismissal laws in the US.

We implement the difference-in-difference test using the following regression:

$$y_{ict} = \beta_i + \beta_c + \beta_t + \beta_1 * Dismissal_{laws}_{c,t} + \varepsilon_{ict} \quad (3)$$

where y is the natural logarithm of a measure of innovation for the USPTO patent class (i). Country c is either the country that underwent a change in laws governing dismissal (“treatment”) or a country that did not experience such a change (“control”). $Dismissal_{laws}_{c,t}$ denotes the index of laws governing dismissal in country c in year t . Thus, $Dismissal_{laws}_{c,t}$ is a constant for the “control” group. Given the country and year dummies, the coefficient β_1 estimates the difference-in-difference. For the test using US versus Germany, β_1 estimates a traditional difference-in-difference since the dismissal law change occurred in the US in 1989.⁶ For the tests using UK versus US and France versus US, since changes in the laws governing dismissal occurred in UK and France over the period of a few years, given the country and year fixed effects, the regression (3) estimates the average treatment effect over repeated

⁶Since the dismissal law change occurred in 1989, denote the before-after time periods by 0 and 1, i.e. $t \in [1985, 1989]$ is denoted as 0 and $t \in [1990, 2002]$ as 1. Since no change in the dismissal law occurred during the time-period [1985, 2002] for Germany,

$$\begin{aligned} E[y_{i,GER,0}] &= \beta_i + \beta_{GER} + \beta_0 + \beta_1 * Dismissal_{laws}_{GER} \\ E[y_{i,GER,1}] &= \beta_i + \beta_{GER} + \beta_1 + \beta_1 * Dismissal_{laws}_{GER} \end{aligned}$$

In contrast for the US,

$$\begin{aligned} E[y_{i,US,0}] &= \beta_i + \beta_{US} + \beta_0 + \beta_1 * Dismissal_{laws}_{US,0} \\ E[y_{i,US,1}] &= \beta_i + \beta_{US} + \beta_1 + \beta_1 * (Dismissal_{laws}_{US,0} + \Delta Dismissal_{laws}_{US}) \end{aligned}$$

Since

$$\beta_1 - \beta_0 = E[y_{i,GER,1}] - E[y_{i,GER,0}]$$

it follows that

$$\beta_1 * \Delta Dismissal_{laws}_{US} = \{E[y_{i,US,1}] - E[y_{i,US,0}]\} - \{E[y_{i,GER,1}] - E[y_{i,GER,0}]\}$$

treatments (see Imbens and Wooldridge 2007, 2008 for difference-in-difference estimations involving multiple groups and multiple treatments).

Notice that compared to the usual difference-in-difference specification, which contains dummies for treatment groups and treatment periods only, including dummies for all the application years as well as the patent classes leads to a much stronger test since we are able to control for time-invariant country and patent class specific determinants of innovation as well as time-varying effects that are common to all countries and all patent classes. The application year fixed effects enable us to also control for the problem stemming from the truncation of citations, i.e., citations to patents applied for in later years would on average be lower than citations to patents applied for in earlier years. Similarly, the patent class fixed effects also enable us to control for time-invariant differences in patenting and citation practices across industries. In addition to these fixed effects, our standard errors are robust to heteroscedasticity and autocorrelation.

These difference-in-difference tests have several attractive features. First, they are not subject to the criticism that country or industry level unobserved factors influencing innovation are correlated with the level of labor laws in a country. This is because these tests exploit *within-country* differences *before* and *after* the labor law change vis-à-vis similar before-after differences in countries that did not experience such a change. Second, by examining the effect of changes in one particular law in one particular country, they provide point estimates of the effect of specific changes in labor laws on innovation using experiments of greatest relevance to policies concerned with promoting innovation.

3.3 Inter-industry Differences in the Effect of Labor Laws on Innovation

In our final set of tests, we investigate inter-industry differences in the effect of labor laws on innovation to examine the hypothesis that the effect of labor laws should be *disproportionately* stronger in industries that exhibit a greater propensity to innovate than in other industries. To understand this hypothesis, consider two industries in two countries: Biotechnology and Textiles in the United Kingdom and France. Firms in the Biotechnology sector have a higher propensity to innovate than firms in the Textile industry while French labor laws are on average more employee-friendly than their UK counterpart (see e.g. Botero et al., 2004; Deakin et al., 2007). According to Manso (2008), incentive contracts that exhibit tolerance to failure motivate innovation. Therefore, compared to the UK, the effect of employee-friendly labor laws in France should be disproportionately higher in Biotechnology than in Textiles. To test this, we examine the *interaction* of the time-varying

country level index of labor laws with our time-varying, industry-level measure of Innovation Intensity. Again, we include country, application year, and patent class dummies to control for time-invariant heterogeneity at these levels. The regression specification is as follows:

$$y_{ict} = \beta_i + \beta_c + \beta_t + \beta_1 \cdot (LaborLaws_{ct} * InnovationIntensity_{i,t-1}) + \beta_2 \cdot LaborLaws_{ct} + \beta_3 \cdot InnovationIntensity_{i,t-1} + \beta X + \varepsilon_{ict} , \quad (4)$$

The Innovation Intensity for patent class i in year $(t - 1)$, $InnovationIntensity_{i,t-1}$, is measured as the median number of patents applied for by US firms in patent class i in year $(t - 1)$. As justified before, instead of using a fixed time window to classify industries based on their propensity to patent, we use a moving window to measure the Innovation Intensity so as to capture the inter-temporal changes in the propensity to innovate caused by technological shocks. Note that the interaction term $(LaborLaws_{ct} * InnovationIntensity_{i,t-1})$ exhibits variation at the level of patent class i in country c in application year t . Since our dependent variable, y_{ict} , also varies at the level of patent class i in country c and application year t , the coefficient β_1 is well-identified and measures the relative effect of labor laws across industries that vary in their innovation intensity. Note that despite the country fixed effects, the coefficient of labor laws (β_2) is identified too since the labor law index exhibits variation across time. Similarly, innovation intensity exhibits time variation as well, and therefore its coefficient (β_3) can be identified despite the presence of patent class fixed effects.

4 Data and Proxies

In this section, we describe the data we use in this study, with a focus on our proxies for innovation, the labor law index and innovation intensity.

To construct proxies for innovation, we use patents filed with the US Patent Office (USPTO) and the citations to these patents, compiled in the NBER Patents File (Hall, Jaffe and Trajtenberg, 2001). The NBER patent dataset provides among other items: annual information on patent assignee names, the number of patents, the number of citations received by each patent, the technology class of the patent and the year that the patent application is filed. The dataset covers all patents filed with the USPTO by firms from around 85 countries. We exploit the technological dimension of the data generated by “*patent classes*”. Over the years, the USPTO has developed a highly elaborate classification system for the technologies to which the patented inventions belong, consisting of about 400 patent classes. During the patent examination process, patents are assigned to detailed technologies as de-

fined by the patent class. The USPTO performs these assignments with care to facilitate future searches of the prior work in a specific area of technology (Kortum and Lerner, 1999).

We date our patents according to the year in which they were applied for. This avoids anomalies that may be created due to the lag between the date of application and the date of granting of the patent (Hall, Jaffe and Trajtenberg, 2001). Note that although we use the application year as the relevant year for our analysis, the patents appear in the database only after they are granted. Hence, we use the patents actually granted (rather than the patent applications) for our analysis.⁷

4.1 Proxies for Innovation

We use three broad metrics to measure innovation. The first is a simple patent count of the number of patents that were filed in a particular year in a specific patent class. As our second metric of innovative activity, we use the citations that are made to the patents in a specific patent class. 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 occurred. Finally, citations help control for country-level differences arising in the number of patents due to differences in the number and size of firms.

As our third measure of innovative activity, we employ the number of patenting firms in a patent class. The USPTO defines “assignee” as the entity to which a patent is assigned. A simple count of the number of assignees in a patent class in a given application year provides a measure of the number of patenting entities. Since patents may be assigned to individuals, corporations or academic departments, the USPTO classifies patents according to the type

⁷A caveat about potential biases created by the use of application year, particularly in the case of foreign patents, is in order. Since foreign firms usually file patents with the domestic patent office and then with the USPTO, readers may believe that the application year recorded with the USPTO does not capture the exact timing of the innovation. However, the Paris Convention which governs such firms filing both in the domestic and foreign country, mandates that if the inventor files a foreign patent application in any other Paris Convention signatory state within 12 months of the domestic filing, overseas patent-granting authorities will treat the application as if it were filed on the first filing date. Therefore, the application year recorded with the USPTO would coincide with the application year for the domestic patent of the foreign firm.

⁸Pakes 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.

of assignees using the “assignee code”. Assignee codes equal to 2 and 3 identify US non-government organizations (mostly corporations) and non-US, non-government organizations (mostly corporations) respectively. These categories account respectively for 47.2% and 31.2% of all patents filed with the USPTO.

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.⁹ Nevertheless, we are aware that using patents has its drawbacks. Not all firms patent their innovations, because some inventions do not meet the patentability criteria and because the inventor might rely on secrecy or other means to protect its innovation. In addition, patents measure only successful innovations. To that extent, our results are subject to the same criticisms as previous studies that use patents to measure innovation (e.g., Griliches, 1990; Kortum and Lerner, 1999).

4.2 Labor Law index

In order to analyze the impact of labor laws on innovation, we have to rely on an empirical proxy for the stringency of employment protection. The existing academic literature offers two main alternatives:

Botero et al. (2004) analyze and code data on employment, collective relations, and social security laws for 85 countries as of 1997 in order to measure the degree of worker protection. This index clearly has the advantage that it covers a wide range of countries. However, as our task is to investigate the causal impact of labor laws on innovation, which necessitates controlling for observable and unobservable time-varying heterogeneity, we cannot use the cross-sectional index constructed by Botero et al. (2004) for our difference-in-difference tests.

Deakin et al. (2007) also perform a “leximetric” analysis, which applies the indexing method to analyze the evolution of differences in employment protection legislation between five countries over time. While Deakin et al. (2007) focus their investigation on five countries only (US, UK, France, Germany, and India), the advantage of their data is its availability for the time-span from 1970 to 2006, which allows us to analyze our research question in an econometrically rigorous way by employing difference-in-difference tests. Furthermore, their sub-division of labor laws into five sub-components (see footnote 3 and Appendix) allows

⁹An alternative to patents as proxies of innovation, R&D spending across different industries could be a potential proxy for innovation intensity. However, in a cross-country setting, this presents several challenges. For example, accounting norms, particularly whether R&D is capitalized or is expensed, would have a mechanical effect on R&D spending. Griliches (1990) emphasized that there is a strong relationship in the US between R&D and the number of patents received at the cross-sectional level, across firms and industries. The median R-squared is of the order of 0.9.

us to trace the impact of labor laws on innovation to a more elementary unit of analysis, letting us determine what the most important aspect of employment protection legislation with respect to innovation is. Focussing on five countries in our analysis does not represent a substantial omission, as these five countries account for 72% of patents filed with the USPTO. The aggregate measure of the stringency of employment protection used in our paper is the simple sum of the five sub-indices (per country and year); higher values represent stricter labor laws, i.e. more employment protection.¹⁰

In addition to its useful time-series properties, the Deakin et al. (2007) index also offers a number of other advantages. While the broad categories used to construct the index broadly correspond to similar parts of the cross-sectional index developed by Botero et al. (2004), Deakin et al. (2007) take into account not just formal or positive laws, but also self-regulatory mechanisms, including collective agreements, which play a functionally similar role in certain legal systems; this feature makes their index more comprehensive than the Botero et al. (2004) index in terms of the range of rules which are analyzed. In addition, the values reported in the index are complemented by more detailed country-level data on the evolution of labor laws in each system. Finally, the components that make up the index are not coded as binary variables, but can take on several intermediate values.

As mentioned above, the index covers employment law in five countries over the time-span 1970-2006. Forty dimensions of labor laws are analyzed, and are grouped into five aspects of labor and employment law: the regulation of alternative forms of labor contracting (e.g. self-employment, part-time work, and contract work), regulation of working time, dismissal rules, employee representation, and rules governing industrial action. By averaging the sub-components for each group per country and year, Deakin et al. (2007) obtain sub-indices for the five aspects of labor and employment law.

With regard to our Hypothesis 2 (“Stronger laws governing dismissal of employees should influence innovation more than other aspects of labor laws.”), the sub-index for the “Regulation of Dismissal” is of particular importance. The index is made up of the following components: The legally mandated notice period; the amount of mandatory redundancy compensation; constraints on dismissal imposed by the law (such as dismissal being lawful only in case of misconduct or serious fault of the employee); parties to be notified in case of dismissal (this ranges from a formal communication to a state body to a simple oral statement to the employee); redundancy selection (e.g. priority rules based on seniority, marital

¹⁰A third possible proxy for the stringency of employment protection legislation is the EPL measure constructed by Nicoletti and Scarpetta (2001) for a set of OECD countries for the years 1990-1998. As this index neither offers the cross-sectional comprehensiveness of the index constructed by Botero et al. (2004), nor the full extent of the longitudinal advantages of the index developed by Deakin et al. (2007), we did not use this measure in our analysis.

status etc.); applicability of priority rules in re-employment; and rules governing unjust dismissal (i.e. the extent of procedural constraints on dismissal imposed by the law; whether reinstatement is the normal remedy for unfair dismissal; the period of service required for an employee to qualify for protection against unjust dismissal).

4.3 Proxy for Innovation Intensity

The “industry” level classification we employ pertains to the *patent classes* in the data. We identify an industry’s (patent class’) propensity to innovate by the number of patents filed by the median US firm in that industry. This corresponds to using the patents under USPTO assignee code “2”.

The choice of the US for the ranking of industries is for several reasons. First, the US has the most populated data across various patent classes and over time. Second, the US had the most well-developed financial markets over our sample period and these have been shown to be necessary for funding of constrained but high-growth sectors (Rajan and Zingales, 1998). Last, but not the least, the US has had the most vibrant research environment in universities and the most open immigration policy for enrolling scholars in these universities.

We then make the assumption that the propensity to innovate is driven primarily by the technological characteristics of firms in that industry. This assumption can be justified along the following grounds. First, Cohen, Nelson and Walsh (1996) find in their survey of patenting across various US industries that the propensity to patent is largely driven by technological characteristics of an industry. Hence, we reason that these technological characteristics carry over to other countries. For example, the correlation in patent class ranking between the US and Germany is 0.676 on average in the time-series, its value ranging from a minimum of 0.63 to a maximum of 0.76.

Second, Hall, Jaffe and Trajtenberg (2001) find that the number of patents filed per year and the number of citations per year to these patents vary with the industry category, with Computers and Communications having the highest number of patents filed per year and the highest number of citations to these patents per year, and the more mature Mechanical industry exhibiting the lowest values on both counts. They describe the reasons for these differences as primarily technological. Cohen et al. (1996) contrast between discrete and complex technologies and argue that firms file more patents and cite each other’s patent more when the technology is “complex”.

While Rajan and Zingales (1998) construct a time-invariant industry level proxy for external financial dependence, our proxy for innovation intensity is *time-varying*. Hall, Jaffe and Trajtenberg (2001) show in Figure 5 of their study that there have been changes in the

share of patents occupied by different industry categories over the period 1978-2002. This is an important observation suggesting that the technological innovation intensity of industries has changed in a relative fashion over time. This point has also been stressed by Kortum and Lerner (1999) who find for example that the number of patents filed in Biotechnology and Software industries has risen considerably since the late 1970s, both absolutely and as a share of total patenting in the United States. Kortum and Lerner (1999) suggest that the principal reason for this pattern is the inter-temporal variation in the level of innovation across different industries, particularly due to the arrival of technological shocks.

4.4 Summary Statistics

Table 1 lists the mean, standard deviation, minimum, and maximum for the following variables (by country): number of patents filed, citations received by these patents, the number of firms filing patents, as well as the aggregate index of labor laws, and dismissal laws, in each of the five countries in our sample. Data for the labor law index is available from 1970 to 2006, while patent data is from 1970 to 2002.

5 Empirical Results

Our main empirical investigation is aimed at determining whether the ex ante value of an innovative strategy relative to that of a conservative one increases or decreases as the labor laws become more employee-friendly. In order to motivate our empirical tests, we first show a plot of the aggregate labor index against two innovation measures, namely, log of patents and log of citations, after accounting for year, country, and industry fixed effects (see Figure 1). It can be seen that there is a clear positive trend between innovation and the stringency of labor laws, which corroborates the hypothesis that strong labor laws in fact foster innovation. In the following pages we present statistical evidence that lends further support to this hypothesis.¹¹

¹¹One concern that should be addressed pre-emptively is that the contracting and legal environments in India might be very different from other countries in our sample. To alleviate this concern, as a robustness check, we also performed all tests detailed on the following pages without observations for India; the results are almost identical.

5.1 Overall Effect of Labor Laws on Innovation

5.1.1 Level regressions

Table 2 shows the results of the basic test of equation (1) using the logarithm of the number of patents, number of patenting firms, and citations to patents as the dependent variables. In columns 1-3, we first report the results from our basic test without any control variables. For each of the three dependent variables, we find the coefficient on the labor law index to be positive and significant at the 1% level. This result indicates that strong labor laws have a positive impact on innovation.

Columns 4-9 present the results controlling for other variables that might affect the level of innovation:

Creditor rights Acharya and Subramanian (2008) provide empirical evidence that when a country’s bankruptcy code is creditor-friendly, excessive liquidations cause levered firms to shun innovation, whereas by promoting continuation upon failure, a debtor-friendly code induces greater innovation. Therefore, first, we control for the extent of creditor protection in a country using the Djankov et al. (2007) index of creditor rights. Consistent with the negative effect of creditor rights on innovation highlighted in Acharya and Subramanian (2008), we find the coefficient of creditor rights to be negative and significant.

Other laws Since the labor laws in a country may be correlated with its other laws, we employ the set of (by construction time-invariant) legal variables included in Acharya and Subramanian (2008): Rule of Law, Antidirector Rights Index and the Efficiency of Judicial System (all from La Porta et al. (1998)). The rule of law and the efficiency of the legal system are positively and significantly correlated with innovation.¹²

Effect of Bilateral Trade While employing patents filed with the USPTO to proxy innovation done in non-US countries avoids heterogeneity from employing patents filed under each country’s individual patenting system, this strategy introduces potential biases. Define the difference between the “true” level of innovation in a country and innovation as measured by USPTO patents and citations as the “USPTO bias”. Given the country, patent class and application year fixed effects in our regressions, the coefficient β_1 in equation (1) would be

¹²Since the rule of law does not vary over time, we estimate its effect by aggregating the country fixed effects. We also controlled for legal origin, Logarithm of days to enforce a contract, and Estimated Cost of Insolvency Proceedings in these regressions, but they were dropped due to multi-collinearity. The absence of an effect of legal origin is consistent with the finding in Deakin et al. (2007) that legal origin has no consistent effect on labor laws.

biased only if time-varying omitted variables at the country/ patent class level that affect the USPTO bias are also correlated with the changes in labor laws.

Nevertheless, we follow Acharya and Subramanian (2008) in employing non-US countries' bilateral trade with the US as a potential determinant of the USPTO bias. Countries that export to the US would file more patents with the USPTO, particularly in the more innovation-intensive industries. MacGarvie (2006) finds that citations to a country's patents are correlated with the level of exports and imports that the country has with the US. Therefore, in our regressions, we add for each country the logarithm of the level of imports and the level of exports that the country has with the US in each year at each 3-digit ISIC industry level, using data from Nicita and Olarreaga (2006).¹³

While imports have no consistent effect, exports are negatively correlated with innovation, although this effect is only significant in columns (6) and (9). Crucially, the effect of labor laws stays positive and statistically significant at the 1% level.

Effects of a Country's Industry-Level Comparative Advantage and its Economic Development A key determinant of innovation is the comparative advantage that a country possesses in its different industries, which could affect our interpretation of β_1 . To see this, consider two countries with different levels of employment protection legislation: call the country with stringent labor laws "country 1" and the country with lax labor laws "country 2". Say that country 1, which has stringent labor laws, has a comparative advantage in Biotechnology while country 2, which has lax labor laws, possesses a comparative advantage in tangible, asset intensive industries such as Cement and Steel. Since Biotechnology firms have a greater propensity to innovate than firms in Cement and Steel, this effect of comparative advantage could show up as an effect of labor laws. We follow Acharya and Subramanian (2008) in employing as our proxy for industry level comparative advantage 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. The data for these measures come from the United Nations Industrial Development Organization (UNIDO)'s statistics.

Relatedly, since richer countries may innovate more and may also file more patents with the US, we also include the logarithm of real GDP per capita.

In sum, to account for the effects of industry-level comparative advantage and a country's economic development, we include the ratio of value added and the logarithm of real GDP per

¹³We match the patent classes to the 3-digit ISIC using a two-step procedure: first, the updated NBER patent dataset (patsic02.dta on Brownwyn Hall's homepage) assigns each patent to a 2-digit SIC. We then employed the concordance from 2-digit SIC to 3-digit ISIC codes. Since every patent is already assigned to a patent class in the original NBER patent dataset, this completes our match from the patent class to the 3-digit ISIC code.

capita in Columns 7-9 of Table 2. We find that the ratio of value added has no significant effect on innovation; this is largely because country level comparative advantages do not change significantly over time and our country fixed effects absorb any time-invariant effects. Crucially, in these specifications, we find that the overall effect of labor laws stays positive and significant at the 1% level for all three innovation proxies.

In addition to being statistically significant, the economic magnitude of the impact of labor laws on innovative activity is also large. In particular, if we use Columns 1-3 of Table 2 to estimate these economic magnitudes, we find that an increase in the labor index by one would, *ceteris paribus*, result in a rise in the number of patents issued by 14.6%.¹⁴ The impact on the number of citations and number of firms is of a similar order of magnitude. Compared to the economic effects for patents, the effect is larger for the number of citations and lower for the number of firms: An increase in the labor law index by one would result in an increase in innovative activity by 12.4% and 20.3% as measured by the number of patenting firms and citations, respectively.

5.1.2 Change-on-Change Regressions

While the regressions employing the levels of the labor index and innovation account for fixed effects at the patent class, country and year level, the coefficient on the labor law index might pick up time-varying unobserved determinants of innovation that are correlated with the labor index. In order to alleviate this concern, we examine the effect of *changes* in labor laws on *changes* in innovation (see equation 2). The results of these regressions are displayed in Table 3. Here, we use a similar set of control variables as in our regressions in Table 2. However, we employ the *changes* in creditor rights, logarithm of exports and imports, ratio of value added and the logarithm of GDP per capita. The legal variables (rule of law, efficiency of the judicial system, anti-director rights) are time-invariant, and hence cannot be included in their first difference. Consistent with the findings in Acharya and Subramanian (2008), we find a strengthening of creditor rights to have a negative effect on innovation. Importantly, the table shows that changes that make labor laws more stringent lead to increases in innovation, but changes in all the other variables are statistically insignificant.

Since a primary concern in a cross-country study such as ours is the effect of country level omitted variables on the laws in the country, these change-on-change regressions address such endogeneity concerns. A potential concern could still be that the changes in the labor laws were effected with the explicit intention of encouraging innovation or that the changes in

¹⁴Using Column 1 of Table 2, we find that $\ln(Patents) = -2.984 + 0.136 * LaborIndex$. Therefore, for example, going from a Labor Law index of 1 to an index value of 2 would result in an increase in the number of patents filed of $\exp(0.136) - 1 = 14.6\%$.

labor laws were correlated with country-level factors at that time that influence innovation as well. In Section 5.4, we argue based on Deakin et al. (2007) that such reverse causality or residual endogeneity concerns were absent in our context. Therefore, these change-on-change regressions enable us to infer a *causal effect* of labor laws on innovation.

5.1.3 Effect of Laws Regulating Dismissal on Innovation

We now take a closer look at the different components of the labor law index in order to determine what the main driver of the result that stricter labor laws have a positive impact on innovation is. Deakin et al.'s (2007) labor index consists of five sub-indices: regulation of dismissal, alternative employment contracts, regulation of working time, employee representation, and rules governing industrial action. According to our hypothesis, labor laws that affect the ex-post likelihood of an employee being dismissed should matter more for innovation than other dimensions of employment protection legislation.

Table 4 presents results of the basic tests of equations 1 and 2 where the aggregate labor index is replaced with its five sub-indices. Columns 1-3 document the results from the fixed effects regressions of the level of the components of labor laws on the level of innovation, while Columns 4-6 display the result of these regressions in the first differences. As can be seen from Table 4, the only dimension of labor laws which has a consistently positive impact on innovation is the “regulation of dismissal”.

This motivates us to focus on the effect of laws regulating dismissal and explore its effect further. In Table 5, we rerun the regression specifications that we employed in Table 2 but with one change: we replace the aggregate labor index with the “regulation of dismissal” component. Importantly, we find that the coefficient of “regulation of dismissal” is positive and statistically significant in all regression specifications, implying that tougher dismissal laws are positively associated with innovation. The effect of the other covariates is consistent with our previously documented findings: As in Table 2, we find that stronger creditor rights have a significantly negative effect on innovation, whereas rule of law, anti-director rights, and the efficiency of the judicial system are positively correlated with innovation. Imports have no significant effect; exports have a negative effect, which, however, is significant in Columns (6) and (9) only. The impact of log GDP per capita, and the measure of comparative advantage (ratio of value added) on innovation is not significant, just as in Table 2.

The economic impact of the regulation of dismissal on innovative activity is substantial. Using the results from Column 1 of Table 5, we infer that the strengthening of dismissal laws as measured by an increase in the dismissal index by one would, other things equal, result in 17.7% more innovation as measured by the number of patents filed. The economic magnitudes for the other two innovation measures are similar.

5.1.4 Difference-in-difference tests

As in the case of the aggregate labor index, from the above results, we cannot infer a causal relationship of laws regulating dismissal on innovation due to concerns of time-varying omitted variables at the country level being correlated with the level of labor laws. In order to make progress on inferring the causal relationship, we exploit the staggered nature of changes in the labor laws in the US, France and UK. Figure 4 and 5 show the large changes in laws regulating dismissal in the UK and France (in the direction of a tougher dismissal rule) in the 1970s vis-a-vis no corresponding changes in the US in this period. Similarly, Figure 6 illustrates that while the US experienced a large change in laws regulating dismissal in 1989 (again in the direction of a tougher dismissal rule), such a change did not occur in Germany during the same period. Thus the changes in the laws governing dismissal in UK, France and US provide a natural experiment to undertake a difference-in-difference test of the impact of a change in the laws governing dismissal on innovation.

Our first test examines the impact of dismissal law changes in the UK in the early 1970s; the “control group” is the US, which did not experience such a law change in that time interval (see Figure 4). The results from this test are reported in columns 1-3 of Table 6; the change in dismissal laws had a positive and significant impact on two innovation proxies (number of patents and patenting firms); the impact on the third proxy (patent citations) is also positive, but not significant. Our second difference-in-difference test looks at the impact of dismissal law changes in France in the early 1970s; the “control group” is again the US (see Figure 5). Results are reported in columns 4-6 of Table 6 and clearly corroborate the hypothesis that tougher dismissal laws have a favorable impact on innovation: The coefficient β_1 , capturing the causal effect of the dismissal law change in France, is positive and significant at the 1% level for all three innovation proxies. The same result obtains in our final natural experiment, where we 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 (see Figure 6).

Overall, the evidence presented in Table 6 lends strong support to the hypothesis that tougher dismissal laws lead *ex ante* to greater innovation. The economic effects of these law changes are quite large. In the US, for example, the dismissal index increased from 0 to 0.167 in 1988/1989. The quantitative effect of this strengthening in employment protection was an increase in innovative activity by 16.1%, as measured by the number of patents.¹⁵ The effect is similar or even larger when the other two innovation proxies are considered; for instance, using the number of citations to proxy for innovation would imply that the strengthening in

¹⁵Using column 7 of Table 6, we find that $\ln(Patents) = 4.146 + 0.897 * LaborIndex$. Therefore, going from a Labor Law index of 0 to an index value of 0.167 results in an increase in the number of patents filed of $\exp(0.897 * 0.167) - 1 = \exp(0.150) - 1 = 16.1\%$.

dismissal laws in the U.S. increased innovative activity by 31% per year.

5.2 Inter-industry differences in the Impact of Labor Laws on Innovation

We now investigate inter-industry differences in the effect of labor laws on innovation to examine the hypothesis that the effect of labor laws should be *disproportionately* larger in industries that exhibit a greater propensity to innovate than in other industries. In other words, we are interested in the differential impact of labor laws on innovation depending on an industry's inherent propensity to innovate. This can best be understood using an example. Consider two polar industries in two countries: Biotechnology and Textiles in the UK and Germany. Firms in the Biotechnology sector have a higher propensity to innovate than firms in the Textile industry while labor laws are on average more stringent in Germany than in the United Kingdom (Deakin et al., 2007). Given these intrinsic differences, the difference in realized innovation between Biotechnology and Textiles would be greater in Germany than in the United Kingdom.

To implement the econometric variant of this example, we perform fixed effect regressions as in equation (4). Here, the principal term of interest is the interaction between country level labor laws and industry (i.e. patent class) level patenting intensity — $LaborLaws_{ct} * InnovationIntensity_{i,t-1}$. Our hypothesis is that the coefficient $\beta_1 > 0$, which would imply that the effect of labor laws is disproportionately higher in industries that have a greater propensity to innovate than in other industries. As the variable $InnovationIntensity$ is constructed using U.S. patents, and we want to avoid mechanical correlation of the dependent variable with $InnovationIntensity$, we only use the innovation proxies based on the number of patenting firms and the number of citations in this set of tests as the dependent variables.

The results of the basic tests are reported in columns 1-2 of Table 7, where we find that the coefficient of the interaction term is indeed positive and statistically significant. As in our previous tests, we control for other determinants of innovation in Columns 3-6. We find that the coefficient of the interaction term stays positive and statistically significant.

The economic magnitude of the effect of the interaction term is also quite significant. Using Column 2 in Table 7 with citations as the innovation measure, we find that

$$\begin{aligned} \ln(Patents) = & 0.054 * (LaborIndex) * (InnovationIntensity) + \\ & +0.137 * LaborIndex - 0.077 * InnovationIntensity \end{aligned}$$

Consider now two patent classes which differ in the median number of patents issued to US

firms by one; then the marginal effect of labor laws on our proxy for innovation is greater by 39.4% $(=(0.137+0.054)/0.137-1)$ for the more innovative patent class than the less innovative one.

5.3 Evidence of the Effect of Labor Laws on 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 labor laws have a similar positive effect on economic growth?

To investigate this question, we examine how changes in labor laws affect industry level growth rates in real value added. We start with a log-linear specification for the effect in levels of labor laws on real-value added:

$$\ln Y_{ict} = \beta_i t + \beta_c t + \gamma_t + \beta_1 * LaborLaws_{c,t} + \beta X + \eta_{ict} \quad (5)$$

where Y_{ict} denotes the real value added in ISIC industry i in country c in year t . γ_t denotes 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, we employ the first-difference transformation on (5) and obtain the following specification:

$$y_{ict} = \beta_i + \beta_c + \beta_t + \beta_1 * \Delta LaborLaws_{c,t} + \beta \cdot \Delta X + \varepsilon_{ict} \quad (6)$$

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) and is identical to that employed in Acharya and Subramanian (2008). 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.

Data on nominal value added are obtained from the UNIDO Industrial Statistics database. We 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, we obtain the CPI data for that country from the International Labour Organization’s Labour Statistics database. Our sample extends from 1970-2003.

We display the results of this test in Table 8. In all regressions, we 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 (2008). In the regressions in columns 1 and 2, we 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, we 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, we 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.¹⁶

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.

As a final test, we present the results from large dismissal law changes on industry level growth rates. These difference-in-difference tests, which use the same dismissal law changes as described in Section 6.1.5, allow us to document the causal effect of the regulation of dismissal laws on industry level growth. The results can be seen in Table 8, Panel B. Our first test examines the impact of dismissal law changes in the UK in the early 1970s; the “control group” is the US, which did not experience such a law change in that time interval

¹⁶The 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.

(see Figure 4); results are reported in column 1 of Table 8, Panel B. Our second difference-in-difference test looks at the impact of dismissal law changes in France in the early 1970s; the “control group” is again the US (see Figure 5). Results are reported in column 2 of Table 8, Panel B. In our final natural experiment, where we 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 (see Figure 6). Results are presented in column 3 of Table 8, Panel B. While the effect of the dismissal law change in the UK (column 1) on growth is not significant, the results from the other 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, we find a negative effect of aggregate labor laws on economic growth. When we disaggregate the labor laws into their sub-components, we 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, we document that the impact of stringent dismissal laws on industry growth is similarly positive and significant in two of our three difference-in-difference tests.

5.4 Political Economy of Changes in Labor Laws

While our tests employing the changes in labor laws on changes in innovation (see Table 3) address important endogeneity concerns at the country level, a residual concern still remains: what if the changes in the labor laws were effected explicitly to boost innovation, or if other country level changes coinciding with the changes in labor laws were correlated with changes in innovation. In this section, we investigate this concern.

Botero et al. (2004) find evidence that labor market regulation is often driven by political considerations: countries with a longer history of leftist governments have more stringent labor regulation. The evidence in Deakin et al. (2007) supports the evidence in Botero et al. (2004) that the primary motivation for labor market (de)regulation is political. Deakin et al. find that a rapid decline in the intensity of labor market regulation in the UK coincided with the election of a Conservative government committed to a policy of labor market deregulation. Similarly, a limited revival of regulation of the labor markets in the UK coincided with the return to office in 1997 of a Labor government which ended the UK’s opting out of the EU Social Charter. Similarly, they find that in France, the election of the socialist government in 1981 led to a series of labor law reforms, the ‘Auroux laws’, which were enacted in 1982 and affected a wide range of issues in both individual and collective labor

law. Since that time, French labor law has tracked the changing political fortunes of the main parties. The change in the regulation of dismissal laws in the US was effected in 1989 when the Worker Adjustment and Retraining Notification Act of 1988 (WARN) was passed. Brugemann (2007) examines various articles in the business press that document the events preceding and following the WARN Act. He does not find any of these articles arguing that this Act was aimed at improving any specific aspect of the economy.¹⁷

6 Conclusion

We know from the tenure system for academic appointments that there is a tradeoff between promoting innovative research by granting faculty a certain period over which their job is guaranteed and entrenching them for too long. This paper showed that this relationship between innovation and ease with which employees can be dismissed by firms exists even in the corporate sector. Using patents and citations as proxies for innovation and a time-varying index of labor laws, we find that innovation is fostered by stringent labor laws, especially by laws governing dismissal of employees.

Why is law necessary? That is, can firms not write such contracts with employees on their own? We do not answer this important question. One possibility is that firm-level contracts, if not enforced by law, lack time-consistency. In this case, the law can provide firms with a commitment device to not punish short-run failures and thereby to incentivize the pursuit of value-maximizing innovative activities. Another possibility is that since innovating firms do not capture all rents from innovation (the remainder are passed on to consumers and other firms through externalities), private contracts written to promote innovation can be improved upon by law by granting employees greater protection. Regardless of the reason for which stringent labor laws are necessary, our results find that they are effective: while stringent labor laws as a whole have a negative impact on (value-added) economic growth, stringency of laws governing dismissal has a positive and significant impact on economic growth.

Overall, we conclude that labor laws are an important part of the policy toolkit for promoting innovative growth. This conclusion complements the evidence in Acharya and Subramanian (2008) who focus on the effect on innovation of another aspect of the legal environment – the creditor or debtor friendliness of the bankruptcy code. They find that debtor-friendly codes, by giving firms a “fresh start” when they falter, promote more innovative pursuits. It is an interesting, open question as to whether creditor rights and labor laws

¹⁷Most of the business press articles focus on firms accelerating layoffs before the law’s passage in an effort to avoid being subject to the new law.

interact in their effects, whether they are substitutes or complements, and indeed, which of the two matters more for innovation.

Appendix – Description of the Labor Law Index

This section briefly describes the five components of the labor law index, as detailed in Deakin, Lele and Siems (2007), namely Alternative Employment Contracts, Regulation of Working time, Regulation of Dismissal, Employee Representation, and Industrial Action.

Alternative Employment Contracts. This sub-index measures the cost of using alternatives to the “standard” employment contract, computed as an average of eight following variables: 1. Stringency as to the determination of the legal status of the worker (equal 1 if the law mandates such a status; 0.5 if the law allows the status to be determined by the contract nature; and 0 if the parties have complete freedom in stipulating the status); 2. Equal treatment of part-time workers relative to full-time ones (equal 1 if part-time workers are legally recognized a right to equal treatment with full-time workers; 0.5 if this right is more limited; and 0 otherwise); 3. Cost of dismissing part-time workers relative to that for full-time workers (equal 1 if part-time workers enjoy proportionate rights to full time workers regarding dismissal protection; and 0 otherwise); 4. Substantive constraints on the conclusion of a fixed-term contract (equal 1 if there is such a constraint; and 0 otherwise); 5. The right to equal treatment of fixed-term workers relative to permanent workers (equal 1 if such a right is present, 0.5 if such a right is more limited, and 0 otherwise); 6. Maximum duration of fixed-term contracts before the employment is deemed permanent (taking scores between 0 and 1, with higher scores indicating a lower allowed duration); 7. Stringency as to the use of agency work (equal 1 if the use of agency labor is prohibited, 0.5 if this use is limited and 0 otherwise); and 8. Equal treatment of agency workers relative to permanent ones (equal 1 if the right to this equal treatment is legally recognized, an intermediate score between 0 and 1 if this right is limited, and 0 otherwise).

Regulation of Working Time. This sub-index measures how employee-focused the law on working time is. The sub-index is computed as an average score of the following seven variables: 1. Annual leave entitlements, which measures the standardized normal length of annual paid leave (taking values between 0 and 1, with higher values indicating longer leave entitlements); 2. Public holiday entitlements (taking values between 0 and 1, with higher values indicating longer public holiday entitlements); 3. Overtime premia (equal 1 if the premium is double time, 0.5 if it is time and a half, and 0 if there is no overtime premium);

4. Weekend working (equal 1 if the normal premium for weekend working is double time, or if weekend working is prohibited or strictly controlled, 0.5 if it is time and a half, and 0 if there is no premium); 5. Limits to overtime working (equal 1 if there is a limit to the number of weekly working hours, including overtime, 0.5 if such limits can be averaged out over a period longer than a week, and 0 if there is no such a limit); 6. Duration of the weekly normal working hours, exclusive of overtime (equal 1 for 35 hours or less, 0 for 50 hours or more, and intermediate values between 0 and 1 for the rest); and 7. Maximum daily working time (scores are normalized to be on a 0-1 scale, with a limit of 8 hours scoring 1, and a limit of 18 hours or more scoring 0).

Regulation of Dismissal. This sub-index measures the extent to which the regulation of dismissal favors the employee. The sub-index is an average score of the following nine variables: 1. Legally mandated notice period (values are normalized to be between 0 and 1, with 12 weeks = 1 and 0 weeks = 0); 2. Legally mandated redundancy compensation made to a worker who is made redundant after 3 years of employment (values are normalized to be between 0 and 1, with 12 weeks = 1 and 0 weeks = 0); 3. Minimum qualifying period of service for normal case of unjust dismissal (values are normalized to be between 0 and 1, with 0 months = 1 and 3 years or more = 0); 4. Procedural constraints on dismissal (taking values of 1, 0.67, 0.33 and 0; the higher of which suggests higher costs of the employer's failure to follow procedural requirements prior to dismissal); 5. Substantive constraints on dismissal (taking values of 1, 0.67, 0.33 and 0; the higher of which suggests stricter requirements on the part of the employer to establish reasons for dismissal); 6. Reinstatement as a normal remedy for unfair dismissal (taking values of 1, 0.67, 0.33 and 0; which suggest, as the remedy for unfair dismissal, respectively reinstatement, a choice of reinstatement or compensation, compensation, no remedy); 7. Notification of dismissal (taking values of 1, 0.67, 0.33 and 0; higher values of which imply more complicated procedure for dismissal notification); 8. Redundancy selection (equal 1 if redundancy dismissal must be based on priority rules, and 0 otherwise); and 9. Priority in re-employment (equal 1 if re-employment must be based on priority rules, 0 otherwise).

Employee Representation. This sub-index measures the strength of employee representation. The sub-index is an average score of the following seven variables: 1. Right to Unionization (taking values of 1, 0.67, 0.33 and 0; higher values indicate better protection of the right to form trade unions); 2. Right to collective bargaining (taking values of 1, 0.67, 0.33 and 0; higher values indicate better protection of the right to collective bargaining); 3. Duty to bargain (equal 1 if the employer has the legal duty to reach an agreement with

worker organizations; and 0 otherwise); 4. Extension of collective agreements (equal 1 if collective agreements are legally extended to third parties at the national or sectoral level, and 0 otherwise); 5. Closed shops (equal 1 if both pre-entry and post-entry closed shops are permitted, 0.5 if pre-entry closed shops are prohibited but post-entry ones are permitted; and 0 if neither type of closed shops is permitted); 6. Codetermination via board membership (equal 1 if unions/ workers have the legal right to nominate directors in companies of a certain size; and 0 otherwise); and 7. Codetermination and information/ consultation of workers (taking values of 1, 0.67, 0.5, 0.33 and 0; higher values of which suggest higher degree of participation by workers in the determination process through work councils and enterprise committees).

Industrial Action. This sub-index measures the strength of legal protection for industrial action. The sub-index is calculated as the average of the following nine variables: 1. Unofficial industrial action (equal 1 if strikes are conditionally not unlawful, and 0 otherwise); 2. Political industrial action (equal 1 if political-oriented strikes are permitted, and 0 otherwise); 3. Secondary industrial action (taking values of 1, 0.5 and 0 if secondary or sympathy strike action is respectively unconstrained, permitted under certain conditions, and prohibited); 4. Lockouts (equal 1 if permitted and 0 otherwise); 5. Right to industrial action (taking values of 1, 0.67, 0.33 and 0; higher values of which suggest better protection of the right to industrial action); 6. Waiting period prior to industrial action (equal 1 if strikes can occur without mandatory prior notification/waiting period, and 0 otherwise); 7. Peace obligation (equal 1 if existence of a collective agreement does not render a strike unlawful, and 0 otherwise); 8. Compulsory conciliation or arbitration (equal 1 if alternative dispute resolution mechanisms before the strike are not mandatory, and 0 otherwise); and 9. Replacement of striking workers (equal 1 if employers are prohibited from dismissing striking workers engaging in a non-violent or non-political strike, and 0 otherwise).

References

- [1] Acharya, V., K. John and R. K. Sundaram, 2000, “On the Optimality of Resetting Executive Stock Options, ” *Journal of Financial Economics*, 57(1), 65–101.
- [2] Acharya, V., K. Subramanian, 2007, “Bankruptcy Codes and Innovation,” Working Paper (unabridged version), London Business School.
- [3] Acharya, V., K. Subramanian, 2008, “Bankruptcy Codes and Innovation,” *Review of Financial Studies*, forthcoming.

- [4] Aghion, P. and P. Howitt, 1992, “A Model of Growth Through Creative Destruction,” *Econometrica*, 60(2), 323–352.
- [5] Allen, F. and D. Gale, 2000, *Comparing Financial Systems*, Cambridge, MA, MIT Press.
- [6] Atanassov, J., and E. H. Kim, 2007, “Labor Laws and Corporate Governance: International Evidence from Restructuring Decisions,” Working Paper, Ross School of Business.
- [7] Besley, T. and R. Burgess, 2004, “Can Labor Regulation Hinder Economic Performance? Evidence from India,” *Quarterly Journal of Economics*, 119(1), 91–134.
- [8] Botero, J., Djankov, S., La Porta, R., F. Lopez-De-Silanes and A. Shleifer, 2004, “The Regulation of Labor,” *Quarterly Journal of Economics*, 119(4), 1339–1382.
- [9] Brügemann, B., 2007, “Employment Protection: Tough to Scrap or Tough to Get?,” *Economic Journal*, 117, 386–415.
- [10] Cohen, W., Nelson, R. and Walsh, J., 1996, “Appropriability Conditions and Why Firms Patent and Why They do Not in the American Manufacturing Sector,” Paper presented at the OECD Conference on New Indicators for the Knowledge-Based Economy.
- [11] Cremer, J., 1995, “Arm’s Length Relationships,” *The Quarterly Journal of Economics*, CX(2), 275–296.
- [12] Deakin, S., P. Lele, and M. Siems, 2007, “The evolution of labour law: Calibrating and comparing regulatory regimes,” *International Labour Review* 146(3-4), 133–162.
- [13] Djankov, S., C. McLiesh and A. Shleifer, 2007, “Private Credit in 129 Countries,” *Journal of Financial Economics*, 85(2), 299–329.
- [14] Griliches, Z., 1990, “Patent statistics as economic indicators: A survey,” *Journal of Economic Literature*, 28, 1661–1707.
- [15] Grossman, G. and E. Helpman, 1991, “Innovation and Growth in the Global Economy,” Cambridge: MIT Press.
- [16] Hall, B. H., A. Jaffe and M. Trajtenberg. 2001. “The NBER Patent Citations Data File: Lessons, Insights and Methodological Tools,” NBER working paper.
- [17] Hall, B., A. Jaffe, and M. Trajtenberg, 2005, “Market value and patent citations,” *RAND Journal of Economics* 32, 101–128.

- [18] Imbens, Guido M. and Jeffrey M. Wooldridge, 2007, “Lecture Note 10: Difference-in-difference estimation,” NBER Summer 2007 on “What’s new in Econometrics,” <http://www.nber.org/minicourse3.html>.
- [35] Imbens, Guido M. and Jeffrey M. Wooldridge, 2008, “Recent Developments in the Econometrics of Program Evaluation,” NBER Working Paper # 14251, www.nber.org/papers/w14251.
- [35] Kortum, S. and J. Lerner, 1999, “What is behind the recent surge in patenting?” *Research Policy*, 28, 1-22.
- [21] La Porta, Rafael, F. Lopez-de-Silanes, A. Shleifer, and R. W. Vishny, 1997, “Legal determinants of external finance,” *Journal of Finance*, 52, 1131-1150.
- [22] La Porta, Rafael, F. Lopez-de-Silanes, A. Shleifer, and R. W. Vishny, 1998, “Law and finance,” *Journal of Political Economy*, 101, 678-709.
- [23] La Porta, Rafael, F. Lopez-de-Silanes, and A. Shleifer, 1999, “Corporate Ownership Around the World,” *Journal of Finance*, vol. 54(2), pages 471-517, 04.
- [24] MacGarvie, 2006, “Do firms learn from international trade?” *The Review of Economics and Statistics*, 88(1), 46-60.
- [25] Manso, Gustavo, 2008, “Motivating Innovation,” Working Paper, MIT Sloan School of Management.
- [26] McKinsey Global Institute, 1997, *France and Germany*, Washington, DC: McKinsey.
- [27] Menezes-Filho, N., and J. Van Reenen, 2003, “Unions and Innovation: A Survey of the Theory and Empirical Evidence,” in John T. Addison and Claus Schnabel, eds., *International Handbook of Trade Unions*, Edward Elgar Publishing Ltd, 293–334.
- [28] Nicita A. and M. Olarreaga, 2006, “Trade, Production and Protection: 1976-2004,” *World Bank Economic Review*, 21(1).
- [29] Nicoletti, G., and S. Scarpetta, 2001, “Interaction between Product and Labour Market Regulations: Do They Affect Employment? Evidence from the OECD Countries,” Conference on “Labour Market Institutions and Economic Outcomes.” Lisbon: Bank of Portugal, June 3– 4, 2001.

- [30] Pakes, A., and M. Shankerman, 1984, “The rate of obsolescence of patents, research gestation lags, and the private rate of return to research resources,” in Zvi Griliches, ed., *R&D, Patents and Productivity*, University of Chicago Press, 98–112.
- [31] Rajan, R. and L. Zingales, 1998, “Financial dependence and growth,” *American Economic Review*, 88,559–586.
- [32] Romer, P., 1986, “Increasing Returns and Long-Run Growth,” *Journal of Political Economy*, 94(5), 1002–1037.
- [33] Scarpetta, S. and T. Tressel, 2004, “Boosting Productivity via Innovation and Adoption of New Technologies: Any Role for Labor Market Institutions?” World Bank Policy Research Working Paper 3273.
- [34] Simon, H.A., 1951, “A Formal Theory of the Employment Relationship,” *Econometrica*, 19, 293–305.
- [35] Stern, Nicholas, 2001, “A Strategy for Development,” Washington DC: World Bank.
- [36] Williamson, O. E., M. L. Wachter, and J. E. Harris, 1975, “Understanding the Employment Relation: The Analysis of Idiosyncratic Exchange,” *The Bell Journal of Economics*, 6(1), 250–278.

Figure 1: **Innovation Proxies vs. Aggregate Labor Index.**

The figure shows a plot of the aggregate labor index against two of the innovation measures we use in our empirical tests, namely, log of patents and log of citations, after accounting for year, country, and industry fixed effects.

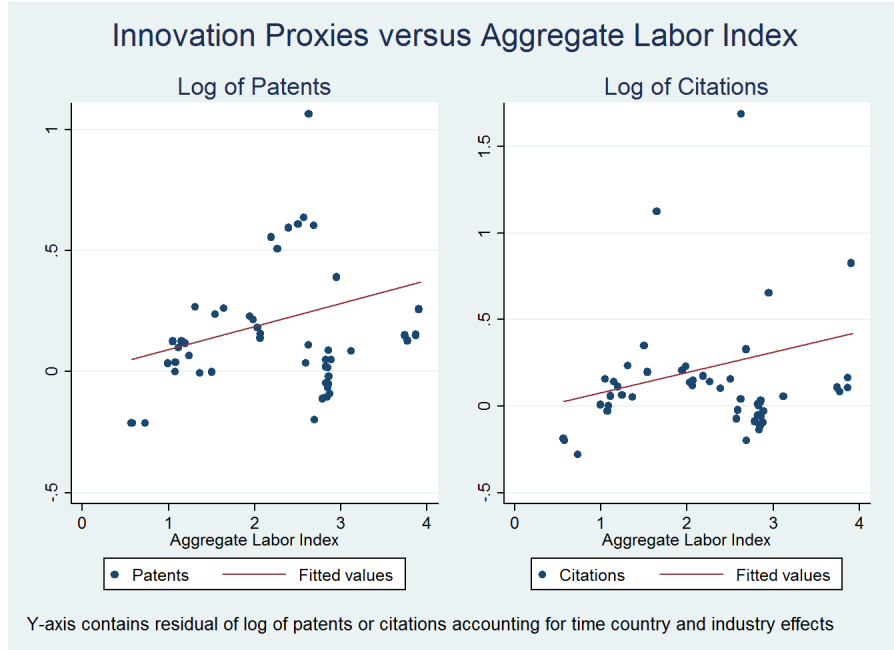


Figure 2: **Aggregate Labor Index.**

The “aggregate labor index” for a given country and year is constructed as the sum of five component indices: alternative employment contracts, regulation of working time, regulation of dismissal, employee representation, and industrial action. Higher values indicate more employment protection / stricter labor laws. The index data is from Deakin et al. (2007).

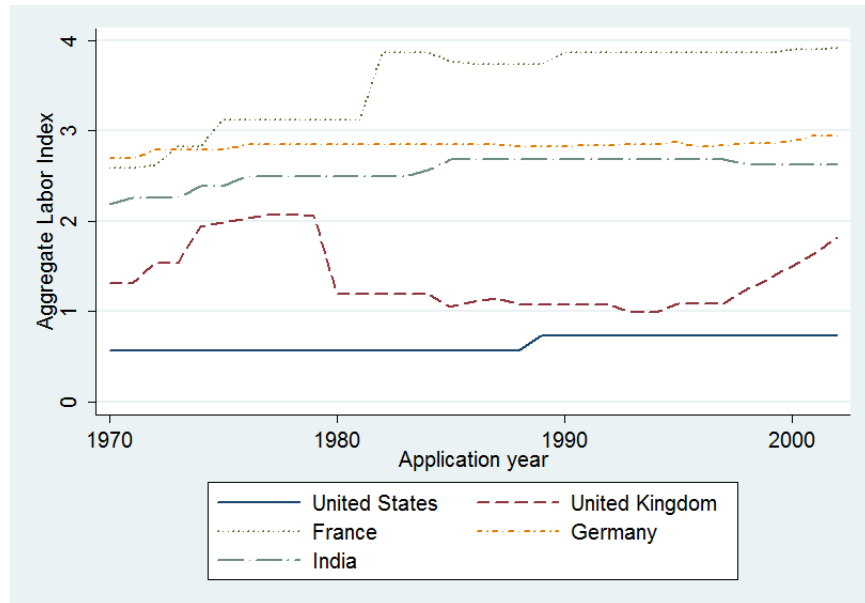


Figure 3: **Regulation of Dismissal.**

The figure shows the strength of the “Regulation of Dismissal” for a given country and year. Higher values indicate more employment protection / stricter laws. The index data is from Deakin et al. (2007).

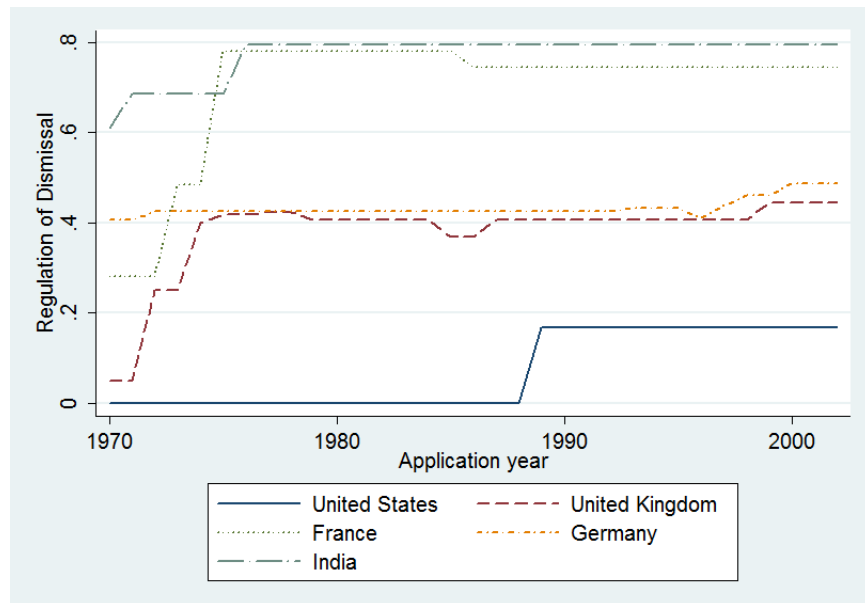


Figure 4: **Regulation of Dismissal, U.S. and U.K.**

The figure shows the index representing the regulation of dismissal for the U.S. and U.K. from 1970-1988.

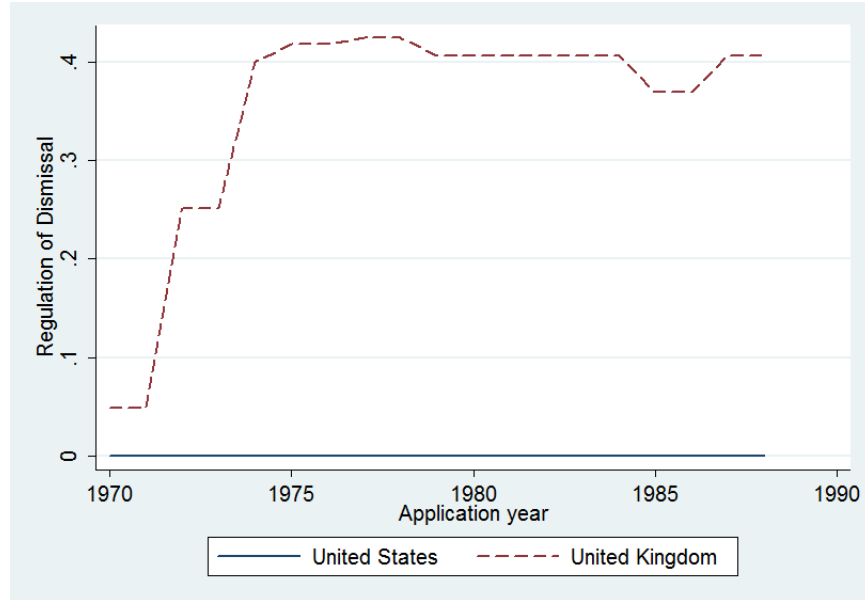


Figure 5: **Regulation of Dismissal, U.S. and France.**

The figure shows the index representing the regulation of dismissal for the U.S. and France from 1970-1988.

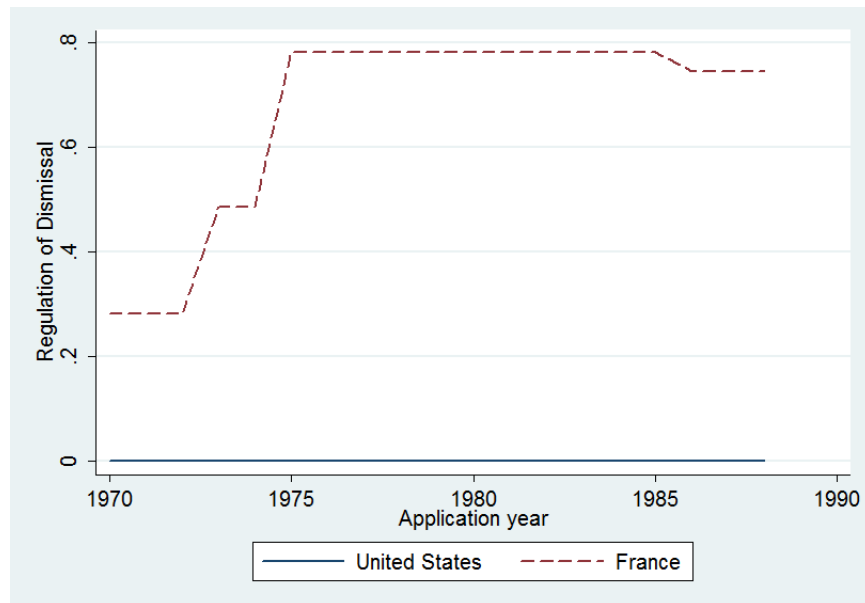


Figure 6: Regulation of Dismissal, U.S. and Germany.

The figure shows the index representing the regulation of dismissal for the U.S. and Germany from 1970-1995.

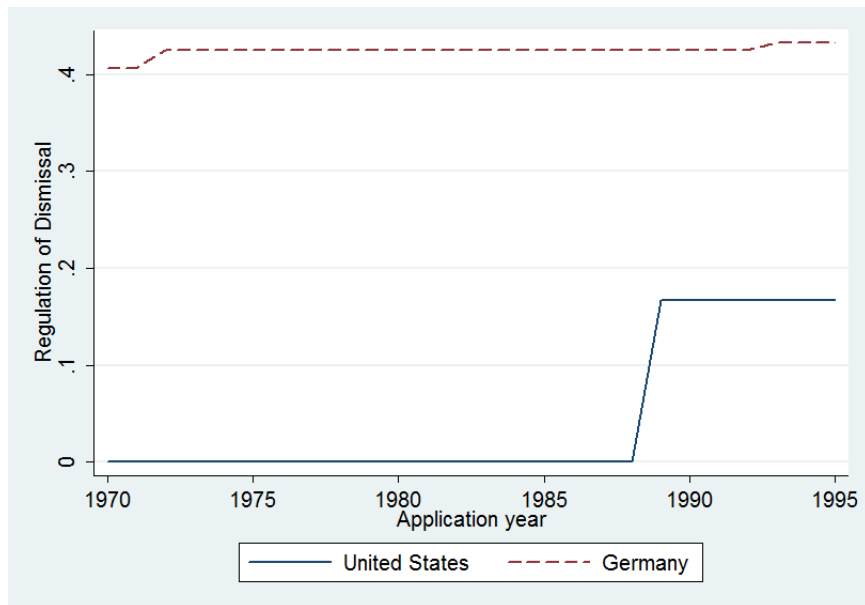


Table 1: Summary Statistics.

The table gives summary statistics for the following variables per country and year: number of patents, number of patenting firms, number of citations, aggregate labor index, and regulation of dismissal. Patent data is from the NBER Patents File (Hall, Jaffe and Trajtenberg, 2001); the labor law index data is from Deakin et al. (2007).

Panel A: United States					
Variable	Observations	Mean	Standard Deviation	Min	Max
Number of patents	13291	120.518	168.881	1	3172
Number of patenting firms	13291	49.122	59.590	1	728
Number of citations	13291	820.045	1317.006	0	16726
Aggregate Labor Index	13291	0.635	0.082	0.564	0.731
Regulation of Dismissal	13291	0.070	0.082	0	0.167
Panel B: United Kingdom					
Variable	Observations	Mean	Standard Deviation	Min	Max
Number of patents	10383	8.152	12.630	1	297
Number of patenting firms	10383	5.501	6.090	1	90
Number of citations	10383	44.474	72.760	0	1353
Aggregate Labor Index	10383	1.360	0.360	0.990	2.069
Regulation of Dismissal	10383	0.377	0.094	0.049	0.444
Panel C: Germany					
Variable	Observations	Mean	Standard Deviation	Min	Max
Number of patents	11722	18.615	24.462	1	365
Number of patenting firms	11722	9.550	9.931	1	113
Number of citations	11722	83.339	121.727	0	1360
Aggregate Labor Index	11722	2.835	0.048	2.692	2.951
Regulation of Dismissal	11722	0.431	0.018	0.407	0.488
Panel D: France					
Variable	Observations	Mean	Standard Deviation	Min	Max
Number of patents	10277	8.085	11.700	1	262
Number of patenting firms	10277	5.157	5.366	1	64
Number of citations	10277	38.271	57.678	0	767
Aggregate Labor Index	10277	3.503	0.456	2.589	3.923
Regulation of Dismissal	10277	0.699	0.150	0.281	0.782
Panel E: India					
Variable	Observations	Mean	Standard Deviation	Min	Max
Number of patents	661	1.852	2.222	1	20
Number of patenting firms	661	1.390	1.088	1	10
Number of citations	661	4.080	8.125	0	88
Aggregate Labor Index	661	2.598	0.126	2.188	2.682
Regulation of Dismissal	661	0.782	0.040	0.61	0.797

Table 2: Fixed Effects Regressions using Aggregate Labor Index.

The OLS regressions below implement the following model:

$$y_{ict} = \beta_i + \beta_c + \beta_t + \beta_1 * LaborLaw_{c,t} + \beta X + \varepsilon_{ict}$$

where y_{ict} is the natural logarithm of a measure of innovation for the USPTO patent class i from country c applied for in year t . $\beta_i, \beta_c, \beta_t$ denote patent class, country and application year fixed effects. β_1 measures the impact of labor laws on the innovation measures. X denotes a set of control variables. The *Creditor Rights Index* is from Djankov, McLiesh, and Shleifer (2007). *Rule of Law, Antidirector Rights Index* and the *Efficiency of Judicial System* are time-invariant legal variables (all from La Porta et al. (1998)). *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. The labor index data is from Deakin et al. (2007). Standard errors are robust to heteroscedasticity and autocorrelation. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable is	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Logarithm of	Number of Patents	Number of Patenting Firms	Number of Citations	Number of Patents	Number of Patenting Firms	Number of Citations	Number of Patents	Number of Patenting Firms	Number of Citations
Labor Index	0.136*** (0.013)	0.117*** (0.012)	0.185*** (0.021)	0.103*** (0.017)	0.053*** (0.016)	0.151*** (0.030)	0.107*** (0.016)	0.058*** (0.016)	0.150*** (0.030)
Creditor Rights Index				-0.058*** (0.009)	-0.056*** (0.009)	-0.057*** (0.015)	-0.062*** (0.011)	-0.060*** (0.010)	-0.056*** (0.016)
Rule of Law				0.295*** (0.021)	0.321*** (0.019)	0.439*** (0.033)	0.157 (0.15)	0.154 (0.13)	0.470*** (0.18)
Antidirector Rights Index				0.119*** (0.014)	0.092*** (0.020)	0.181*** (0.020)	0.109*** (0.019)	0.081*** (0.015)	0.183*** (0.025)
Efficiency of Judicial System				1.200*** (0.031)	1.011*** (0.029)	1.462*** (0.050)	1.246*** (0.056)	1.066*** (0.051)	1.452*** (0.075)
Log Imports				0.018 (0.056)	0.041 (0.051)	-0.056 (0.095)	0.017 (0.056)	0.040 (0.051)	-0.056 (0.095)
Log Exports				-0.079 (0.060)	-0.050 (0.056)	-0.240** (0.099)	-0.080 (0.061)	-0.051 (0.056)	-0.240** (0.099)
Ratio of Value Added							0.017 (0.031)	0.004 (0.030)	0.004 (0.050)
Log of per capita GDP							0.250 (0.28)	0.302 (0.25)	-0.056 (0.32)
Constant	-2.984*** (0.12)	-3.415*** (0.11)	-5.146*** (0.17)	-12.08*** (0.29)	-11.02*** (0.28)	-19.28*** (0.49)	-13.75*** (1.93)	-13.04*** (1.68)	-18.91*** (2.18)
US Patent class dummies	Y	Y	Y	Y	Y	Y	Y	Y	Y
Country dummies	Y	Y	Y	Y	Y	Y	Y	Y	Y
Application year dummies	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	46334	46334	42918	32941	32941	30159	32941	32941	30159
R-squared	0.84	0.83	0.80	0.84	0.84	0.82	0.84	0.84	0.82

Table 3: Regressions in First Differences using Aggregate Labor Index.

The OLS regressions below implement the following model:

$\Delta y_{ict} = \beta_c + \beta_t + \beta_1 * \Delta Labor Laws_{c,t} + \beta \Delta X + \varepsilon_{ict}$ where y_{ict} is the natural logarithm of a measure of innovation for the USPTO patent class i from country c applied for in year t . Δ is the first difference operator. β_c, β_t denote country and application year fixed effects. β_1 measures the impact of labor laws on the innovation measures. X denotes a set of control variables. 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. The labor index data is from Deakin et al. (2007). Standard errors are robust to heteroscedasticity and autocorrelation. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable is	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
First Difference of	Number of	Number of	Number of	Number of	Number of	Number of	Number of	Number of	Number of
Logarithm of	Patents	Patenting Firms	Citations	Patents	Patenting Firms	Citations	Patents	Patenting Firms	Citations
Labor Index (F.D.)	0.079*** (0.023)	0.057** (0.024)	0.167*** (0.054)	0.083*** (0.028)	0.062*** (0.026)	0.112* (0.058)	0.083*** (0.029)	0.055** (0.027)	0.118** (0.060)
Creditor Rights Index (F.D.)				-0.022*** (0.007)	-0.016** (0.007)	0.004 (0.016)	-0.022*** (0.007)	-0.017** (0.007)	0.005 (0.016)
Log Imports (F.D.)				-0.035 (0.038)	0.017 (0.035)	-0.113 (0.087)	-0.036 (0.038)	0.017 (0.035)	-0.114 (0.087)
Log Exports (F.D.)				-0.021 (0.038)	-0.031 (0.037)	-0.112 (0.084)	-0.021 (0.038)	-0.031 (0.037)	-0.111 (0.084)
Ratio of Value Added (F.D.)							0.009 (0.023)	0.009 (0.022)	0.036 (0.047)
Log of per capita GDP (F.D.)							0.030 (0.20)	0.262 (0.19)	-0.333 (0.40)
Constant	-0.034*** (0.002)	-0.030*** (0.002)	-0.120*** (0.005)	-0.057*** (0.003)	-0.049*** (0.003)	0.000 (0.13)	-0.057*** (0.005)	-0.054*** (0.005)	0.013 (0.13)
US Patent class dummies	N	N	N	N	N	N	N	N	N
Country dummies	Y	Y	Y	Y	Y	Y	Y	Y	Y
Application year dummies	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	41759	41759	38486	29024	29024	26475	29024	29024	26475
R-squared	0.23	0.20	0.11	0.31	0.29	0.15	0.31	0.29	0.15

Table 4: Regressions using Components of Labor Index.

The OLS regressions in columns (1-3) implement the following model:

$$y_{ict} = \beta_i + \beta_c + \beta_t + \beta_1 * IA_{c,t} + \beta_2 * IB_{c,t} + \beta_3 * IC_{c,t} + \beta_4 * ID_{c,t} + \beta_5 * IE_{c,t} + \varepsilon_{ict}$$

while the OLS regressions in columns (4-6) implement:

$$\Delta y_{ict} = \beta_c + \beta_t + \beta_1 * \Delta IA_{c,t} + \beta_2 * \Delta IB_{c,t} + \beta_3 * \Delta IC_{c,t} + \beta_4 * \Delta ID_{c,t} + \beta_5 * \Delta IE_{c,t} + \varepsilon_{ict}$$

where y_{ict} is the natural logarithm of a measure of innovation for the USPTO patent class i from country c applied for in year t . Δ is the first difference operator. $\beta_i, \beta_c, \beta_t$ denote patent class, country and application year fixed effects. $\beta_1 - \beta_5$ measure the impact on measures of innovation (Columns 1-3) and changes in innovation (Columns 4-6) of the labor law and changes thereof for the five components of the labor law index: Alternative employment contracts ($IA_{c,t}$), Regulation of working time ($IB_{c,t}$), Regulation of dismissal ($IC_{c,t}$), Employee representation ($ID_{c,t}$), and Industrial action ($IE_{c,t}$). The labor index data is from Deakin et al. (2007). Standard errors are robust to heteroscedasticity and autocorrelation. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable is Logarithm of	(1)			(2)			(3)			(4)			(5)			(6)		
	Number of Patents	Number of Patents	Number of Citations	Number of Patents	Number of Patents	Number of Citations	Number of Patents	Number of Patents	Number of Citations	Number of Patents	Number of Patents	Number of Citations	Number of Patents	Number of Patents	Number of Citations	Number of Patents	Number of Patents	Number of Citations
Regulation of dismissal	0.124*** (0.043)	0.167*** (0.040)	0.153*** (0.068)	0.124*** (0.043)	0.167*** (0.040)	0.153*** (0.068)	0.071 (0.070)	0.146* (0.082)	0.270* (0.16)	0.071 (0.070)	0.146* (0.082)	0.270* (0.16)	0.071 (0.070)	0.146* (0.082)	0.270* (0.16)	0.071 (0.070)	0.146* (0.082)	0.270* (0.16)
Regulation of working time	-0.006 (0.077)	-0.028 (0.076)	0.684*** (0.15)	-0.006 (0.077)	-0.028 (0.076)	0.684*** (0.15)	-0.110 (0.11)	0.049 (0.13)	-0.018 (0.26)	-0.110 (0.11)	0.049 (0.13)	-0.018 (0.26)	-0.110 (0.11)	0.049 (0.13)	-0.018 (0.26)	-0.110 (0.11)	0.049 (0.13)	-0.018 (0.26)
Alternative employment contracts	-0.165*** (0.048)	-0.287*** (0.047)	0.193** (0.085)	-0.165*** (0.048)	-0.287*** (0.047)	0.193** (0.085)	-0.010 (0.072)	-0.032 (0.084)	-0.090 (0.16)	-0.010 (0.072)	-0.032 (0.084)	-0.090 (0.16)	-0.010 (0.072)	-0.032 (0.084)	-0.090 (0.16)	-0.010 (0.072)	-0.032 (0.084)	-0.090 (0.16)
Employee representation	0.542*** (0.10)	0.640*** (0.10)	-0.571*** (0.21)	0.542*** (0.10)	0.640*** (0.10)	-0.571*** (0.21)	0.389*** (0.13)	0.171 (0.15)	0.289 (0.32)	0.389*** (0.13)	0.171 (0.15)	0.289 (0.32)	0.389*** (0.13)	0.171 (0.15)	0.289 (0.32)	0.389*** (0.13)	0.171 (0.15)	0.289 (0.32)
Industrial action	-0.060 (0.13)	-0.221* (0.12)	1.136*** (0.23)	-0.060 (0.13)	-0.221* (0.12)	1.136*** (0.23)	-0.179 (0.16)	-0.168 (0.18)	0.625* (0.36)	-0.179 (0.16)	-0.168 (0.18)	0.625* (0.36)	-0.179 (0.16)	-0.168 (0.18)	0.625* (0.36)	-0.179 (0.16)	-0.168 (0.18)	0.625* (0.36)
Constant	-2.728*** (0.14)	-3.099*** (0.13)	-5.658*** (0.22)	-2.728*** (0.14)	-3.099*** (0.13)	-5.658*** (0.22)	-0.907*** (0.024)	-0.865*** (0.024)	-1.658*** (0.29)	-0.907*** (0.024)	-0.865*** (0.024)	-1.658*** (0.29)	-0.907*** (0.024)	-0.865*** (0.024)	-1.658*** (0.29)	-0.907*** (0.024)	-0.865*** (0.024)	-1.658*** (0.29)
US Patent Class dummies	Y	Y	Y	Y	Y	Y	N	N	N	N	N	N	N	N	N	N	N	N
Country dummies	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Application Year dummies	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	46334	46334	42918	46334	46334	42918	41759	41759	38486	41759	41759	38486	41759	41759	38486	41759	41759	38486
R-squared	0.84	0.83	0.80	0.84	0.83	0.80	0.23	0.17	0.11	0.23	0.17	0.11	0.23	0.17	0.11	0.23	0.17	0.11

Table 5: Fixed Effects Regressions using Regulation of Dismissal Index.

The OLS regressions below implement the following model:

$$y_{ict} = \beta_i + \beta_c + \beta_t + \beta_1 * DismissalIndex_{c,t} + \beta X + \varepsilon_{ict}$$

where y_{ict} is the natural logarithm of a measure of innovation for the USPTO patent class i from country c applied for in year t . $\beta_i, \beta_c, \beta_t$ denote patent class, country and application year fixed effects. β_1 measures the difference-in-difference effect of the change of the regulation of dismissal. X denotes a set of control variables. The *Creditor Rights Index* is from Djankov, McLiesh, and Shleifer (2007). *Rule of Law, Antidirector Rights Index* and the *Efficiency of Judicial System* are time-invariant legal variables (all from La Porta et al. (1998)). *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 Nicta 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. The dismissal index data is from Deakin et al. (2007). Standard errors are robust to heteroscedasticity and autocorrelation. ***, **, * and * denote significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable is	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Logarithm of	Number of Patents	Number of Patenting Firms	Number of Citations	Number of Patents	Number of Patenting Firms	Number of Citations	Number of Patents	Number of Patenting Firms	Number of Citations
Regulation of Dismissal	0.163*** (0.042)	0.173*** (0.039)	0.227*** (0.063)	0.872*** (0.11)	0.940*** (0.088)	1.188*** (0.12)	0.874*** (0.11)	0.938*** (0.090)	1.208*** (0.12)
Creditor Rights Index				-0.058*** (0.009)	-0.047*** (0.009)	-0.059*** (0.014)	-0.058*** (0.012)	-0.048*** (0.010)	-0.050*** (0.016)
Rule of Law				0.314*** (0.021)	0.339*** (0.019)	0.463*** (0.033)	0.328*** (0.15)	0.299** (0.14)	0.744*** (0.18)
Antidirector Rights Index				0.097*** (0.013)	0.089*** (0.010)	0.146*** (0.018)	0.098*** (0.020)	0.085*** (0.016)	0.168*** (0.024)
Efficiency of Judicial System				1.344*** (0.040)	1.233*** (0.034)	1.655*** (0.053)	1.340*** (0.058)	1.244*** (0.050)	1.576*** (0.077)
Log Imports				0.009 (0.056)	0.034 (0.051)	-0.056 (0.095)	0.009 (0.056)	0.034 (0.051)	-0.055 (0.095)
Log Exports				-0.094 (0.061)	-0.063 (0.056)	-0.248** (0.100)	-0.094 (0.061)	-0.064 (0.056)	-0.246** (0.100)
Ratio of Value Added							0.019 (0.031)	0.008 (0.030)	0.010 (0.050)
Log of per capita GDP							-0.027 (0.29)	0.073 (0.26)	-0.500 (0.33)
Constant	-2.754*** (0.12)	-3.246*** (0.11)	-4.841*** (0.17)	-13.63*** (0.43)	-13.50*** (0.35)	-21.34*** (0.56)	-13.46*** (1.94)	-13.96*** (1.67)	-18.19*** (2.24)
US Patent class dummies	Y	Y	Y	Y	Y	Y	Y	Y	Y
Country dummies	Y	Y	Y	Y	Y	Y	Y	Y	Y
Application year dummies	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	46334	46334	42918	32941	32941	30159	32941	32941	30159
R-squared	0.83	0.83	0.80	0.84	0.84	0.82	0.84	0.84	0.82

Table 6: **Difference-in-Difference Tests using the Regulation of Dismissal Index.**

The OLS regressions below implement the following model:

$$y_{ict} = \beta_i + \beta_c + \beta_t + \beta_1 * Dismissal_{law_{s,t}} + \epsilon_{ict}$$

where y_{ict} is the natural logarithm of a measure of innovation for the USPTO patent class i from country c applied for in year t . $\beta_i, \beta_c, \beta_t$ denote patent class, country and application year fixed effects. $Dismissal_{law_{s,t}}$ denotes the index of laws governing dismissal in country c in year t . β_1 measures the difference-in-difference effect of the change of the regulation of dismissal. In this table, we focus on regressions examining “large” changes in the regulation of dismissal in three countries. Columns 1-3 report the results examining the impact of dismissal law changes in the U.K. in the early 1970s; the “control group” is the U.S., which did not experience such a law change in that time interval. Columns 4-6 report the results examining the impact of dismissal law changes in France in the early 1970s; the “control group” is again the U.S. Columns 7-9 report the results examining the impact of dismissal law changes in the U.S. in 1989; the “control group” is Germany, which did not experience such a law change in the sample period. The dismissal index data is from Deakin et al. (2007). Standard errors are robust to heteroscedasticity and autocorrelation. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	(1) UK & US; UK dismissal law changes in early 1970s; data from 1970-1988		(2)		(3)		(4) France & US; France dismissal law change in early 1970s; data from 1970-1988		(5)		(6)		(7) Germany & US; US dismissal law change in 1989; data from 1970-1995		(8)		(9)		
Dependent Variable is	Number of Patents	Number of Patents	Number of Patents	Number of Patents	Number of Citations	Number of Citations	Number of Patents	Number of Patents	Number of Patents	Number of Citations	Number of Citations	Number of Patents	Number of Patents	Number of Patents	Number of Patents	Number of Citations	Number of Citations	Number of Citations	
Logarithm of Dismissal laws	0.151** (0.072)	0.176** (0.072)	0.024 (0.12)	0.406*** (0.047)	0.463*** (0.046)	0.361*** (0.080)	0.897*** (0.14)	0.897*** (0.14)	0.463*** (0.046)	0.361*** (0.080)	0.361*** (0.080)	0.897*** (0.14)	0.897*** (0.14)	0.897*** (0.14)	0.692*** (0.12)	0.692*** (0.12)	1.619*** (0.19)	1.619*** (0.19)	1.619*** (0.19)
Constant	4.080*** (0.018)	3.251*** (0.017)	6.148*** (0.032)	4.328*** (0.022)	3.522*** (0.022)	2.660*** (0.059)	4.146*** (0.022)	4.146*** (0.022)	3.522*** (0.022)	2.660*** (0.059)	2.660*** (0.059)	4.146*** (0.022)	4.146*** (0.022)	4.146*** (0.022)	3.362*** (0.019)	3.362*** (0.019)	6.188*** (0.029)	6.188*** (0.029)	6.188*** (0.029)
US Patent class dummies	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Country dummies	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Application year dummies	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	13946	13946	13812	13835	13835	13667	20039	20039	13835	13667	13667	20039	20039	20039	20039	20039	19875	19875	19875
R-squared	0.91	0.90	0.87	0.91	0.91	0.87	0.86	0.86	0.91	0.87	0.87	0.86	0.86	0.86	0.86	0.86	0.83	0.83	0.83

Table 7: Relative Impact of Labor Laws on Aggregate Innovation in Different Industries.

The OLS regressions below implement the following model:

$$y_{ict} = \beta_i + \beta_c + \beta_t + \beta_1 \cdot LaborLaws_{ct} * InnovationIntensity_{i,t-1} + \beta_2 \cdot LaborLaws_{ct} + \beta_3 \cdot InnovationIntensity_{i,t-1} + \beta X + \varepsilon_{ict}$$

where y_{ict} is the natural logarithm of a measure of innovation for the USPTO patent class i from country c applied for in year t . $\beta_i, \beta_c, \beta_t$ denote patent class, country and application year fixed effects. The Innovation Intensity for patent class i in year $(t-1)$, $InnovationIntensity_{i,t-1}$, is measured as the median number of patents applied by US firms in patent class i in year $(t-1)$. X denotes a set of control variables. The *Creditor Rights Index* is from Djankov, McLiesh, and Shleifer (2007). *Rule of Law*, *Antidirector Rights Index* and the *Efficiency of Judicial System* are time-invariant legal variables (all from La Porta et al. (1998)). *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. The labor law index data is from Deakin et al. (2007). Standard errors are robust to heteroscedasticity and autocorrelation. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable is	(1)	(2)	(3)	(4)	(5)	(6)
Logarithm of	Number of	Number of	Number of	Number of	Number of	Number of
(Labor Index)	Patenting Firms	Citations	Patenting Firms	Citations	Patenting Firms	Citations
* (Innovation Intensity)	0.075*** (0.017)	0.054** (0.027)	0.080*** (0.020)	0.054* (0.030)	0.075*** (0.021)	0.050* (0.030)
Labor Index	0.043** (0.021)	0.137*** (0.035)	-0.019 (0.028)	0.099** (0.044)	-0.016 (0.028)	0.101** (0.043)
Innovation Intensity	-0.150*** (0.037)	-0.077 (0.062)	-0.209*** (0.055)	-0.129 (0.097)	-0.203*** (0.055)	-0.126 (0.098)
(Creditor Rights Index)			0.034** (0.014)	0.026 (0.040)	0.035*** (0.013)	0.023 (0.040)
* (Innovation Intensity)			-0.087*** (0.017)	-0.073 (0.045)	-0.095*** (0.017)	-0.065 (0.047)
Creditor Rights Index			0.319*** (0.026)	0.461*** (0.052)	0.194 (0.16)	0.722*** (0.19)
Rule of Law			0.100*** (0.012)	0.195*** (0.021)	0.086*** (0.019)	0.205*** (0.030)
Antidirector			1.048*** (0.032)	1.483*** (0.053)	1.071*** (0.058)	1.374*** (0.079)
Rights Index					0.027 (0.053)	-0.112 (0.095)
Efficiency of					-0.061 (0.058)	-0.268*** (0.100)
Judicial System					0.021 (0.031)	0.019 (0.051)
Log Imports					0.212 (0.32)	-0.499 (0.39)
Log Exports					-12.29*** (2.19)	-15.92*** (2.82)
Ratio of Value Added					Y	Y
Log of per capita GDP					Y	Y
Constant	-3.195*** (0.14)	0.710*** (0.11)	-11.16*** (0.31)	-19.61*** (0.56)		
US Patent class dummies	Y	Y	Y	Y	Y	Y
Country dummies	Y	Y	Y	Y	Y	Y
Application year dummies	Y	Y	Y	Y	Y	Y
Observations	41609	38890	32336	29712	31087	28741
R-squared	0.83	0.81	0.84	0.82	0.84	0.82

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

The OLS regressions below implement the following model:

$$\Delta y_{ict} = \beta_i + \beta_c + \beta_t + \beta_1 * \Delta LaborLaws_{c,t} + \beta * \Delta X + \epsilon_{ict}$$

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 Nicta 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.

	Panel A		
Dependent Variable is First Difference in	(1)	(2)	(3)
	ln(Real Value Added)	ln(Real Value Added)	ln(Real Value Added)
Labor Index (F.D.)	-0.096* (0.041)	-0.101** (0.032)	
Creditor Rights Index (F.D.)	-0.076*** (0.013)	-0.080*** (0.007)	
Log Imports (F.D.)	(0.001)	-0.000 (0.000)	
Log Exports (F.D.)	(0.000)	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** (0.022)	-0.114*** (0.029)	0.066 (0.051)
Country, Year, and ISIC class dummies	Y	Y	Y
Observations	751	751	1446
R-squared	0.38	0.71	0.28
	Panel B		
Dependent Variable is First Difference in	(1)	(2)	(3)
	ln(Real Value Added)	ln(Real Value Added)	ln(Real Value Added)
Regulation of dismissal (F.D.)	0.009 (0.14)	0.640*** (0.074)	0.328* (0.15)
Constant	0.088*** (0.009)	0.077*** (0.015)	0.105*** (0.014)
Country, Year, and ISIC class dummies	Y	Y	Y
Observations	331	330	434
R-squared	0.31	0.35	0.31