Labor Laws and Innovation[1]

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First draft: November 18, 2008

This draft: March 5, 2009

[1]We are grateful to Amit Seru for his comments and suggestions, and to Hanh Le for excellent research assistance.

Abstract

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Can stringent labor laws be efficient? Possibly, if they provide firms with a commitment device to not punish employees' short-run failures and thereby spur the pursuit of value-maximizing innovative activities. In this paper, we provide empirical evidence that strong labor laws indeed appear to have ex ante a *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 the more innovation-intensive sectors of the economy. Finally, we find that while the overall effect of stringent labor laws is to dampen economic growth, stringent laws governing dismissal promote economic growth, consistent with the evidence that they encourage firm-level innovation.

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

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

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, in particular, whether the legal framework governing 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 literature[1] 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 spur 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.[3] 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 this evidence, 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).

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

[2] For 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).

[3] Similarly, but for their ex ante effects in encouraging innovative and high-impact research, academic employment contracts of tenure-track type whereby new hires are awarded an explicit contract of fixed length, subject to minimum interim standards, would be hard to rationalize.

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 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.[4] 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.[5]

Employing this data, we test the following hypotheses:

[4]More 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.

[5]An alternative to the Deakin et al. (2007) index is the one developed by Botero et al. (2004), which covers more countries but does not have any time-series variability. Another 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).

Hypothesis 1: Stronger labor laws lead to greater innovation.

Hypothesis 2: 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 five essential 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 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 17.0% 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 correlated 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 studying the motivation behind these labor law changes and by examining any reverse causal effects, 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, implying that it is primarily tougher dismissal laws that give rise to the positive effect of labor laws on innovation.

Fourth, 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 1970-1985 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 21% 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.

Fifth, 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. 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 is that on the interaction of the proxy for patenting intensity with the Labor Law index. In regressions allowing for fixed effects for country, patent class and application year, we find that the coefficient on this interaction term is significantly positive, implying that the effect of labor laws is disproportionately higher in industries that have a greater propensity to innovate.

Having tested for the positive effect of labor laws on innovation, we inquire what such an effect implies for country-level *economic growth*. While the endogenous growth theory (see Aghion and Howitt (1992)) implies that this positive effect of labor laws on innovation should translate into a similar positive effect on economic growth, other theories suggest that stringent labor laws, which grant excessive bargaining power to organized labor, blunt investment incentives and thereby country-level economic growth (see Stern (2001) for example). Indeed, existing empirical evidence finds support for this inimical effect of labor laws on economic growth (see Besley and Burgess (2004)). Motivated by these conflicting predictions, 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.

Taken together, these tests enable us to conclude that innovation is fostered by stringent labor laws, especially by laws governing dismissal of employees and in those sectors of the economy that are more innovation-intensive. Furthermore, while the overall effect of stringent labor laws is to dampen economic growth, laws that govern dismissal of employees are an exception since they encourage economic growth through greater firm-level innovation. In additional tests, we confirm that the direction of causality runs from labor laws to innovation and rather than being the other way around; this is also true of the relationship between laws governing dismissal and growth.

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 fire its employees ex post (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 ex ante 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.[6] Another reason why the law may be necessary to protect employee dismissals and promote innovation is that firms may be run by short-termist or myopic top management and lack of efficient firm-level governance of their actions might prevent efficient long-term contracts being written with employees. The law can improve the so-called "internal governance" of firms (Acharya, Myers and Rajan, 2008) by effectively lengthening the horizon of employees and indirectly inducing the top management to provide better incentives to employees by investing for the long run. The specific reason(s) why the labor law may be necessary for efficiency is an important topic for future research.

[6] It 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.

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) find that heavier regulation of labor leads to adverse consequences for labor market participation and unemployment and conclude that government interventions in the labor market are driven primarily by political economic considerations and not by any reasons of efficiency. Atanassov and Kim (2007) examine the interaction between labor laws and investor protection laws and find that rigid employment laws lead to higher likelihood of value-reducing major asset sales, particularly when investor protection is weak. They find that assets are sold to forestall layoffs, even if these asset sales hurt performance. Besley and Burgess (2004) conclude from their study of manufacturing performance in Indian states that pro-worker labor laws are associated with lower levels of investment, productivity, and output. In contrast to these studies which document the negative effects of labor laws, our study finds that stringent labor laws motivate a firm and its employees to pursue value-enhancing innovative activities.

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 find a negative impact of unions on innovation, European studies do not support these findings. Our study pools together five representative countries that span three different legal "origins" and account for over 70% of patents filed in the US. While Menezes-Filho and Van Reenen (2003) focus on laws governing unions, we examine all dimensions of labor laws and pay particular attention to laws governing dismissal of employees.

Our work is closely related to the literature on endogenous growth (see Aghion and Howitt, 1992), which posits that investment in 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 indeed have a positive ex-ante effect on innovation and economic growth.

In less directly related work, Simon (1951) and Williamson, Wachter and Harris (1975) argues that stronger labor laws may also have an ex-post efficiency aspect to them. While the former study argues that strong labor laws provide insurance to employees against risks associated with loss of income and employment, the latter claims that strong labor laws reduce transaction costs derived from the incompleteness of the employment contract. While our study provides direct support to the theoretical conclusions of Manso (2008), the stance that strong labor laws may be efficient is in line with that in the above studies.

3 Data and Main Proxies

We describe first our proxies for innovation and the labor law index and the data used for the same.

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 defined 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]

3.1 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

[7] A 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.

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

patent may be revealed over a period of time and may be difficult to evaluate at the time the innovation occurs. 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.

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).

3.2 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

[9] As an alternative to patents, 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.

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) 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 accounting for various sources of endogeneity. Furthermore, their sub-division of labor laws into five sub-components (see footnote 4 and the Appendix) allows 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.

As Figure 1 shows, the aggregate index of labor laws developed by Deakin et al. (2007) (hereafter "the labor law index") exhibits substantial time-series variation. In addition to its useful time-series properties, the labor law index also offers a number of other advantages. While the broad categories used to construct this index largely 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 their index are complemented by more detailed country-level data on the evolution of labor laws in each system. Finally, the components that make up their index are not coded as binary variables, but can take on several intermediate values.

As mentioned above, the labor law 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: (i) the regulation of alternative forms of labor contracting (e.g. self-employment, part-time work, and contract work); (ii) regulation of working time; (iii) dismissal rules; employee representation; and (v) 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. This sub-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 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). As Figure 2 shows, the sub-index for Regulation of dismissal also varies across time.

3.3 Summary Statistics

Table 1 lists the mean, standard deviation, minimum, and maximum for the following variables (by country) for the five countries in our sample: 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. Data for the labor law index is available from 1970 to 2006. Since the patent data ends in 2002, we terminate our sample in 2002.

4 Empirical Results

Our main empirical investigation is aimed at determining whether stronger labor laws lead to greater innovation. To motivate our empirical tests, we first show a plot of the aggregate labor law index against two innovation measures, namely, log of patents and log of citations, after accounting for year, country, and industry fixed effects (see Figure 3). We notice 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.[10]

Inferring a causal relationship between country-level labor laws and innovation presents the challenge that country-level labor laws are expected to be largely correlated with other country-level unobserved factors. However, since the labor law index exhibits 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 third

[10] One 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.

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. After examining the effect of labor laws on innovation, we enquire whether this effect translates into an effect on country level economic growth. Finally, we examine concerns regarding reverse-causality in the relationship of labor laws to innovation and economic growth.

4.1 Overall Effect of Labor Laws

4.1.1 Level regressions

To start with, we regress the levels of our innovation proxies on the level of the labor index. We employ a fixed effects specification where we control for unobserved factors at the country, time and industry (i.e. patent class) levels:

$$y_{ict} = \beta_i + \beta_c + \beta_t + \boldsymbol{\beta}_1 * LaborLaws_{c,t} + \beta \cdot X + \varepsilon_{ict} \tag{1}$$

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 and are clustered at the patent class level.

Table 2 shows the results of the 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 are positively correlated with innovation.

Columns 4-9 show results after controlling for other variables that may affect 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. We find the coefficient on 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 highlighted by the law and finance literature (La Porta et al. (1997, 1998)): Rule of Law, Antidirector Rights Index and the Efficiency of Judicial System (all from La Porta et al. (1998)). All three legal variables are positively and (almost in every specification) significantly correlated with innovation.[11]

A related concern is that the contracting and legal environments in India might be very different from other countries in our sample, and that India might be driving the results in our cross-country panel regressions. To alleviate this concern, as a robustness check, we also performed all tests detailed on the previous pages without observations for India; the results are almost identical.

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. Given

[11]Since the rule of law does not vary over time, we estimate its effect by aggregating the country fixed effects. In omitted tests, we also controlled for legal origin, Logarithm of days to enforce a contract, and Estimated Cost of Insolvency Proceedings in these regressions. These variables were dropped due to multicollinearity. 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.

the country, patent class and application year fixed effects in our regressions, the coefficient β_1 in equation (1) would be biased only if time-varying omitted variables at the country/ patent class level that affect these biases are also correlated with the changes in labor laws.

Nevertheless, we employ 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. 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).[12] 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.

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. As our proxy for industry level comparative advantage, we employ 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. We find in Columns 7-9 of Table 2 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-invarying effects. No-

[12] We 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.

tably, in these specifications, we find that the overall effect of labor laws stays positive and significant for all three innovation proxies.

Economic magnitudes 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 *17.0%*.[13] 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.

4.1.2 Change-on-change regressions

Given the fixed effects in equation (1), 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:

$$\Delta y_{ict} = \beta_c + \beta_t + \boldsymbol{\beta}_1 * \Delta LaborLaws_{c,t} + \beta \cdot \Delta X + \varepsilon_{ict} \tag{2}$$

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

[13] Using Column 1 of Table 2, we find that $ln(Patents) = -4.130 + 0.157 * LaborIndex$. 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 $exp(0.157) - 1 = 17.0\%$.

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, instead of variables measured at levels, 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. Importantly, the table shows that changes that make labor laws more stringent lead to increases in innovation (significant in all regression specifications in Table 3 except (5) and (8)), but changes in all the other variables are statistically insignificant.[14]

Creditor Rights Changes Could labor law changes be correlated with creditor rights changes through some country-level unobserved factors? Since strong creditor rights have also been shown to negatively affect innovation (Acharya and Subramanian, 2008), a positive correlation between increases (decreases) in the strength of creditor rights and stringency of labor laws might imply that the effects associated with changes in labor laws might in fact be due to changes in creditor rights.

We examine this concern in Columns 10-12 of Table 3 by excluding observations for the years after the creditor rights change. Since in our sample, India and UK changed their creditor rights in 1993 and 1985 respectively, we only include observations before these years for these two countries. This prevents us from including the first difference of the creditor rights index in the specification. We find in Columns 10-12 that the positive overall effect of stringent labor laws on innovation documented in the previous columns persists. We therefore conclude that the positive effect of stringent labor laws on innovation is not driven by creditor rights changes.

Discussion The assumption required to identify β_1 in (2) is that *time-varying* unobserved determinants of *changes* in innovation at the country level are uncorrelated with *changes*

[14]Note that while the coefficient on the creditor rights index is highly significant and negative in Table 2, it is not significant in Table 3. The reason is that identification in the change-on-change regressions relies on time series variation in the creditor index; however, only India and UK changed creditor rights during our sample period.

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 encouraging 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, we investigate such reverse causality and residual endogeneity concerns and argue they were absent in our context.

4.2 Effect of Laws Regulating Dismissal

Our next set of tests is designed to shed light on our Hypothesis 2 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 equation (1) with the five components of the labor index.

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 their 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 at the 1% level in all regression specifications, implying that tougher dismissal laws are associated with greater innovation. Furthermore, as in Table 2, we find that stronger creditor rights have a significantly negative effect on innovation, whereas rule of law, 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 14.9% more innovation as measured by the number of patents filed. The economic magnitudes for the other two innovation measures are similar.

4.2.1 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 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 *difference-in-difference* tests.

Figures 1 and 2 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 2002. 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 US in 1989. A naive estimate of the effect of these law changes would be to simply compute the difference in innovation before and after the labor law change. However, this estimate would also be affected by time-trends that coincide with the dismissal law change as well as other economy wide factors. To control for such factors, we also estimate this difference in innovation for Germany, which did not undergo any change in labor laws between 1970 and 1995. The difference estimated for Germany provides an answer to the counter-factual question: "what would have been the difference in innovation in US 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 examine these difference-in-difference tests for the other two "natural experiments" as well: (i) UK versus US for the time period 1970-1978 to investigate the effect of the change in dismissal laws in UK; and (ii) France versus US for the time period 1970-1985 to investigate the effect of the change in dismissal laws in France.

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

$$y_{ict} = \beta_i + \beta_c + \beta_t + \boldsymbol{\beta}_1 * Dismissal\_laws_{c,t} + \varepsilon_{ict} \tag{3}$$

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 $\boldsymbol{\beta}_1$ estimates the difference-in-difference. For the test using US versus Germany, $\boldsymbol{\beta}_1$ estimates a traditional difference-in-difference since the dismissal law change occurred in the US in

1989.[15] 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 difference-in-difference over multiple policy changes (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.

Table 6 shows the results of these difference-in-difference tests. Our first test examines the impact of dismissal law changes in the UK in the early 1970s; the "control group" is

[15] Since the dismissal law change occured 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,

$$\begin{aligned} E\left[y_{i,GER,0}\right] &= \beta_i + \beta_{GER} + \beta_0 + \boldsymbol{\beta}_1 * Dismissal\_laws_{GER} \\ E\left[y_{i,GER,1}\right] &= \beta_i + \beta_{GER} + \beta_1 + \boldsymbol{\beta}_1 * Dismissal\_laws_{GER} \end{aligned}$$

In contrast for the US,

$$\begin{aligned} E\left[y_{i,US,0}\right] &= \beta_i + \beta_{US} + \beta_0 + \boldsymbol{\beta}_1 * Dismissal\_laws_{US,0} \\ E\left[y_{i,US,1}\right] &= \beta_i + \beta_{US} + \beta_1 + \boldsymbol{\beta}_1 * \left(Dismissal\_laws_{US,0} + \Delta Dismissal\_laws_{US}\right) \end{aligned}$$

Since

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

it follows that

$$\boldsymbol{\beta}_1 * \Delta Dismissal\_laws_{US} = \left\{E\left[y_{i,US,1}\right] - E\left[y_{i,US,0}\right]\right\} - \left\{E\left[y_{i,GER,1}\right] - E\left[y_{i,GER,0}\right]\right\}$$

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 of the three innovation proxies (number of patents and patenting firms); the impact on the other proxy (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 15.3%, as measured by the number of patents.[16] 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 dismissal laws in the U.S. increased innovative activity by 31% per year.

Discussion 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.

[16] Using column 7 of Table 6, we find that $ln(Patents) = 4.119 + 0.854 * LaborIndex$. 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 $exp(0.854 * 0.167) - 1 = exp(0.143) - 1 = 15.3\%$.

Second, the difference-in-difference tests address concerns that the results obtained above are a spurious combination of (i) a general trend of labor laws, in particular laws governing dismissal, becoming stricter over time; and (ii) a rising trend in USPTO patent applications (and grants) since the year 1985 (see, for example, Kortum and Lerner (1999)). As seen in columns 1-6 of Table 6, the difference-in-difference tests for UK-vs-US and France-vs-US employ respectively samples till 1978 and 1985 respectively. Given these time periods, the sample excludes years containing the rising trend in USPTO patent applications.

Third, given the small sample of countries in our analysis, a relevant question to ask is whether the overall effects of labor laws hold in the time-series for each of the five countries? However, country-by-country regressions cannot be run with year dummies since the year dummies capture all the variation in the index for a country. Since not controlling for general macroeconomic factors and technological shocks time-trends through year dummies represents a severe omission, we cannot draw any meaningful inference from such country-by-country regressions. Hence, we rely instead on the difference-in-difference tests which examine the effect of dismissal law changes on innovation *in three different countries* relative to countries that did not experience such changes, thereby controlling for a coincident arrival of technological shocks to different countries. Kortum and Lerner (1999) show, for instance, that technological shocks have historically arrived at common times in different countries. By including another country as a control group, these difference-in-difference tests largely neutralize the effect of global technology shocks.

Further, by examining the effect of changes in one particular law in one particular country, the difference-in-difference tests 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.

4.3 Inter-industry Differences

4.3.1 Differences based on Innovation Intensity of Industries

We now investigate inter-industry differences in the effect of labor laws on innovation to examine our Hypothesis 3 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 a 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:

$$\begin{aligned} y_{ict} &= \beta_i + \beta_c + \beta_t + \boldsymbol{\beta}_1 \cdot (LaborLaws_{ct} * InnovationIntensity_{i,t-1}) \\ &\quad + \beta_2 \cdot LaborLaws_{ct} + \beta_3 \cdot InnovationIntensity_{i,t-1} + \beta X + \varepsilon_{ict} \ , \end{aligned} \tag{4}$$

where $InnovationIntensity_{i,t-1}$ denotes the Innovation Intensity for patent class i in year $(t-1)$. We follow Acharya and Subramanian (2008) in measuring $InnovationIntensity_{i,t-1}$ as the median number of patents applied for by US firms in patent class i in year $(t-1)$. Since the proxy for Innovation Intensity is time-varying, it captures 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 on 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.

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, we avoid mechanical correlation of the dependent variable with $InnovationIntensity$, by using 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

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

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% (=0.054/0.137) for the more innovative patent class than the less innovative one.

4.3.2 Differences based on Labor Intensity of Industries

Does the effect of labor laws on innovation permeate the labor intensive industries as well? Examining this question is important in our context: it is possible that the effect of stringent labor laws on innovation is weaker, perhaps even negative, in the labor-intensive industries due to higher costs of ex-post rigidity introduced by strong labor laws.

While a comprehensive answer of this important question lies beyond the scope of this paper, we can examine whether the effect of labor laws on innovation manifests in the traditionally labor intensive industries as well. For this purpose, we rely on the "industry" classification provided by Hall, Jaffe, and Trajtenberg (2001) in the form of six broad patent categories. In particular, we focus on the "Mechanical" category,[17] which consists of the following sub-categories: Metal Working; Motors, Engines & Parts; Transportation; Materials Processing & Handling; Optics; and Miscellaneous Mechanical. Among the six patent categories, the Mechanical category includes industries that are most labor intensive and therefore contains the most unionized workforce in any country. We employ a dummy, $LaborIntensity_i$, which equals 1 if patent class i belongs to the category Mechanical and zero otherwise, as a proxy for labor intensity. We add the *interaction* of this proxy for labor intensity with labor laws and dismissal laws after including country, application year, and patent class dummies. The regression specification is as follows:

$$y_{ict} = \beta_i + \beta_c + \beta_t + \boldsymbol{\beta}_1 \cdot (LaborLaws_{ct} * LaborIntensity_i) + \beta_2 \cdot LaborLaws_{ct} + \beta X + \varepsilon_{ict} \ , \tag{5}$$

$$\begin{aligned} y_{ict} &= \beta_i + \beta_c + \beta_t + \boldsymbol{\beta}_1 \cdot (Dismissal\_Laws_{ct} * LaborIntensity_i) \\ &\quad + \beta_2 \cdot Dismissal\_Laws_{ct} + \beta X + \varepsilon_{ict} \ . \end{aligned} \tag{6}$$

[17]The other categories include Chemical, Computers and Communication, Drugs and Medical, Electrical and Electronic and Others.

Note that given the patent class dummies, we exclude the LaborIntensity dummy itself from the specification.

Table 8 presents the results of this investigation. In Columns 1-3 (4-6), we add the interaction of the aggregate labor index (dismissal index) with our proxy for labor intensity; all these regressions contain our usual set of control variables. We find across Columns 1-6 that the coefficient of Labor Laws and Dismissal Laws stay positive and statistically significant. Furthermore, the coefficient of the interactions are positive and significant, implying that somewhat surprisingly, the effect of labor laws and dismissal laws on innovation is in fact relatively more pronounced in the labor-intensive sectors of the economy.

4.4 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:

$$\ln Y_{ict} = t\beta_i + t\beta_c + \gamma_t + \boldsymbol{\beta}_1 * LaborLaws_{c,t} + \beta X + \eta_{ict} \tag{7}$$

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 $t\beta_i$ and $t\beta_c$ 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 (7) and obtain the following specification:

$$y_{ict} = \beta_i + \beta_c + \beta_t + \boldsymbol{\beta}_1 * \Delta LaborLaws_{c,t} + \beta \cdot \Delta X + \varepsilon_{ict} \tag{8}$$

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

We obtain data on nominal value added 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 9. 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 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.[18]

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

4.4.1 Difference-in-difference tests

To make further progress on the causal effects of laws governing dismissal on economic growth, we examine the effects of large dismissal law changes on industry level growth rates using *difference-in-difference* tests. In these tests, we use the same dismissal law changes as described in Section 4.2.1.

The results can be seen in Table 9, 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 (see Figure 4); results are reported in column 1 of Table 9, 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 9, 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).

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

Results are presented in column 3 of Table 9, Panel B. The evidence from all three natural experiments indicates 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 Discussion

It is important to further examine the direction of causality from labor laws to innovation and economic growth. Was it the case that labor laws changed for reasons other than promoting growth and innovation, so that our evidence above can be interpreted truly as a causal effect of the change on innovation and economic growth? Or, was it the case that the labor law changes were part of an overall package to promote or give an extra boost to growth and innovation, so that the evidence above exhibits some reverse causality? Note that in either of these cases, the evidence lends support to our claim that labor laws can affect the extent of innovative activity and, in turn, economic growth. Nevertheless, we examine reverse causality in our tests below and also discuss the political economy of the changes in labor laws. Finally, we discuss the relative merits of employing US patents to proxy innovation internationally.

5.1 Causality or reverse-causality?

If the labor law changes were effected to provide an extra boost to growth and innovation *already occurring* due to some other changes in the economy, then we might see an "effect" of the change even prior to the change itself. We investigate this effect in our change-on-change regressions and in our difference-in-difference setting.

5.1.1 Change-on-change regressions

First, we run our change-on-change regressions using *lags* of the dependent variable:

$$\Delta y_{ic,t-l} = \beta_c + \beta_t + \boldsymbol{\beta}_1 * \Delta LaborLaws_{c,t} + \beta \cdot \Delta X + \varepsilon_{ict} \tag{9}$$

$$\Delta y_{ic,t-l} = \beta_c + \beta_t + \boldsymbol{\beta}_1 * \Delta DismissalLaws_{c,t} + \beta \cdot \Delta X + \varepsilon_{ict} \tag{10}$$

where $l \geq 1$ denotes the number of lags and $\Delta y_{ic,t-l} = y_{ic,t-l} - y_{ic,t-l-1}$. Columns 1-5 of Panel A of Table 10 shows the results of these regressions. In Columns 1-3 (4-6), we observe that changes in labor laws (dismissal laws) at time t have no statistically significant effect on our innovation proxies at time $(t-1)$. Thus, we infer that *changes* in aggregate labor laws and *changes* in laws governing dismissal do not have an "effect" prior to the change itself, which alleviates concerns about reverse causality with respect to our measures of innovation.

In Columns 7-9 of Panel A, we run the regressions (9) and (10) using the continuously compounded growth in real value added. In Column 7, we find that *changes* in aggregate labor laws at time t have a negative and statistically significant effect on growth in real value added at time $(t-1)$. Motivated by this evidence, we re-run (9) for $l = 2$ and find in Column 8 that changes in aggregate labor laws at time t have no statistically significant effect on growth in real value added at time $(t-2)$. In Column 9, we find that changes in dismissal laws at time t have no statistically significant effect on growth in real value added at time $(t-1)$. Collectively, these tests suggest that while changes in laws governing dismissal do not precede economic growth, strengthening of other labor laws in general may occur following an economic recession (perhaps due to political economy effects).

5.1.2 Dynamic effect of changes in dismissal laws

We also examine the dynamic effects of the changes in laws governing dismissal on our proxies for innovation and on economic growth using the difference-in-difference setting provided by the change in dismissal laws in the US in 1989. Here, we follow Bertrand and Mulainathan (2003) in decomposing our change in variable into three separate time periods: (i) Dismissal Law Change (-2,0), which captures any effects from two years before to the of the change; (ii) Dismissal Law Change (1,2), which captures the effects in the year after the change and two years after the change; and (iii) Dismissal Law Change ($\geq$3), which captures the effect three years after the change and beyond. Panel B of Table 10 shows the results of these regressions. A *positive* and significant coefficient on Dismissal Law Change (-2,0) would be symptomatic of reverse causation. However, we find that while this coefficient is negative and statistically significant in Columns 1-2, it is statistically insignificant in Columns 3-4. As seen in the coefficients of Dismissal Law Change (1,2) and Dismissal Law Change ($\geq$3) in Columns 1-3 of Panel B, we note that while the dismissal law change has an effect on the innovation proxies in the first two years,[19] the effect of the law change lasts three years and beyond; in fact, this "long-run" effect is economically greater than the effect in the first two years. These effects are consistent with the long gestation periods involved with innovative projects. In Column 4 of Panel B, we find that the positive effects of the dismissal law change on economic growth manifest in the third year and beyond.

5.2 Political Economy of Changes in Labor Laws

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

[19] The effect in the first two years of the law change is consistent with evidence in Kondo (1999) that there is about a one-and-a-half year lag between patent applications and R&D investment.

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.[20]

5.3 USPTO Patents as a Proxy for Innovation

To compare innovation done by firms across countries, it is crucial to employ *patents filed in a single jurisdiction* by firms from these countries. Since enforcement of intellectual property protection may vary across jurisdictions, comparing domestic patents filed in the various countries would not accurately measure differences in ex-post innovation or the ex-ante incentives for innovation in these countries. In contrast, comparing patents granted in one jurisdiction alleviates such concerns of heterogeneity and provides standardization across patents in the strength of patent protection, the duration of protection, the penalties for patent infringement and therefore the nature of patent enforcement, and the patenting practices followed by the jurisdiction's patent office for all firms filing in the jurisdiction irrespective of which country the firms belong to.

Given its status as the technological leader, the US is the natural single jurisdiction of choice. Lall (2003) notes that "most researchers on international technological activity use

[20] Most 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.

US patent data, for two reasons. First, practically all innovators who seek to exploit their technology internationally take out patents in the USA, given its market size and technological strength. Second, the data are readily available and can be taken to an extremely detailed level." Furthermore, the US has the most advanced patenting system in the world (Kortum and Lerner, 1999) and most innovating firms internationally file patents in the US (Cantwell and Hodson, 1991).[21] Finally, US patents are a high quality indicator of international technological activity.[22]

However, using patents filed with the USPTO introduces potential biases since it is likely that foreign firms file patents with the USPTO because they need to sell their products in the US.[23] Hence, the controls we employed in our tests to control for such systematic biases for comparative advantages and bilateral trade patterns were quite important.

6 Conclusion

We know from the tenure-track system for academic appointments that there is a trade-off 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? 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

[21] Cantwell and Hodson (1991) found in their study of patenting practices of the world's largest firms (from the Fortune listings) that over 85% of all these firms had recorded patenting in the US.

[22] Cantwell and Anderson (1996) note that the pattern of patenting in the US is a good indicator of technological activity in all industrialized and newly industrializing countries. Soete and Wyatt (1983) also note that although international patenting propensities remain lower than domestic patenting propensities, *international patents are on average of higher 'quality'*.

[23] Paci, Sassu, and Usai (1997) find that firms apply for a patent abroad mainly to: (i) protect goods to be exported to the countries concerned; (ii) protect goods that may be subsequently produced in the foreign country; (iii) guarantee the payment of royalties from the granting of production licences; and (iv) exchange know-how and other technological information.

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 spur 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. Yet another possibility is that the firm may be run by short-termist CEOs and efficient long-term employee contracts may not get written, in which case the labor law can help lengthen the horizon of firm's decision-making. Regardless of the reason for which stringent labor laws are necessary, our results find that they are effective in promoting innovation; and, while stringent labor laws as a whole have a negative impact on 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 offered by 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 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 if 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).

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Figure 1: **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).

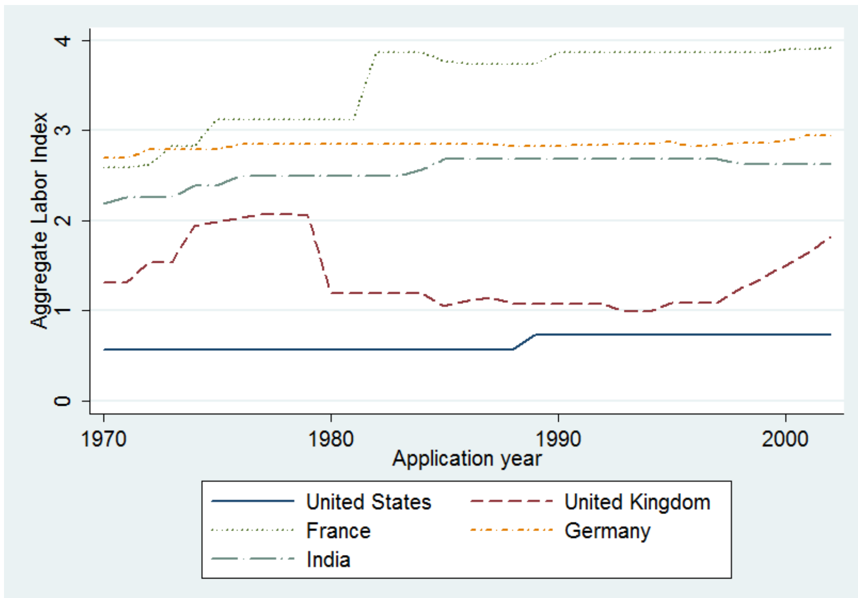

Figure 2: **Regulation of Dismissal.**
The figure shows the strength of the "Regulation of Dismissal" for a given country and year. Higher values indicate more employment protection / stricter laws. The index data is from Deakin et al. (2007).

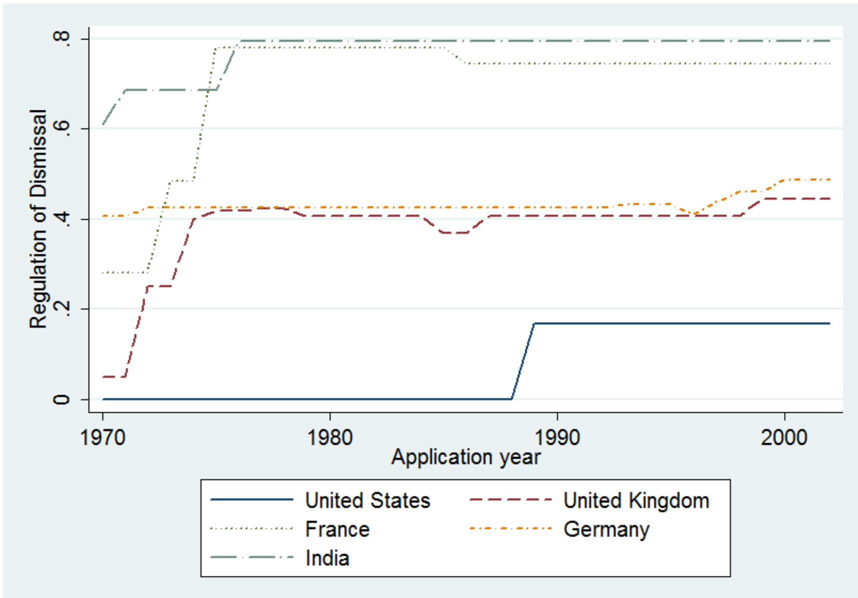

Figure 3: **Innovation Proxies vs. Aggregate Labor Index.**
The figure shows a plot of the aggregate labor index against two of the innovation measures we use in our empirical tests, namely, log of patents and log of citations, after accounting for year, country, and industry fixed effects.

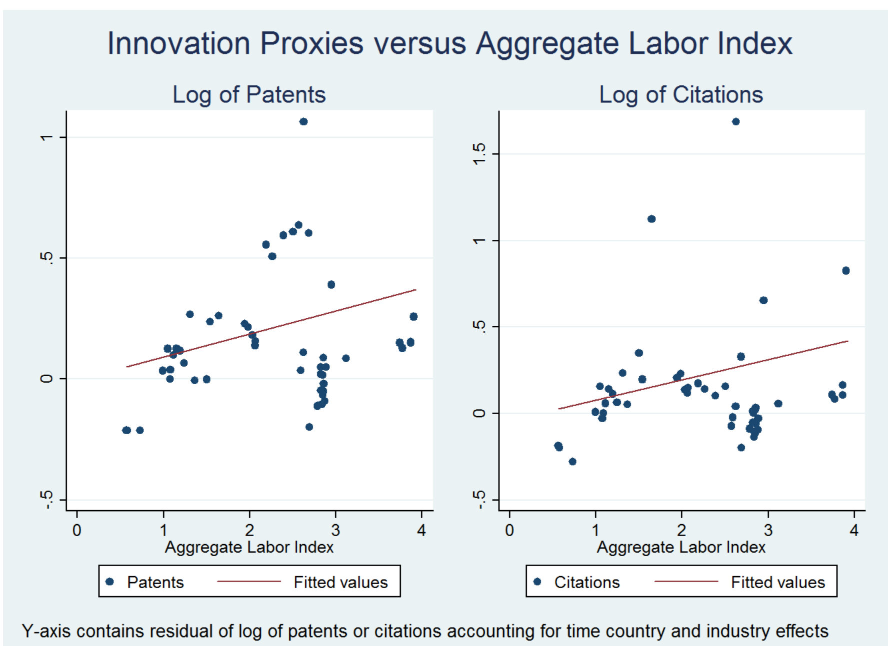

Figure 4: **Regulation of Dismissal, U.S. and U.K.**
The figure shows the index representing the regulation of dismissal for the U.S. and U.K. from 1970-1978.

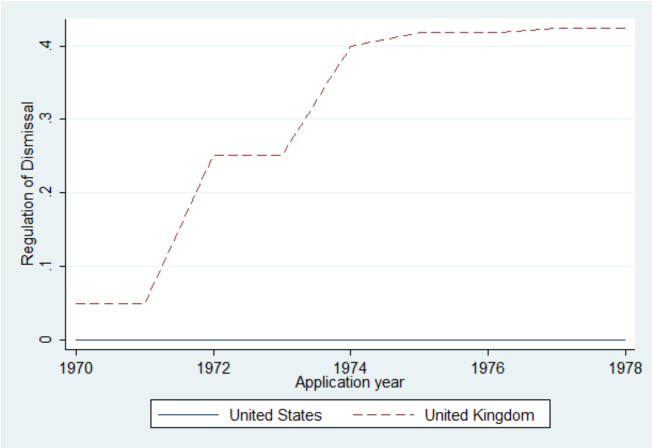

Figure 5: **Regulation of Dismissal, U.S. and France.**
The figure shows the index representing the regulation of dismissal for the U.S. and France from 1970-1985.

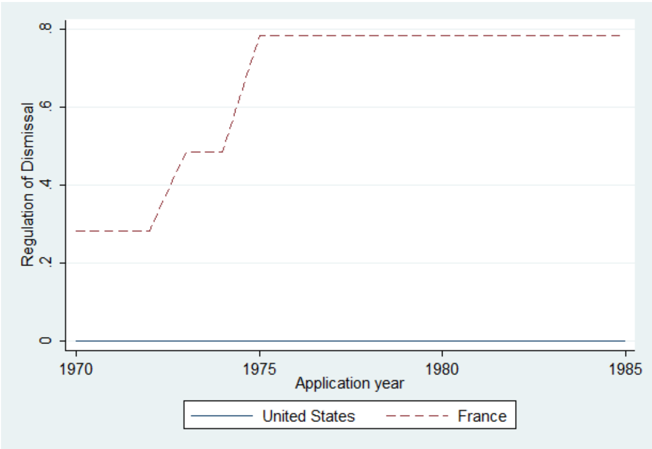

Figure 6: **Regulation of Dismissal, U.S. and Germany.**
The figure shows the index representing the regulation of dismissal for the U.S. and Germany from 1970-1995.

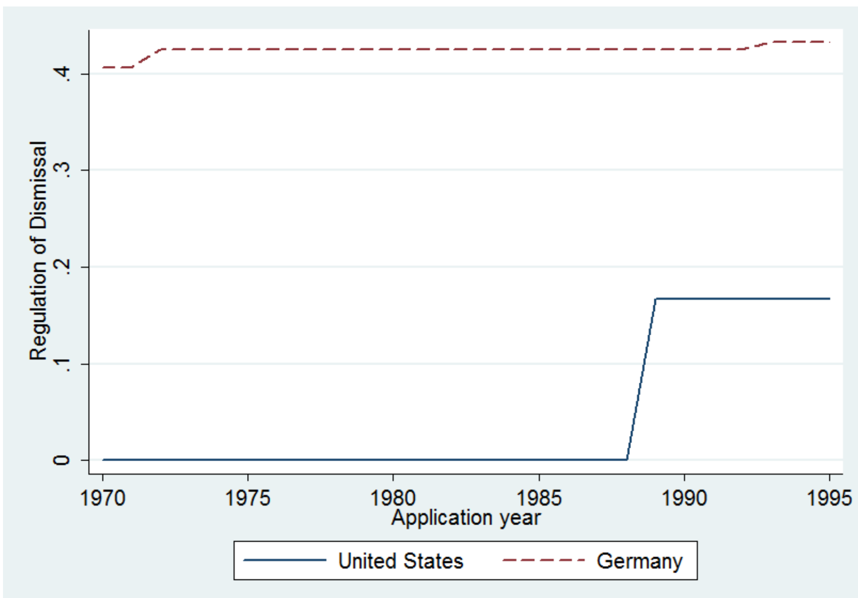

Table 1: **Summary Statistics.**

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:

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

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 Logarithm of	(1) Number of Patents	(2) Number of Patenting Firms	(3) Number of Citations	(4) Number of Patents	(5) Number of Patenting Firms	(6) Number of Citations	(7) Number of Patents	(8) Number of Patenting Firms	(9) Number of Citations
Labor Index	0.157***	0.117***	0.185***	0.088***	0.032*	0.116***	0.092***	0.035*	0.114***
	(0.016)	(0.012)	(0.021)	(0.024)	(0.019)	(0.033)	(0.022)	(0.018)	(0.033)
Creditor Rights Index				-0.103***	-0.095***	-0.118***	-0.106***	-0.098***	-0.116***
				(0.026)	(0.021)	(0.033)	(0.028)	(0.022)	(0.034)
Rule of Law				0.327***	0.292***	0.393***	0.195	0.187	0.478***
				(0.026)	(0.021)	(0.039)	(0.17)	(0.13)	(0.17)
Antidirector				0.075***	0.054**	0.123***	0.066*	0.047*	0.128***
Rights Index				(0.028)	(0.021)	(0.035)	(0.034)	(0.025)	(0.039)
Efficiency of				1.348***	1.051***	1.522***	1.392***	1.086***	1.493***
Judicial System				(0.043)	(0.034)	(0.060)	(0.073)	(0.057)	(0.083)
Log Imports				0.043	0.042	-0.054	0.042	0.041	-0.054
				(0.065)	(0.051)	(0.095)	(0.065)	(0.051)	(0.095)
Log Exports				-0.062	-0.049	-0.238**	-0.063	-0.050	-0.238**
				(0.070)	(0.056)	(0.099)	(0.070)	(0.056)	(0.099)
Ratio of Value Added							0.017	0.004	0.004
							(0.036)	(0.030)	(0.050)
Log of per capita GDP							0.240	0.190	-0.152
							(0.31)	(0.24)	(0.30)
Constant	-4.130***	-3.415***	-5.146***	-13.75***	-10.89***	-19.03***	-15.35***	-12.16***	-18.02***
	(0.12)	(0.11)	(0.17)	(0.34)	(0.28)	(0.49)	(2.08)	(1.61)	(2.07)
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 3: **Regressions in First Differences using Aggregate Labor Index.**

The OLS regressions below implement the following model:

$\Delta y_{ict} = \beta_c + \beta_t + \boldsymbol{\beta}_1 * \Delta LaborLaws_{c,t} + \beta \Delta X + \varepsilon_{ict}$ 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 difference operator: $\Delta.X = (X_t) - (X_{t-1})$. 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).

The tests in columns (1-9) employ the whole sample, while columns (10-12) employ a sub-sample which consists of observations prior to country-level creditor rights changes; this sub-sample consists of all observations for US, France, and Germany (as these countries don't experience any creditor rights changes between 1978 and 2002), as well as observations for India and UK prior to their respective creditor rights changes (i.e., observations prior to 1993 in the case of India, and prior to 1985 in the case of UK).

Standard errors are robust to heteroscedasticity and autocorrelation. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Dependent Variable is First Difference of Logarithm of	Patents	Firms	Citations	Patents	Firms	Citations	Patents	Firms	Citations	Patents	Firms	Citations
Δ.(Labor Index)	0.084***	0.056**	0.167***	0.081**	0.030	0.110*	0.084**	0.033	0.116*	0.089**	0.050	0.118*
	(0.031)	(0.028)	(0.054)	(0.035)	(0.032)	(0.058)	(0.036)	(0.033)	(0.060)	(0.042)	(0.040)	(0.070)
Δ.(Creditor Rights Index)				0.000	-0.015	-0.027	0.001	-0.014	-0.026			
				(0.042)	(0.038)	(0.070)	(0.042)	(0.038)	(0.070)			
Δ.(Log Imports)				-0.050	-0.039	-0.114	-0.051	-0.039	-0.115	-0.009	-0.002	-0.031
				(0.048)	(0.046)	(0.087)	(0.048)	(0.046)	(0.087)	(0.051)	(0.051)	(0.093)
Δ.(Log Exports)				-0.021	-0.038	-0.113	-0.021	-0.038	-0.112	-0.021	-0.012	-0.125
				(0.047)	(0.047)	(0.084)	(0.047)	(0.047)	(0.084)	(0.055)	(0.053)	(0.086)
Δ.(Ratio of Value Added)							0.008	0.016	0.036	-0.022	-0.014	-0.000
							(0.029)	(0.028)	(0.047)	(0.034)	(0.031)	(0.052)
Δ.(Log of per capita GDP)							-0.204	-0.150	-0.308	-0.937***	-0.836***	-0.876**
							(0.25)	(0.23)	(0.40)	(0.27)	(0.25)	(0.43)
Constant	-0.042***	-0.035***	-0.120***	-0.072***	-0.060***	-0.003	-0.068***	-0.056***	0.009	-0.056***	-0.042***	-0.142***
	(0.003)	(0.003)	(0.005)	(0.005)	(0.004)	(0.13)	(0.007)	(0.007)	(0.13)	(0.014)	(0.013)	(0.022)
US Patent class dummies	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
Application year dummies	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	41759	41759	38486	29024	29024	26475	29024	29024	26475	24684	24684	22774
R-squared	0.20	0.17	0.11	0.28	0.24	0.15	0.28	0.24	0.15	0.32	0.27	0.18

Table 4: **Regressions using Components of Labor Index.**

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

$y_{ict} = \beta_i + \beta_c + \beta_t + \boldsymbol{\beta}_1 * lA_{c,t} + \boldsymbol{\beta}_2 * lB_{c,t} + \boldsymbol{\beta}_3 * lC_{c,t} + \boldsymbol{\beta}_4 * lD_{c,t} + \boldsymbol{\beta}_5 * lE_{c,t} + \varepsilon_{ict}$

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

$\Delta y_{ict} = \beta_c + \beta_t + \boldsymbol{\beta}_1 * \Delta lA_{c,t} + \boldsymbol{\beta}_2 * \Delta lB_{c,t} + \boldsymbol{\beta}_3 * \Delta lC_{c,t} + \boldsymbol{\beta}_4 * \Delta lD_{c,t} + \boldsymbol{\beta}_5 * \Delta lE_{c,t} + \varepsilon_{ict}$

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 difference operator: $\Delta.X = (X_t) - (X_{t-1})$. $\beta_i, \beta_c, \beta_t$ denote patent class, country and application year fixed effects. β_1 - β_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 ($lA_{c,t}$), Regulation of working time ($lB_{c,t}$), Regulation of dismissal ($lC_{c,t}$), Employee representation ($lD_{c,t}$), and Industrial action ($lE_{c,t}$). 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.

	(1)	(2)	(3)	(4)	(5)	(6)
	Regressions in LEVELS			**Regressions in FIRST DIFFERENCES**		
Dependent Variable is Logarithm of	Number of Patents	Number of Patenting Firms	Number of Citations	Number of Patents	Number of Patenting Firms	Number of Citations
Regulation of dismissal	0.092*	0.167***	0.153**	0.110	0.146*	0.270*
	(0.051)	(0.040)	(0.068)	(0.090)	(0.082)	(0.16)
Regulation of working time	-0.037	-0.028	0.684***	0.031	0.049	-0.018
	(0.093)	(0.076)	(0.15)	(0.14)	(0.13)	(0.26)
Alternative employment contracts	-0.190***	-0.287***	0.193**	0.021	-0.032	-0.090
	(0.057)	(0.047)	(0.085)	(0.093)	(0.084)	(0.16)
Employee representation	0.709***	0.640***	-0.571***	0.253	0.171	0.289
	(0.12)	(0.10)	(0.21)	(0.17)	(0.15)	(0.32)
Industrial action	-0.181	-0.221*	1.136***	-0.163	-0.168	0.625*
	(0.15)	(0.12)	(0.23)	(0.21)	(0.18)	(0.36)
Constant	-3.741***	-3.099***	-5.658***	-1.041***	-0.865***	-1.658***
	(0.16)	(0.13)	(0.22)	(0.029)	(0.024)	(0.29)
US Patent Class dummies	Y	Y	Y	N	N	N
Country dummies	Y	Y	Y	Y	Y	Y
Application Year dummies	Y	Y	Y	Y	Y	Y
Observations	46334	46334	42918	41759	41759	38486
R-squared	0.83	0.83	0.80	0.20	0.17	0.11

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

The OLS regressions below implement the following model:

$y_{ict} = \beta_i + \beta_c + \beta_t + \boldsymbol{\beta}_1 * DismissalIndex_{c,t} + \beta X + \varepsilon_{ict}$

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 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 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)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent Variable is 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	0.139***	0.173***	0.227***	0.808***	0.927***	1.136***	0.808***	0.927***	1.156***
	(0.049)	(0.039)	(0.063)	(0.11)	(0.089)	(0.13)	(0.12)	(0.090)	(0.13)
Creditor Rights Index				-0.109***	-0.072***	-0.125***	-0.109***	-0.072***	-0.114***
				(0.023)	(0.018)	(0.030)	(0.027)	(0.021)	(0.031)
Rule of Law				0.166***	0.175***	0.215***	0.155	0.174	0.505***
				(0.026)	(0.022)	(0.040)	(0.19)	(0.14)	(0.18)
Antidirector				-0.363***	-0.278***	-0.373***	-0.365***	-0.279***	-0.320***
Rights Index				(0.017)	(0.013)	(0.022)	(0.039)	(0.030)	(0.041)
Efficiency of				0.715***	0.618***	0.870***	0.716***	0.619***	0.843***
Judicial System				(0.054)	(0.043)	(0.070)	(0.061)	(0.048)	(0.075)
Log Imports				0.035	0.036	-0.054	0.034	0.036	-0.053
				(0.065)	(0.051)	(0.095)	(0.065)	(0.051)	(0.095)
Log Exports				-0.076	-0.062	-0.245**	-0.075	-0.062	-0.243**
				(0.070)	(0.056)	(0.10)	(0.070)	(0.056)	(0.100)
Ratio of Value Added							0.020	0.008	0.010
							(0.037)	(0.030)	(0.050)
Log of per capita GDP							0.019	0.003	-0.492
							(0.32)	(0.25)	(0.31)
Constant	-3.824***	-3.246***	-4.841***	-6.226***	-6.001***	-11.23***	-6.324***	-6.018***	-8.761***
	(0.12)	(0.11)	(0.17)	(0.42)	(0.34)	(0.57)	(1.84)	(1.43)	(1.84)
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:

$y_{ict} = \beta_i + \beta_c + \beta_t + \boldsymbol{\beta}_1 * Dismissal\_laws_{c,t} + \varepsilon_{ict}$

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. $\beta_i, \beta_c, \beta_t$ denote patent class, country and application year fixed effects. $Dismissal\_laws_{c,t}$ 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)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	UK & US; UK dismissal law changes in early 1970s; data from 1970-1978			**France & US; France dismissal law change in early 1970s; data from 1970-1985**			**Germany & US; US dismissal law change in 1989; data from 1970-1995**		
Dependent Variable is 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	0.149*	0.222***	0.187	0.376***	0.422***	0.339***	0.854***	0.692***	1.619***
	(0.083)	(0.069)	(0.12)	(0.054)	(0.045)	(0.078)	(0.15)	(0.12)	(0.19)
Constant	1.397***	1.135***	3.013***	4.307***	3.524***	2.665***	4.119***	3.362***	6.188***
	(0.033)	(0.027)	(0.042)	(0.024)	(0.021)	(0.057)	(0.024)	(0.019)	(0.029)
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	6633	6633	6568	11623	11623	11474	20039	20039	19875
R-squared	0.92	0.92	0.89	0.91	0.91	0.88	0.85	0.86	0.83

Table 7: **Relative Impact of Labor Laws on Aggregate Innovation in Different Industries based on their Innovation Intensity.**

The OLS regressions below implement the following model:

$y_{ict} = \beta_i + \beta_c + \beta_t + \boldsymbol{\beta}_1 \cdot LaborLaws_{ct} * InnovationIntensity_{i,t-1} + \beta_2 \cdot LaborLaws_{ct} + \beta_3 \cdot InnovationIntensity_{i,t-1} + \beta X + \varepsilon_{ict}$

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.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable is Logarithm of	Number of Patenting Firms	Number of Citations	Number of Patenting Firms	Number of Citations	Number of Patenting Firms	Number of Citations
(Labor Index)	0.075***	0.054**	0.079***	0.054*	0.074***	0.050*
* (Innovation Intensity)	(0.017)	(0.027)	(0.020)	(0.030)	(0.021)	(0.030)
Labor Index	0.043**	0.137***	-0.044	0.065	-0.037	0.073
	(0.021)	(0.035)	(0.030)	(0.047)	(0.030)	(0.047)
Innovation Intensity	-0.150***	-0.077	-0.202***	-0.126	-0.196***	-0.124
	(0.037)	(0.062)	(0.056)	(0.098)	(0.055)	(0.098)
(Creditor Rights Index)			0.031**	0.024	0.031**	0.021
* (Innovation Intensity)			(0.014)	(0.040)	(0.013)	(0.041)
Creditor Rights Index			-0.131***	-0.132**	-0.128***	-0.112*
			(0.028)	(0.059)	(0.030)	(0.062)
Rule of Law			0.285***	0.418***	0.220	0.718***
			(0.025)	(0.051)	(0.16)	(0.19)
Antidirector			0.054**	0.137***	0.052	0.161***
Rights Index			(0.024)	(0.039)	(0.032)	(0.047)
Efficiency of			1.097***	1.541***	1.093***	1.411***
Judicial System			(0.037)	(0.062)	(0.068)	(0.091)
Log Imports					0.029	-0.110
					(0.053)	(0.095)
Log Exports					-0.061	-0.267***
					(0.058)	(0.100)
Ratio of Value Added					0.020	0.019
					(0.031)	(0.051)
Log of per capita GDP					0.114	-0.554
					(0.31)	(0.38)
Constant	-3.195***	0.710***	-11.02***	-19.38***	-11.52***	-15.38***
	(0.14)	(0.11)	(0.31)	(0.54)	(2.12)	(2.68)
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: **Relative Impact of Labor Laws on Aggregate Innovation in Different Industries based on their Labor Intensity.**

The OLS regressions below implement the following model:

$y_{ict} = \beta_i + \beta_c + \beta_t + \boldsymbol{\beta}_1 \cdot LaborLaws_{ct} * LaborIntensity_i + \beta_2 \cdot LaborLaws_{ct} + \beta_3 \cdot LaborIntensity_i + \beta X + \varepsilon_{ict}$

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. $LaborLaws_{c,t}$ denotes either the aggregate labor index (columns 1-3), or the index of laws governing dismissal (columns 4-6) in country c in year t. We measure $LaborIntensity_i$ as a dummy variable taking the value of one if patent class i pertains to the labor-intensive patent category "Mechanical" (see Appendix 1 in Hall, Jaffe, and Trajtenberg (2001)), zero otherwise. β_1 measures the impact of labor laws on innovation in the labor-intensive patent category "Mechanical" relative to the other patent categories.

X denotes the set of the following 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 Logarithm of	(1) Number of Patents	(2) Number of Firms	(3) Number of Citations	(4) Number of Patents	(5) Number of Firms	(6) Number of Citations
Labor Intensity * Labor Index	0.058***	0.073***	0.092***			
	(0.022)	(0.015)	(0.025)			
Labor Index	0.077***	0.016	0.091***			
	(0.023)	(0.019)	(0.033)			
Labor Intensity * Regulation of Dismissal				0.149	0.175**	0.267**
				(0.10)	(0.072)	(0.12)
Regulation of Dismissal				0.764***	0.876***	1.078***
				(0.12)	(0.093)	(0.13)
Creditor Rights Index	-0.107***	-0.098***	-0.117***	-0.110***	-0.072***	-0.114***
	(0.028)	(0.022)	(0.034)	(0.027)	(0.021)	(0.031)
Rule of Law	0.197	0.189	0.484***	0.154	0.172	0.504***
	(0.17)	(0.13)	(0.17)	(0.19)	(0.14)	(0.18)
Antidirector	0.067**	0.048*	0.130***	-0.365***	-0.278***	-0.320***
Rights Index	(0.034)	(0.025)	(0.039)	(0.039)	(0.030)	(0.041)
Efficiency of	1.392***	1.086***	1.493***	0.715***	0.617***	0.840***
Judicial System	(0.073)	(0.057)	(0.083)	(0.061)	(0.048)	(0.075)
Log Imports	0.043	0.042	-0.056	0.033	0.034	-0.058
	(0.065)	(0.051)	(0.095)	(0.065)	(0.051)	(0.095)
Log Exports	-0.064	-0.051	-0.245**	-0.076	-0.063	-0.249**
	(0.070)	(0.056)	(0.099)	(0.070)	(0.056)	(0.100)
Ratio of Value Added	0.016	0.003	0.004	0.019	0.007	0.009
	(0.036)	(0.030)	(0.050)	(0.037)	(0.030)	(0.050)
Log of per capita GDP	0.234	0.183	-0.166	0.018	0.002	-0.496
	(0.31)	(0.24)	(0.30)	(0.32)	(0.25)	(0.31)
Constant	-15.32***	-12.11***	-17.95***	-6.285***	-5.972***	-8.684***
	(2.08)	(1.61)	(2.07)	(1.84)	(1.43)	(1.83)
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	32941	32941	30159	32941	32941	30159
R-squared	0.84	0.84	0.82	0.84	0.84	0.82

Table 9: **Effect of Labor Laws on Industry Level Growth.**

The OLS regressions below implement the following model:

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

where y_{ict} is the natural logarithm of real value added in ISIC industry i in country c in year t. Δ denotes the difference operator: $\Delta.X = (X_t) - (X_{t-1})$. $\beta_i, \beta_c, \beta_t$ 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. Data on nominal value added are obtained from the UNIDO Industrial Statistics database. CPI data from the US Bureau of Labor Statistics was used to deflate the value added data in order to obtain real values; as CPI data for India was not available from the US Bureau of Labor Statistics, the CPI data for that country was obtained from the International Labour Organization's Labour Statistics database. The labor law index data is from Deakin et al. (2007). The *Creditor Rights Index* is from Djankov, McLiesh, and Shleifer (2007). *Log Imports* is the log of a country's imports from the US in a given 3-digit ISIC industry in a given year; *Log Exports* is the log of a country's exports to the US in a given 3-digit ISIC industry in a given year (export and import data are from Nicita and Olarreaga, 2006). *Ratio of Value Added* is the ratio of value added in the 3-digit ISIC in a year to the total value added by that country in that year (from UNIDO). *Log of per capita GDP* is the logarithm of real GDP per capita. Standard errors are robust to heteroscedasticity and autocorrelation. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A

	(1)	(2)	(3)
Dependent Variable is First Difference in	ln(Real Value Added)	ln(Real Value Added)	ln(Real Value Added)
Δ.(Labor Index)	-0.095*	-0.097**	
	(0.040)	(0.032)	
Δ.(Creditor Rights Index)	-0.016	-0.022	
	(0.026)	(0.020)	
Δ.(Log Imports)	-0.001	-0.014	
	(0.043)	(0.034)	
Δ.(Log Exports)	-0.009	0.024	
	(0.069)	(0.047)	
Δ.(Ratio of Value Added)		6.573***	
		(1.67)	
Δ.(Log of per capita GDP)		1.252***	
		(0.27)	
Δ.(Regulation of dismissal)			0.299***
			(0.056)
Δ.(Regulation of working time)			-0.120
			(0.14)
Δ.(Altern. empl. contracts)			-0.149
			(0.086)
Δ.(Employee representation)			-0.117
			(0.15)
Δ.(Industrial action)			0.353
			(0.32)
Constant	-0.068**	-0.106***	0.066
	(0.022)	(0.028)	(0.051)
Country, Year, and ISIC dummies	Y	Y	Y
Observations	751	751	1446
R-squared	0.36	0.69	0.28

Panel B

	(1)	(2)	(3)
	UK & US; UK dismissal law changes in early 1970s; data from 1970-1978	*France & US;France dismissal law change in early 1970s; data from 1970-1985*	*Germany & US; US dismissal law change in 1989; data from 1970-1995*
Dependent Variable is First Difference in	ln(Real Value Added)	ln(Real Value Added)	ln(Real Value Added)
Δ.(Regulation of Dismissal)	0.230***	0.878***	0.328*
	(0.029)	(0.069)	(0.15)
Constant	0.113***	-0.003	0.105***
	(0.012)	(0.009)	(0.014)
Country, Year, and ISIC dummies	Y	Y	Y
Observations	151	276	434
R-squared	0.55	0.54	0.31

Table 10: **Tests of Reverse Causality.**

Panel A:
Δ denotes the difference operator: $\Delta.X = (X_t) - (X_{t-1})$;
L denotes the lag operator; therefore: $L\Delta.X = (X_{t-1}) - (X_{t-2})$ and $L2\Delta.X = (X_{t-2}) - (X_{t-3})$.
Panel B reports 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 (from 1970-1995).
Dismissal Law Change (-2,0) is a dummy that takes the value of one for the years 1987-1989 for the U.S., zero otherwise; *Dismissal Law Change (1,2)* is a dummy that takes the value of one for the years 1990-1991 for the U.S., zero otherwise; finally, *Dismissal Law Change (≥3)* is a dummy that takes the value of one for the years 1992 and thereafter for the U.S., zero otherwise.
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). Standard errors are robust to heteroscedasticity and autocorrelation. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A

Dependent variable is	(1) LΔ.ln (Patents)	(2) LΔ.ln (Firms)	(3) LΔ.ln (Citations)	(4) LΔ.ln (Patents)	(5) LΔ.ln (Firms)	(6) LΔ.ln (Citations)	(7) LΔ.ln(Real V.A.)	(8) L2Δ.ln(Real V.A.)	(9) LΔ.ln(Real V.A.)
Δ.(Labor Index)	-0.022	-0.019	-0.073				-0.102***	0.014	
	(0.032)	(0.030)	(0.052)				(0.015)	(0.023)	
Δ.(Regulation of Dismissal)				0.036	0.031	-0.212			-0.023
				(0.093)	(0.085)	(0.15)			(0.073)
Constant	-0.013***	-0.011***	-0.118***	-0.014***	-0.012***	-0.115***	0.063	0.064	0.064
	(0.003)	(0.003)	(0.005)	(0.003)	(0.003)	(0.005)	(0.052)	(0.052)	(0.052)
Country dummies	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year dummies	Y	Y	Y	Y	Y	Y	Y	Y	Y
ISIC class (industry) dummies	N	N	N	N	N	N	Y	Y	Y
Observations	38790	38790	37162	38790	38790	37162	1446	1446	1446
R-squared	0.04	0.03	0.11	0.04	0.03	0.11	0.27	0.27	0.27

Panel B

Dependent variable is	(1) ln(Patents)	(2) ln(Firms)	(3) ln(Citations)	(4) Δ.ln(Real Value Added)
Dismissal Law Change(-2,0)	-0.132***	-0.119***	-0.014	-0.050
	(0.027)	(0.022)	(0.034)	(0.059)
Dismissal Law Change(1,2)	0.071**	0.071***	0.218***	-0.169**
	(0.032)	(0.026)	(0.040)	(0.070)
Dismissal Law Change(≥3)	0.173***	0.144***	0.309***	0.103**
	(0.029)	(0.024)	(0.036)	(0.042)
Constant	4.278***	3.492***	5.695***	-0.018
	(0.035)	(0.028)	(0.042)	(0.048)
Country dummies	Y	Y	Y	Y
Year dummies	Y	Y	Y	Y
Patent class dummies	Y	Y	Y	N
ISIC class (industry) dummies	N	N	N	Y
Observations	20039	20039	19875	434
R-squared	0.85	0.86	0.83	0.34