Labor Laws and Innovation[1]

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Abstract

Labor Laws and Innovation

We show that dismissal laws—unlike other types of labor laws—spur firm-level innovation. Dismissal laws prevent employers from arbitrarily discharging employees and thereby limit employers' ability to hold up innovating employees after an innovation is successful. By reducing the possibility of hold-up, these laws enhance employees' innovative efforts and encourage firms to invest in risky, but potentially mould-breaking, projects. We find support for these predictions in empirical tests which exploit country-level changes in dismissal laws in the United States, United Kingdom, France, and Germany: more stringent dismissal laws foster innovation, particularly in innovation-intensive industries.

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

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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, we investigate whether the legal framework governing the relationships between employees and their employers affects 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 discussed 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 clear 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—even if as an unintended consequence—provide firms a commitment device to not punish short-run failures and to not hold up their employees in case of successful innovations, thereby spurring employees to undertake activities that are value-maximizing in the long-run?

This question assumes importance on two counts. First, as highlighted by the literature on endogenous growth (Romer, 1990; Grossman and Helpman, 1991; and Aghion and Howitt, 1992), innovative investments spur technological progress in a country and are, therefore, an essential ingredient of economic growth. This theory stresses the role of laws and institutions that nurture innovation and, thereby, generate positive externalities that can permanently raise a country's long-run growth rate. Second, recent evidence suggests that wrongful discharge laws—laws that prevent firms from arbitrarily discharging employees—passed by U.S. states encourage innovation and new firm creation (Acharya et al., 2012).

Laws that impose hurdles on dismissal only capture *one particular* form of restriction on the employer-employee relationship. Labor laws, however, affect many other aspects of the employer-employee relationship and, therefore, exhibit considerable variety. For example, one important

[1] Botero et al. (2004), for example, argue 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 U.S. For a study articulating this theme, see the study of France and Germany by the McKinsey Global Institute (1997).

category of labor laws impacts workers' ability to unionize, while another one governs workers' rights to engage in militant action in the form of strikes. In this paper, we ask whether the positive effect of labor laws on innovation is restricted to laws that inhibit dismissal; or is it the case that *any* restriction placed on the employer-employee relationship secularly encourages innovation? We find that *only dismissal laws* have an ex ante positive incentive effect by encouraging firms and their employees to engage in more successful, and more significant, innovative pursuits. Other forms of labor laws, however, do not generate such ex ante positive incentive effects on innovation. We provide this evidence using country-level changes in dismissal laws from 1970–2002 for four countries – U.S., U.K., France, and Germany.

Since innovation involves considerable exploration, the difficulty in describing innovative activities ex ante, combined with the possibility of ex post renegotiation, make it difficult to write complete contracts in innovative settings (Aghion and Tirole, 1994). Therefore, to appropriate a larger share of the substantial payoff from successful innovation, innovative firms may hold up, i.e., fire, employees that contributed to such an innovation. In fact, a recent high-profile court case filed against the video-game company Activision by its former employees West and Zampella highlights such possible hold-up.[3] Dismissal laws can help to limit the occurrence of hold-up and thereby increase the employee's innovative effort. This theoretical argument, which is formalized in Acharya et al. (2012), leads to the following empirical predictions:

HYPOTHESIS 1: *Stronger dismissal laws lead to greater innovation.*

Because the ex ante incentive effect should matter more in the innovative sectors, we test:

HYPOTHESIS 2: *Stronger dismissal laws lead to relatively more innovation in the innovation-intensive industries than in traditional industries.*

Because other aspects of labor laws do not have this ex ante incentive effect, we also test:

HYPOTHESIS 3: *Labor laws other than those governing dismissal of employees do not exhibit a positive effect on innovation.*

We provide evidence supporting the hypotheses by exploiting changes in dismissal laws at the country level. We employ data on patents issued by the United States Patent and Trademark Office (USPTO) to U.S. and foreign firms as well as citations to these patents as constructed by Hall et al.

[3]The lawsuit alleges that Activision fired West and Zampella after they completed the video-game development and before they received the royalties for their work. For details see *http://ve3d.ign.com/articles/news/54192/Activision-Counter-Sues-Fired-Infinity-Ward-Founders-Suit-Scanned-Broken-Down-Transcribed.*

(2001). We measure innovation using the number of patents applied for (and subsequently granted), the number of all subsequent citations to these patents, and, as our theoretical motivation implies more risk-taking subsequent to the passage of stronger dismissal laws, the standard deviation of citations. As our primary explanatory variable, we employ an index of dismissal laws developed by Deakin et al. (2007). They construct this index by analyzing in detail *every* legal change pertaining to dismissal of employees in five countries — U.S., U.K., France, Germany, and India — over the period 1970–2006. The index 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 using the Deakin et al. index forces us to focus our analysis on five countries, these countries account for about 70% of the patents filed with the USPTO during our sample period.[4]

We conduct our tests at two levels of aggregation: (i) country-level, where we only exploit variation in innovation across time within a country; and (ii) industry-level, where we exploit variation both across time and within different industries of a country. The "industry" level classification we employ is very granular and corresponds to around 500 "patent classes" that the USPTO defines. To test Hypothesis 1, we first examine the correlation between our innovation proxies in a given country and year and dismissal laws in a given country in the previous year, as well as two years prior. In estimating this correlation, we control for unobserved heterogeneity at the country-level (through country fixed effects), secular time trends and macro effects (through year dummies) as well as several country- and industry-level variables. The presence of the country and year fixed effects enables us to estimate this correlation as a difference-in-difference, i.e., the before-after difference in innovation in a country and year in which there was a change in dismissal laws vis-à-vis the before-after difference in a country and year where there was no such change. We find that more stringent dismissal laws in a particular year are positively correlated with subsequent innovation.

As a specific source of endogeneity, changes in a country's government (i.e., changes in its political leanings) may confound our results, as could the correlation of dismissal law changes with economic growth and periods of business cycle contractions. To directly control for these sources of endogeneity in the difference-in-difference tests, we re-run our basic panel regressions after including: (i) a time-varying proxy for the political leanings of a country's government; (ii)

[4]Due to very limited patenting with the USPTO, we exclude India from our tests. However, all results remain robust to the inclusion of India in the sample.

the GDP growth rate to control for economic growth; and (iii) country-specific periods of business cycle contractions. We find that the effect of dismissal laws on innovation remains robust.

Despite controlling for an exhaustive set of observable variables that may influence innovation and the passage of dismissal laws, we are careful not to ascribe a causal interpretation to the above correlation since the possibility remains that unobserved factors accompanying law changes may lead to the correlation. As the *centerpiece* of our identification strategy, we undertake triple-difference tests where we absorb *all* variation at the country-year level through *country*year* fixed effects and identify the effect of dismissal laws on innovation within industries in a country. This identification strategy is motivated by Hypothesis 2 above, which predicts that the effect of dismissal laws should be disproportionately stronger in industries that exhibit a greater propensity to innovate than in other industries. To conduct these tests, we employ two proxies for an industry's innovation intensity. First, we use the National Science Foundation's measure of the number of R&D scientists and engineers employed per thousand employees in an industry in the U.S. Second, based on firm-level data from the U.S., we use the median ratio of R&D expenditure to assets in an industry in a given year. By interacting these proxies with the dismissal law index, we find that the coefficient on this interaction term is significantly positive, which implies that the effect of dismissal laws is more pronounced in industries that have a greater propensity to innovate. These tests serve two important purposes. First, they highlight the channel for the main effect – the industry's propensity to innovate. Second, they ensure that neither changes in a country's government nor economic growth, country-specific business cycles, nor *any other country-level variable* that correlates with dismissal law changes accounts for our findings.

Having controlled for all possible omitted variables at the country level, we then undertake triple-difference tests that account for possible placebo effects at the country, industry level. The hypothesized effect of dismissal laws on innovation stems from the increased effort by a firm's employees due to the reduced possibility of hold-up. Since individual inventors are not employed by a firm, this predicted effect of dismissal laws should not manifest for innovation by individual inventors. However, individual inventions may be affected by other, possibly omitted, country- and industry-level variables in a similar fashion as innovation by firms. Therefore, stand-alone inventors provide a control group whose innovative output should not be affected by changes in dismissal laws. Hence, we employ innovation by firms minus innovation by individual inventors as the dependent variable to net out any confounding effects driven by omitted variables at the country, industry level. Reassuringly, our results continue to hold. Both sets of triple-difference tests together provide evidence of the causal effect of dismissal laws on innovation.

Finally, we shed light on Hypothesis 3. Deakin et al. (2007) not only construct a dismissal law index, but they also generate indices to measure other dimensions of labor laws (for example, laws governing industrial action, or employee representation). This enables us to study the effect of these other dimensions of labor laws on innovation. We find that dismissal laws are the only aspect of labor law that has a consistently positive and significant effect on innovation.

In other tests, we confirm that the direction of causality runs from dismissal laws to innovation rather than vice versa. Further, we show that our results are not driven by physical capital deepening, that is, labor substitution as a response to the strengthening of dismissal laws: the concern is that more stringent dismissal laws could hasten the adoption of more innovative, labor-saving technologies instead of providing stronger incentives for innovation. However, we do not find a significant association of dismissal laws with either firm-level R&D nor capital expenditure.

In summary, we conclude that stronger dismissal laws encourage innovation. The effect is economically significant. Since we identify the intended effects using specific law changes, consider a typical law change as an example. The U.K. increased the procedural hurdles relating to dismissal of employees in 1987, which increased the dismissal law index by 0.0378. Using our coefficient estimates from the country-level tests, we find that this law change increased annual number of patents, citations, and standard deviation of citations by 1.3%, 1.6%, and 2.2% respectively.

The cross-country tests complement the findings in Acharya et al. (2012), who show that the staggered adoption of common-law exceptions to the "employment-at-will" principle (so-called "Wrongful-Discharge Laws") in several U.S. states resulted in more innovation and entrepreneurship by U.S. firms. Apart from the different setting (cross-country law changes and tests vis-à-vis U.S. state law changes), this study differs from Acharya et al. (2012) in other key ways. First, since the cross-country setting provides variation stemming from passage of other labor laws as well, we are able to confirm here that dismissal laws are salient in engendering positive incentives for innovation, while other dimensions of labor laws do not have this salutary effect. Second, since our cross-country tests exploit *country-level* changes in dismissal laws, these time-series tests provide point estimates of the effect of changes in dismissal laws on innovation using experiments of greatest relevance to country-level policies concerned with promoting innovation.

The rest of the paper is organized as follows. Section 2 places our study relative to the extant literature. Section 3 discusses the political economy of dismissal laws. Section 4 presents the theoretical motivation. Section 5 discusses the main data and proxies used in our tests. Section 6 describes the empirical results. Finally, Section 7 concludes.

2 Related literature

Our study complements the findings in Acharya et al. (2012), who show that the staggered adoption of common-law exceptions to the "employment-at-will" principle (so-called "Wrongful-Discharge Laws") in several U.S. states resulted in more innovation by U.S. firms. Our paper also contributes to the body of literature that examines the effect of laws governing the employer-employee relationship (e.g., Botero et al., 2004; Besley and Burgess, 2004; Atanassov and Kim, 2009; Bassanini et al., 2009). In contrast to these studies which document negative effects of labor laws, our study finds that some types of stringent labor laws can motivate a firm and its employees to pursue value-enhancing innovative activities. Our study resembles that of Menezes-Filho and Van Reenen (2003) in documenting some positive effects of labor laws. However, 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 study relates to MacLeod and Nakavachara (2007), who develop a theoretical model and provide empirical evidence that the passage of wrongful discharge laws across several U.S. states enhances (reduces) employment in industries requiring high (low) relationship specific-investment. Garmaise (2011) uses legal enforcement of employee non-compete agreements (NCAs) across U.S. states as a proxy for laws that limit human capital mobility and finds that such laws enhance executive stability. Lavetti et al. (2012) argue that NCAs can reduce investment hold-ups and increase productive efficiency. Using survey data, they find that physicians with NCAs have stronger incentive contracts, are more productive, earn higher wages, and have higher within-job earnings growth. NCAs also increase returns to both tenure and experience, suggesting that they promote general as well as firm-specific human capital investment. Saint-Paul (2002a) argues theoretically that employment protection may alter the pattern of specialization in favor of low-risk, mature goods and "secondary innovation" which is focused on improving existing products rather than creating new ones. Lerner and Wulf (2007) report that long-term incentives provided to corporate R&D heads of U.S. publicly listed firms are associated with greater firm-level innovation. Finally, Chemmanur and Tian (2012) show that firms with more anti-takeover provisions are more innovative, as these provisions insulate managers from short-term pressures arising from the equity market.

Our paper also relates to recent studies showing that laws and contracts that exhibit tolerance to failure can be instrumental in fostering innovation and economic growth. Acharya and Subramanian (2009) report that the ex post inefficient continuations engendered by debtor-friendly bankruptcy laws encourage ex ante risk-taking and, thereby, promote firm-level innovation and country-level economic growth. Manso (2011) shows theoretically that the optimal contract to motivate innovation not only exhibits tolerance for short-term failure but also, in fact, rewards interim failure to create the incentives for successful innovation in the long-term; Ederer and Manso (2012) find evidence supporting this thesis. Tian and Wang (2011) show that tolerance for failure among venture capitalists spurs innovation in their portfolio firms.

3 The political economy of labor market (de-)regulation

Labor laws—labor market regulation that enhances employees' bargaining power vis-à-vis employers—can take two forms (see Deakin et al., 2007): formal or positive law, as well as regulatory mechanisms that are functionally equivalent to formal laws (such as collective agreements). Such labor market regulation is often driven by political considerations: countries with a longer history of left-leaning governments tend to have more stringent labor regulation (Botero et al., 2004). Consistent with such an association, Deakin et al. (2007) also document that the primary motivation for labor market (de-)regulation is political. For example, they find that a considerable decrease in the intensity of labor market regulation in the U.K. during the 1980s and early 1990s coincided with the election of a Conservative government committed to labor market deregulation. Similarly, they report that a limited renaissance of the regulation of labor markets in the U.K. was triggered by the return to office in 1997 of a Labor government, which also ended U.K.'s opting out of the EU Social Charter. In France, the election of a Socialist government in 1981 led to a series of labor law reforms aimed at shifting the balance of power towards employees—the "Auroux laws". These laws, which were enacted in 1982 under the presidency of Francois Mitterrand, covered a wide range of aspects in both individual and collective labor law. Since that time, French labor law has mirrored changes in the distribution of power between the main political parties (Deakin et al., 2007).

While political forces are critical in shaping labor regulation, Saint-Paul (2002b) argues that the political impetus for employment protection legislation is itself closely linked to economic growth in a country. He asserts that higher economic growth reduces the political support for dismissal laws. However, since incumbent workers are most fearful of losing jobs during periods of slow economic growth, the political support for dismissal laws should be high in such periods. As empirical evidence for his thesis, Saint-Paul (2002b) points out that in many European countries employment protection increased in the early 1970s and was difficult to reduce in the 1980s as this was a period of slow economic growth.

4 Theoretical motivation

4.1 Theoretical arguments underlying the hypotheses

Acharya et al. (2012) present a theoretical framework which also serves as the main motivation for our tests in this paper. The model features an all-equity firm choosing between two projects that differ mainly in their degree of innovation. For instance, in the case of a pharmaceutical company these two projects can be thought of as inventing and launching a new drug, or manufacturing and launching a generic substitute for an existing drug. Launching a generic substitute involves uncertainties due to customer demand and competition. In contrast, inventing and launching a new drug, while resulting in higher terminal payoffs in the case of success, entails additional uncertainties associated with the process of exploration and discovery, and thus involves significantly more risk.

The firm, which is risk-neutral, hires a risk-averse employee to work on the project; the employee is particularly averse to the risk of being dismissed from employment. A key friction in the model is that contracts are incomplete in the spirit of the theory on property rights (Grossman and Hart, 1986; Hart and Moore, 1990; and Hart, 1995). As highlighted by this theory, bilateral relationships can suffer from hold-up problems when contracts are incomplete. Since "...the opportunity for bad faith and the duty of good-faith are products of incomplete contracts" (Bagchi, 2003), specifically, when contracts are incomplete, an employer and an employee cannot commit to a contract that prohibits either of them from acting in bad faith ex post.

Contractual incompleteness introduces the possibility of hold-up, where the firm fires the employee after an innovation is successful. As the payoffs from a successful innovation are often large, innovative firms may not be able to credibly commit ex ante to not armtwist employees ex post in order to appropriate a larger share of the ex post surplus. The likelihood of such hold-up, in turn, dampens the ex ante innovative effort by the employee. Given this friction, dismissal laws impose limits on the firm's ability to discharge an employee in bad faith after a successful innovation. By reducing the possibility of hold-up, these laws enhance employees' innovative efforts and encourage firms to invest in risky, but potentially mould-breaking, projects.[5] Thus, stringent dismissal laws may lead to more risk-taking and innovation.

Alternatively, stringent dismissal laws may also encourage shirking by employees, resulting in lower innovative effort and less innovation. Furthermore, laws and regulations could be "incomplete" in similar ways as contracts; legal incompleteness and uncertainty stemming from interpretation of legal rules by courts may lead to underinvestment in innovative effort. We will examine empirically in Section 6 whether the effect of dismissal laws on innovation is positive or negative.

Given the "unknown unknowns" that characterize innovative ventures, contractual incompleteness and the consequent temptation to act in bad faith are more likely in innovative industries when compared to "brick-and-mortar" ones. Consequently, dismissal laws may play a more important role in alleviating the underinvestment problem in innovative industries. Thus, the effect of dismissal laws on innovation is likely to be *disproportionately* more pronounced in innovative industries when compared to "brick-and-mortar" ones.

Alternatively, the institutional environment may endogenously respond to the greater likelihood of hold-up in the innovation intensive industries.[6] For example, innovation-intensive industries (as opposed to brick-and-mortar ones) may develop sophistication in describing the complexities involved in innovative activities in an ex ante contract. Also, before a dismissal law change, innovation may have been concentrated only in industries where contractual incompleteness and hold-up are not important concerns. In either case, we should see no impact of the changes in dismissal laws on innovation in the innovation-intensive sectors. The tests in Section 6 will shed light on the

[5] As innovative projects are riskier than routine projects, the lower threat of termination (induced by stronger dismissal laws) matters more for innovative projects than for routine projects. This leads the employee to increase his investment relatively more with the innovative project than with the routine project. Since an increase in the employee's investment increases the likelihood of project success, a disproportionate increase in the employee's investment in the innovative project (relative to the routine project) leads to a similar increase in the value of the project. Therefore, the firm finds risky, innovative projects to be more value-enhancing than routine projects.

[6] We would like to thank the referee for highlighting this possibility.

intra-industry effects of dismissal law changes.

4.2 Discussion

Could parties commit to contractual features in the employment contract to avoid inefficiencies stemming from contractual incompleteness? According to Tirole (1999), the complexities involved in innovative ventures make it difficult to *comprehensively* describe innovative activities, making it difficult to commit ex ante to avoid Pareto-improving renegotiation ex post, reducing the credibility of any ex ante commitment through contractual features.[7] Consider severance packages, for example. Empirical evidence indicates that for employees below the level of senior management in a firm, such severance packages are quite uncommon.[8] This observation is consistent with the argument in Manso (2011), who shows that even when complete contracts can be written, the firm may find it prohibitively costly ex ante to commit to not fire its employees ex post.

The ex ante allocation of property rights over innovation outcomes can also affect the likelihood of an innovation (Aghion and Tirole, 1994; Hart, 1995). In particular, the employee's incentives to exert effort are greater if the employee owns the property rights over the innovation than if the employer is the owner. However, such an allocation of property rights is uncommon in practice.[9] Thus, the commonly observed employer ownership of property rights may exacerbate the market failure that leads to the positive effect of dismissal laws on innovation hypothesized in Section 4.

Apart from the employer holding up the employee, the employee could also hold up the employer, for example, by stealing trade secrets and then seeking employment elsewhere. Noncompete covenants, which expressly forbid employees from indulging in such hold-up, are common in employment contracts, particularly for technical workers and upper-level management.[10] However, the effects of dismissal laws on innovation differ from those of legal restrictions on the mobility of human capital. Dismissal laws primarily have the effect of limiting an employer's ability to

[7] Given these difficulties, revenue-sharing rules or severance payments contracted ex ante, contracts that explicitly specify ex post performance, or messaging mechanisms cannot fully address the incentive problems generated by contractual incompleteness (see Hart, 1995, for details).

[8] Narayanan and Sundaram (1998) find that only 7% of the Fortune 1000 and S&P 500 non-financial firms examined from 1980 to 1994 had "tin parachutes", i.e., severance agreements for employees who are not officers of the company. Furthermore, the incidence of "tin parachutes" was limited to change-of-control events such as a merger or acquisition.

[9] For example, according to Cooley (1985), 84% of American patents are awarded to employed inventors, and almost all of these patents are assigned to the inventors' employers. Furthermore, employment contracts usually specify that an innovation made by an employee shortly after quitting the firm belongs to the former employer (see Aghion and Tirole, 1994, citing Neumeyer, 1971, p. 1199).

[10] In the United States, for example, surveys report that nearly 90% of such employees have signed noncompete agreements (Kaplan and Strömberg, 2003).

hold up the employee when the innovation is firm-specific (and therefore has to be implemented within the incumbent firm). In contrast, legal restrictions on the mobility of human capital limit the employee's ability to hold up the firm when the innovation is generic (and can therefore be implemented by the employee in a new firm). By exploiting the fact that innovations can be either firm-specific or generic, Acharya et al. (2012) show in an extension to their basic model that the positive effect of dismissal laws on innovation remains robust to accounting for the presence of legal restrictions on mobility of human capital.

5 Empirical analysis

5.1 Why focus on innovation?

Our theoretical arguments above apply broadly to the effect of dismissal laws on risk-taking, not only in an innovation context. However, our focus on innovation is motivated by the following considerations. First, as argued in the introduction, endogenous growth theory highlights the central role of laws and institutions that foster innovative investment, and thereby significantly stimulate economic growth. Therefore, the role of labor laws in fostering innovation (even if as an unintended consequence) is of broad interest to academics and policy makers alike.

Focussing on innovation also offers significant advantages from an empirical perspective. The risks involved in a project can only be measured based on the *variance* in the *outcomes* from the project. Patents—which have long been used as proxies for innovative activity (see Griliches, 1981, Pakes and Griliches, 1980, and Griliches, 1990)—represent such outcome-based measures of risky, innovative investments. In contrast, neither capital expenditures nor R&D expenditures, which are input-based measures of investment, provide this advantage.

Furthermore, unlike capital expenditures or R&D expenditures, the *quality* of the risky investment can be measured using the trail of citations to patents. A simple count of patents does not distinguish breakthrough innovations from less significant or incremental technological discoveries.[11] In contrast, citations capture the economic *importance* and drastic nature of innovation, which enables us to proxy for the value-enhancing aspect of innovative activities. Intuitively, the rationale behind using patent citations to identify important innovations is as follows: if firms

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

are willing to further invest in a project that is building upon a previous patent, the cited patent is likely to be influential and economically significant. Furthermore, patent citations arrive over time, suggesting that the importance of an investment may be revealed later in its life and may be difficult to evaluate when the investment occurs. Since our patent data records all future citations (until 2002) made to a patent, the quality and value of the investment can be measured.

Finally, our theoretical motivation also suggests that risk-taking with respect to innovative projects increases after the passage of stricter dismissal laws. The standard deviation of the citations received by patents can be used as a direct proxy for the risk involved in an innovative project.

We now describe the data we use, the various proxies we construct, and the dismissal law index.

5.2 Proxies for innovation

We follow Acharya and Subramanian (2009) in using U.S. patents to proxy innovation by international firms. To construct these proxies for innovation, we use data on patents filed with the USPTO and the citations to these patents, compiled in the NBER Patents File (Hall et al., 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."* The USPTO assigns patents to about 500 patent classes to facilitate future searches of the prior work (see Kortum and Lerner, 1999).

We follow the practice in the patent literature in dating the patents by 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 et al., 2001). Note that although we use the application 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.

We employ the number of patents and citations to these patents as our primary proxies for innovation. To capture innovative risk-taking by firms, we also employ the standard deviation of citations. For each country and year (country, patent class, and year), we first sum the number of citations each firm receives; we then calculate the standard deviation of these citations per country and year (country, patent class, and year).

5.3 Dismissal law changes

Deakin et al. (2007) use the indexing method to code the differences between five countries' (United States, United Kingdom, France, Germany, and India) legal systems as they relate to labor law.[12] They categorize labor law into five areas: (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) employee representation; (iv) rules governing industrial action; and, (v) regulation of dismissal. Deakin et al. (2007) analyze in detail the evolution of employment protection legislation along these five dimensions in the five countries from 1970 to 2006. They translate individual law changes into changes in a labor law index, in which higher values indicate a higher degree of protection of the interests of employees vis-à-vis employers.

The Deakin et al. (2007) index offers several advantages. First, the long time-series, which captures comprehensively all country-level changes in labor laws, enables us to conduct difference-in-difference tests that alleviate econometric concerns about country-level omitted variables. Second, the categorization of labor laws into different components allows us to assess the impact on innovation of dismissal laws vis-à-vis other categories of labor laws. Third, the index takes into account not only formal laws but also self-regulatory mechanisms, which makes the index particularly comprehensive with respect to the range of rules analyzed. For example, in certain legal systems, collective bargaining agreements—which do not constitute formal law—play a functionally similar role to formally enacted laws. Finally, the numerical values reported in the index are complemented by a detailed description of *all the relevant law changes* in each country.

Guided by our theoretical motivation, we mainly focus on one dimension of labor laws, namely dismissal laws—laws that prevent employers from arbitrarily discharging employees—and how such laws affect firms' innovation. Deakin et al. (2007) code dismissal laws as a specific sub-index of the labor law index. This sub-index (hereafter "Dismissal Law index" or "Regulation of Dismissal

[12]The Botero et al. (2004) index presents an alternative to the Deakin et al. (2007) index that we use. Although Botero et al. (2004)'s index is constructed for 85 countries, the index is available only for the year 1997. Therefore, it is not suitable to investigate the *causal* impact of labor laws on innovation, which necessitates controlling for observable and unobservable *time-varying* heterogeneity. 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). Furthermore, the EPL index only measures the aggregate stringency of a country's labor laws, while in this study we are interested in one particular dimension of these laws, namely dismissal rules.

index") consists of the following dimensions of employment protection legislation: rules governing unjust dismissal; the legally mandated notice period; the amount of mandatory redundancy compensation; constraints on dismissal imposed by the law; parties to be notified in case of dismissal; redundancy selection; and applicability of priority rules in re-employment. Please refer to the Appendix for a more detailed discussion of the index components. Figure 1 depicts the evolution of the dismissal law index for the four countries in the sample; higher values represent stricter laws governing dismissal. In the same graph, we plot the real GDP growth rate for each country, as well as business cycle troughs. It is clear from the graph that while stricter dismissal laws are more likely to be passed in periods of economic contractions, this relationship is not strong (the correlation equals -0.18). Nonetheless, we control for real GDP growth in our tests.

Table 1 details each dismissal law change during the time period 1970-2006; these law changes generate the variation observed in Figure 1. As an illustration, consider a few specific law changes. In France, before 1973, the employer was not required to notify an employee in case of a dismissal. In 1973, this aspect of dismissal law was strengthened by requiring the employer to provide the employee with written reasons for the dismissal. This change is reflected as an increase of 0.0367 in the "Regulation of Dismissal" index. In 1975, the law was further strengthened and the employer had to obtain the permission of a state/ local body prior to any individual dismissal; this law change results in an increase of 0.074 in the "Regulation of Dismissal" index. In 1986, this law was weakened; now the employer only had to notify the state/ local body prior to an individual dismissal (in contrast to requiring their permission earlier), which resulted in a decrease of 0.0367 in the "Regulation of Dismissal" index.

Figure 1 (together with Table 1) indicates that the numerous legal changes provide substantial time-series variation, which we exploit in our statistical tests.

5.3.1 Summary statistics

We report summary statistics for each of the countries in Table 2, separately for the country-, industry-, and firm-level samples. The table lists the mean, median, standard deviation, minimum, and maximum for the dismissal law index, the number of patents filed, citations received by these patents, the standard deviation of citations, the ratio of R&D expenses to assets, and the ratio of capital expenditures to assets. The dismissal law index is available from 1970 to 2006 while the patent data end in 2002.

A casual look at the summary statistics suggests that across countries, more stringent dismissal laws tend to be associated with less innovation. This inter-country variation may be driven by many factors other than dismissal laws, factors which are omitted in a simple comparison of time-series averages. The tests in the next section are designed to address such concerns of endogeneity. By exploiting variation within countries (and industries) over time, they answer whether *within* a given country, increases in dismissal protection lead to more or less innovation activity.

6 Results

6.1 Fixed-effects panel regressions using the country-level sample

6.1.1 Basic Tests

First, we estimate fixed-effects panel regressions with innovation proxies as dependent variables and the dismissal law index as explanatory variable:

$$y_{ct} = \beta_c + \beta_t + \beta_1 * DismissalLaws_{c,t-k} + \beta X_{ct} + \varepsilon_{ct} \tag{1}$$

where y_{ct} is the natural logarithm of a measure of innovation from country c in year t. β_c and β_t denote country and application year fixed effects, respectively. $DismissalLaws_{c,t-k}$ denotes the k^{th} lag of the dismissal law index for country c, measuring the stringency of dismissal laws. β_1 measures the impact of dismissal laws on our innovation proxies. X_{ct} is a set of control variables. The country fixed effects control for time-invariant unobserved factors at the country level. The application year fixed effects account for global technological shocks; further, they allow us to control for the problem stemming from the truncation of citations, i.e., the number of citations to patents applied for in later years is on average lower than the number of citations to patents applied for in earlier years. β_1 in (1) estimates the "difference-in-difference" in a generalized multiple treatment groups, multiple time periods setting (see Imbens and Wooldridge, 2009).

Figure 2 illustrates the difference-in-difference for the change in laws governing dismissal in the U.S. in 1989, when the Worker Adjustment and Retraining Notification Act became effective at the federal level. Since Germany did not experience a change in dismissal laws in 1988, Germany serves as the control group.[13] In this figure, we plot across time the ratio of realized number of patents in a particular year to that in 1989 – the year of the U.S. dismissal law change. We find that while the number of patents is relatively in sync for U.S. and Germany until 1989, post 1989, these measures for the U.S. break ahead of those for Germany.

Panel A of Table 3 shows the results of the test of equation (1). In these tests, we do not include any control variables. Columns 1–3 and 4–6 employ respectively the first and second lags of the dismissal law index, which enables us to estimate the impact of dismissal law changes on innovation one and two years after the change respectively. In tests that we omit in the interest of brevity, we also find similar effects on innovation three years after the change. Overall, the coefficient of dismissal laws is positive and significant, which indicates that stronger dismissal laws are positively correlated with innovation, as suggested by Hypothesis 1.

Economic magnitudes: Because we identify the hypothesized effect using specific law changes, we also assess the economic magnitude of the effect using individual law changes. Consider the effect of the law changing procedural constraints on dismissal in the U.K. in 1987 when it became harder for employers to avoid a finding of unjust dismissal in case of a lack of due process. This law change corresponds to an increase of 0.0378 in the dismissal law index. Using Columns 1-3 in Panel A of Table 3, this law change corresponds to an increase in annual number of patents, citations, and standard deviation of citations by 1.3%, 1.6%, and 2.2% respectively.

6.1.2 Tests controlling for other country-level effects

Next, we repeat the above tests after adding control variables that enable us to account for other time-varying determinants of innovation. Specifically, we first control for creditor rights changes and economic development. Acharya and Subramanian (2009) 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, we control for the extent of creditor protection in a country by using the time-varying index of creditor rights developed by Armour, Deakin, Lele, and Siems (2009).[14] Furthermore, as the degree of innovation in a country may vary with its level of economic

[13] Germany underwent no dismissal law changes between 1973 and 1992.

[14] The Armour et al. index is the sum of binary variables describing individual dimensions of creditor protection; these variables pertain to three groups: (1) legal rules restricting the debtor from entering into transactions that may harm creditors' interests; (2) variables describing credit contracts; (3) variables pertaining to liquidation procedures

development, we also control for the log of real GDP in a country and year. Panel B of Table 3 shows the results of these tests.

Consistent with Acharya and Subramanian (2009), we find that stronger creditor rights discourage innovation as seen in the negative and statistically significant coefficient of creditor rights. Moreover, we find a negative correlation between our proxies for innovation and log of real GDP although the coefficient is not statistically significant. Crucially, after including these controls, we find that the positive effect of dismissal laws on innovation persists. Furthermore, the coefficient magnitudes are very similar to those reported in Panel A of Table 3.

6.2 Dynamic Effects

To investigate the possibility of reverse causality, we examine the dynamic effects of changes in dismissal laws on innovation. To this end, we include the contemporaneous dismissal law index and up to three lags and forward values of the dismissal law index. Furthermore, we examine the persistence of the effect of dismissal law changes on subsequent innovation activity by also including the sixth lag of the dismissal law index. As in Table 3, Panel B, we include creditor rights and log of per capital GDP as control variables. Table 4 shows the results of these regressions. A positive and significant coefficient on the lead terms of the dismissal law index would indicate an effect of dismissal laws prior to their actual passage and could therefore be symptomatic of reverse causation. Reassuringly, we observe that this is not the case: the effect of dismissal law changes on innovation manifests only *after* their passage, not contemporaneously or prior to law passage. Dismissal law changes have a long run impact on innovation, as evidenced by the significant coefficient on lag three of the dismissal index. However, these effects are smaller than the short run effects, and they dissipate within six years after a dismissal law change, as seen in the coefficient of the sixth lag of the dismissal law index being insignificant.

and rehabilitation proceedings. Higher values of the creditor rights index imply more creditor protection. For further details, see Armour, Deakin, Lele, and Siems (2009). An alternative to using the Armour et al. (2009) index would be the Djankov et al. (2007) index of creditor rights. We employ the Armour et al. index for two reasons: first, as the coding is done by the same team of researchers, the methodology applied in the creditor index coding is consistent with the dismissal law index coding that we employ in this paper. Second, the Armour et al. index coding starts in 1970—as does most of our other data employed in this study—while the Djankov et al. coding is available from 1978 only. However, results are similar when we employ the Djankov et al. index instead of the Armour et al. index.

6.3 Fixed-effects panel regressions using the industry-level sample

Next, we exploit variation in innovation within industries by measuring our innovation proxies at the country and industry level. We employ the following OLS models to test our hypotheses:

$$y_{ict} = t\beta_{j\leftarrow i} + t\beta_c + \beta_i + \beta_t + \beta_1 * DismissalLaws_{c,t-k} + \beta \cdot X_{ict} + \varepsilon_{ict} \quad (2)$$

where y_{ict} is the natural logarithm of a measure of innovation for the USPTO patent class i from country c in year t. The patent class fixed effects β_i control for average differences in technological advances across the different industries as well as time-invariant differences in patenting and citation practices across industries. $t\beta_{j\leftarrow i}$ denotes a time trend for the industry j to which patent class i belongs;[15] $t\beta_c$ denotes a time trend for country c. Since other country or industry-level factors accompanying the dismissal law changes could lead to country-specific as well as industry-specific time trends, these tests enable us to isolate better the pure effect of dismissal law changes on innovation. The other variables are as defined in equation (1). Since the dismissal law index varies at the country, year level and our innovation proxies are measured at the patent class level, we estimate standard errors that are clustered at the country, year level.

In these tests, apart from creditor rights changes and economic development, we also control for other industry- and country-level variables that may affect innovation. *(i) Bilateral trade:* Using U.S. patents to proxy innovation in non-U.S. countries avoids concerns of heterogeneity stemming from employing patents filed under each country's patenting system. However, this strategy introduces a potential bias: countries that export to the U.S. may file more patents with the USPTO, particularly in their export-intensive industries.[16] To avoid biased estimates, we add as controls the logarithm of the level of imports and the level of exports that a given country has with the U.S. in each year in each 3-digit ISIC industry. These variables are available from 1978 onwards.[17] *(ii) Industry-level comparative advantage:* A possible determinant of innovation

[15] Since there are about 500 patent classes in all, we estimate the linear industry trends at the patent category level, which encompasses several patent classes. There are six patent categories.

[16] 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 U.S.

[17] The data are from Nicita and Olarreaga (2006). 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.

is the comparative advantage that a country possesses in its different industries. 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.[18]

The results of these tests are reported in Table 5. We find that the overall effect of dismissal laws on innovation is positive and significant for all three innovation proxies in these tests. Comparing the coefficient magnitudes with those from the country-level tests reported in Table 3, we notice that the effect of dismissal laws on innovation is larger when measured at the industry-level than at the country-level. The industry-level tests exploit variation in the effect of dismissal laws within industries, while the country-level tests exploit variation in the effect of dismissal laws within countries. The industry-level tests allow the average effect of dismissal laws on innovation to vary across industries while the country-level tests do not. As Hypothesis 2 proposes, dismissal laws should have a larger effect in more innovation-intensive industries when compared to less innovation-intensive ones. By possibly reflecting large effects in the innovation-intensive industries, the resulting large coefficient estimates in Table 5 suggest that the results from the industry-level tests are consistent with Hypothesis 2. We test Hypothesis 2 more extensively in Section 6.5.

Economic magnitudes: Using Columns 1–3 of Table 5, the law change relating to procedural constraints on dismissal in the U.K. in 1987 corresponds to an increase in annual number of patents, citations, and standard deviation of citations by 7.8%, 21.1%, and 4.7% respectively.

6.4 Addressing identification concerns

Despite the fixed effects and country- and industry-specific time trends, we cannot necessarily attribute a causal interpretation to the observed relationship between dismissal laws and innovation since residual unobserved factors accompanying law changes may lead to this correlation.

First, to cater to their political constituencies, more left-leaning governments may be inclined to strengthen labor laws (see e.g., Botero et al., 2004; Deakin et al., 2007). Leftist governments may also be more likely to invest in education and other public services, which may have a positive impact on innovation in a given country. Therefore, other factors coinciding with changes in government may hinder identification. Second, dismissal law changes may be also correlated with GDP growth (business cycles) in a country. On the one hand, lower economic growth (i.e., contractions in the

[18]Data for these measures are from the United Nations Industrial Development Organization (UNIDO)'s statistics.

business cycle) may encourage the adoption of more stringent dismissal laws. On the other hand, innovation should foster economic growth, as suggested by the endogenous growth theory (Aghion and Howitt, 1992). Thus, any effect of economic growth/business cycles on dismissal laws could hinder the identification as well.

We now address the concerns stemming from these sources of endogeneity. First, we directly control for the effect of changes in a country's government by employing a time-varying proxy for the political leanings of a country's government: the variable *Government* captures the balance of power between left and right-leaning parties in a given country's parliament. This variable takes on values from one to five, with one denoting a hegemony of right-wing (and center) parties, and five denoting a hegemony of social-democratic and other left parties.[19] Table 6 reports in detail the years in which the political leanings of elected governments changed, as well as the years in which dismissal laws were altered. The table shows that more left-leaning governments indeed tend to pass stricter dismissal laws. Numerically, the variable *Government* is positively correlated with the dismissal law index (the correlation is 0.49). Second, we also include GDP growth and country-specific indicators for periods of business cycle contractions. We report the results in Table 7. Columns 1–3 focus on the aggregate country-level sample corresponding to equation (1), while Columns 4–6 employ the disaggregated industry-level sample corresponding to equation (2).[20]

We find that the political persuasion of a country's government is not significantly associated with our proxies for innovation in most specifications. Furthermore, we find that innovation is negatively correlated with times of business cycle contractions, though these correlations are significant only in the specifications from the industry-level sample (Columns 4–6). Crucially, however, we observe that the coefficient on the dismissal law index remains positive and significant in all instances. Comparing the coefficients with and without controlling for these sources of endogeneity (Table 7, Columns 1–3, versus Table 3; and Table 7, Columns 4–6, versus Table 5) shows that accounting for the possible endogeneity of dismissal law changes does not materially affect the economic magnitude of the documented effect.

[19] This variable is from Armingeon et al. (2008), who collect annual political and institutional data for 23 democratic countries from 1960 to 2006. Our variable *Government* is denoted "govparty" in Armingeon et al. (2008).

[20] In Table 7 and subsequent tests, we only report results using the first lag of the dismissal law index to save space.

6.5 Triple-difference tests controlling for *all* country-level variation

The previous tests account for important sources of endogeneity. However, the concern remains that some *unobservable* time-varying country-level omitted variables that are correlated with changes in dismissal laws may confound our results. To address these endogeneity concerns, we conduct a test where we include *country*year* fixed effects, that is, the interaction of country dummies with year dummies. These fixed effects absorb all variation at the country-year level, which allows us to account for *all* sources of omitted variables for *each* country, year combination in our sample. The identification strategy is motivated by Hypothesis 2, in which we argue that the effect of dismissal laws should be *disproportionately* stronger in industries that exhibit a greater propensity to innovate than in other industries.

We measure an industry's propensity to innovate using two proxies. First, we proxy innovation intensity using the National Science Foundation's measure of the number of R&D scientists and engineers employed per thousand employees in a (manufacturing) industry in the U.S.[21] The second measure employs firm-level data for the U.S. and proxies innovation intensity as the median of *R&D/Assets* per industry and year.[22] Since the U.S. remains the front-runner in innovation, these U.S.-based measures come close to the efficient level of innovative intensity for any industry. Furthermore, given technological commonalities, an industry that is innovation intensive in the U.S. is likely to be so in another country too, which enables us to proxy innovation intensity for a particular non-U.S. industry using the U.S. measure as well.

[21]The data for this innovation intensity measure are taken from Table A-54 of the 1993 National Science Foundation/SRS, Survey of Industrial Research and Development. For each of the 2-digit SIC manufacturing industries, we calculate the average number of scientists employed over the 1983–1993 period. To merge the SIC industries to patent classes, we use the assignment of SIC codes for each patent from the NBER patent file. Specifically, for all countries available in the NBER patent file, we determine for each patent class the SIC that most patents were assigned to over the 1970–2002 period; that SIC is used as the representative SIC for that patent class. This innovation intensity measure is available for 15 2-digit SIC manufacturing industries, or 245 patent classes in our sample; as we use the time-series average of the number of scientists employed, this measure does not have any time-series variation.

[22]For all firms headquartered in the U.S., we calculate the ratio of R&D expenses to total assets using Compustat data; missing observations for R&D are replaced by zero. This ratio is winsorized at the 99th percentile. We then calculate the median of *R&D/Assets* per 2-digit SIC industry and year, take the lagged value, and match the SIC industries to NBER patent classes using the matching procedure described before. This measure is available for 446 patent classes in our sample and exhibits time-series variation.

In this test, we interact the dismissal law index with the innovation intensity of an industry:

$$\begin{aligned} y_{ict} &= \beta_{c,t} + t\beta_{j\leftarrow i} + \beta_i + \beta_1 \cdot \left(DismissalLaws_{c,t-1} * InnovationIntensity^{US}_{i,t}\right) \\ &\quad + \beta_2 \cdot InnovationIntensity^{US}_{i,t} + \beta X_{ict} + \varepsilon_{ict} \end{aligned} \tag{3}$$

The *country*year* fixed effects ($\beta_{c,t}$) allow us to control for all observed and unobserved variables at the country-year level. These fixed effects subsume the direct effect of dismissal laws. Note that the interaction term ($DismissalLaws_{c,t-1} * InnovationIntensity^{US}_{i,t}$) varies at the level of industry i in country c in application year t. Since our dependent variable, y_{ict}, exhibits equivalent variability, the coefficient of interest β_1 is identified in the presence of country*year fixed effects. β_1 measures the relative effect of dismissal laws across industries that vary in their innovation intensity; Hypothesis 2 predicts that $\beta_1 > 0$.

The results of this triple-difference test are reported in Table 8. In Panel A, we employ the number of R&D scientists and engineers as our innovation-intensity proxy, while in Panel B we use *R&D/Assets*. In Columns 1–3 of each Panel, we include all four sample countries, while in Columns 4–6 we exclude observations pertaining to the U.S. In all instances, the coefficient of the interaction term β_1 is positive and statistically significant, indicating that the positive impact of dismissal laws on innovation is significantly more pronounced in innovation intensive industries.

Economic magnitudes: In this setting, the direct effect of dismissal laws is subsumed in the country*year fixed effects, and the coefficient β_1 captures the magnitude of the second derivative $\frac{\partial^2 y_{ict}}{\partial DismissalLaws \partial InnovationIntensity}$. We therefore evaluate economic magnitudes by comparing the marginal effect of dismissal laws $\frac{\partial y_{ict}}{\partial DismissalLaws}$ between a high innovation-intensive industry (e.g., the 90th percentile of $InnovationIntensity$) and a low innovation-intensive industry (e.g., the 10th percentile of $InnovationIntensity$). The 90th and 10th percentile values of the number of R&D scientists and engineers equals 62.7 and 6.5 respectively. Therefore, using Columns 1–3 of Panel A, we estimate that the effect of dismissal laws on innovation in the high innovation-intensive industries is greater than the effect in the low innovation-intensive industries by 75.4%, 119.6% and 25.2% for the number of patents, citations, and standard deviation of citations, respectively.

6.5.1 Triple-difference tests accounting for industry-level placebo effects

Next, we further alleviate endogeneity concerns stemming from time-varying omitted variables at the country- and industry-level by identifying a control group of innovating entities that would be affected by such omitted variables but should be unaffected by dismissal law changes. As highlighted in our theoretical motivation, the hypothesized effect of dismissal laws on innovation stems from the increased dismissal protection for *firm employees.* Dismissal law changes should not have an impact on individual inventors, who are not employed by a firm. Therefore, they provide a relevant control group to net out possible placebo effects. Based on this intuition, we conduct the following triple-difference test, in which we examine the effect of dismissal laws on innovation by firms minus the innovation generated by stand-alone inventors:

$$Ln(y_{ict,\text{ firms}} - y_{ict,\text{ individuals}}) = t\beta_{j\leftarrow i} + t\beta_c + \beta_i + \beta_c + \beta_t + \beta_1 * DismissalLaws_{c,t-1} + \beta X_{ict} + \varepsilon_{ict} \quad (4)$$

where $y_{ict,\text{ firms}}$ and $y_{ict,\text{ individuals}}$ represent measures of innovation by firms and individuals in a patent class i, country c, and year t.[23] X_{ict} is the set of control variables, and $t\beta_{j\leftarrow i}$ and $t\beta_c$ denote trends at the industry- and country-level respectively. In Table 9, we find the coefficient β_1 to be positive and statistically as well as economically significant. These triple-difference tests enable us to control for any omitted country- or industry-level variable that affects the passage of dismissal laws and affects innovation performed by all agents in the economy.

We can conclude with a reasonable degree of certainty that within countries, more stringent dismissal laws did indeed foster innovation and that our results are not affected by endogeneity stemming from other country- or industry-level confounding factors that may have coincided with the dismissal law changes.

6.6 Effect of other dimensions of labor laws

Next, we test our Hypothesis 3 that dimensions of labor laws other than those that affect the ex post likelihood of an employee being dismissed from employment do not have a positive effect on innovation. For this purpose, we contrast the effect of dismissal laws with other dimensions of labor regulation. Deakin et al. (2007) analyze forty different dimensions of labor and employment

[23] As individual-specific identifiers are not available in the patent data set (as opposed to firm-specific identifiers), we cannot construct a measure for the standard deviation of citations for individual inventors.

law and group them into five categories, each represented by a longitudinal labor law (sub-)index: (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) regulation of dismissal – our "dismissal law index"; (iv) employee representation; and (v) rules governing industrial action.[24] Table 10 presents results of these tests; the only dimension of labor laws which has a consistently positive and significant impact on innovation is the "regulation of dismissal" component.

6.7 Physical capital deepening?

The positive effects of dismissal laws on innovation documented in this paper, instead of being an outcome of better incentives to innovate, could be alternatively due to firms' efforts to save on labor costs by shifting to less labor-intensive and more innovative, capital-intensive, technologies. If this were indeed the case, we should observe an increase in capital- and/or R&D-expenditures after the strengthening of dismissal laws. To test this, we use detailed data on firm-level R&D expenditure and CAPEX from Compustat Global. The sample for these tests spans 1989 (first year of available Compustat Global data) to 2006 (last year of Deakin et al., 2007, labor law index coding). For these tests, we remove financial institutions (SIC 6000-6999), utilities (SIC 4900-4999), and governmental and quasi-governmental enterprises (SIC 9000 and above) from the sample. In addition to the time-varying control variables from Table 10, we control for leverage (*Debt/Assets*), profitability (*RoA*), the asset market-to-book ratio (*Market-to-Book*), and firm size (*Ln(Market Equity)*); we also include firm and year fixed effects in all models. Summary statistics for the dependent variables are reported in Table 2. We present the results in Table 11; the dependent variable in Columns 1 and 2 is *R&D/Assets*, while it is *CAPEX/Assets* in Columns 3 and 4.[25]

As is evident from Table 11, we do not find any evidence of stricter dismissal laws leading to capital deepening as measured by capital- and/or R&D-expenditures.

[24] While the correlation between different labor law components is positive and significant, the tests do not encounter any multi-collinearity problem.

[25] *R&D/Assets* is the ratio of research and development expense to total assets; missing R&D observations are set to zero. *CAPEX/Assets* is the ratio of capital expenditures to total assets. *Debt/Assets* is total interest bearing debt to assets. *RoA* is the ratio of EBITDA to total assets. *Market-to-Book* is the market value of assets divided by the book value of assets, where the market value of assets is the book value of assets plus the market value of common equity less the sum of the book value of common equity and balance sheet deferred taxes. *Ln(Market Equity)* is the log of the market value of equity (in million USD). We winsorize all firm-level variables at the 99th percentile; *RoA*, *Market-to-Book*, and *Ln(Market Equity)* are additionally winsorized at the 1st percentile.

7 Conclusion

We showed that innovation is causally determined by laws governing the ease with which firms can dismiss their employees. We provided this evidence using patents and citations as proxies for innovation and dismissal law changes across countries. Since the outcomes of innovation are unpredictable, they are difficult to contract ex ante (Aghion and Tirole, 1994), which renders private contracts to motivate innovation susceptible to renegotiation. Such possibility of renegotiating contracts dilutes their ex ante incentive effects. Since laws are considerably more difficult for private parties to alter than firm-level contracts, legal protection of employees in the form of stringent dismissal laws can introduce the time-consistency in firm behavior absent with only private contracting. Because endogenous growth theory (Aghion and Howitt, 1992) posits that firm-level innovation fosters country-level economic growth, assessing the aggregate welfare implications of labor laws is an important topic for future research. Our study highlights one important positive effect of dismissal laws, namely their ability to spur innovation, that must be factored into such an assessment.

Appendix – Components of the dismissal law index

The dismissal law index is one of the five labor law sub-indices constructed by Deakin et al. (2007). The components of the other sub-indices (Alternative Employment Contracts, Regulation of Working Time, Employee Representation, Industrial Action) can be found in Deakin et al. (2007). The dismissal law sub-index of the labor law index of Deakin et al. (2007) measures the extent to which the regulation of dismissal favors the employee. The sub-index is an average score of the following nine variables (the information below is copied from Deakin et al., 2007):

Variable	Description
Legally mandated notice period (for all dismissals)	Measures in weeks the length of notice that has to be given to a worker with 3 years' employment. The scores are normalized so that 0 weeks = 0, and 12 weeks = 1.
Legally mandated redundancy compensation	Measures the amount of redundancy compensation payable to a worker made redundant after 3 years of employment, measured in weeks of pay. The scores are normalized so that 0 weeks = 0, and 12 weeks = 1.
Minimum qualifying period of service for a normal case of unjust dismissal	Measures the period of service required for a worker to qualify for general protection against unjust dismissal. The scores are normalized so that 3 years or more = 0 , 0 months = 1.
Law imposes procedural constraints on dismissal	Equals 1 if a dismissal is necessarily unjust if the employer fails to follow procedural requirements prior to dismissal. Equals 0.67 if failure to follow procedural requirements normally leads to a finding of unjust dismissal. Equals 0.33 if failure to follow procedural requirement is but one of the factors taken into account in unjust dismissal cases. Equals 0 if there are no procedural requirements for dismissal. Further gradations between 0 and 1 reflect changes in the strength of the law.
Law imposes substantive constraints on dismissal	Equals 1 if dismissal is only permissible for serious misconduct or fault of the employee. Equals 0.67 if dismissal is lawful for a wider range of legitimate reasons (misconduct, lack of capability, redundancy, etc.). Equals 0.33 if dismissal is permissible if it is "just" or "fair", as defined by case law. Equals 0 if employment is at will (i.e. no cause of dismissal is normally permissible). Further gradations between 0 and 1 reflect changes in the strength of the law.
Reinstatement is normal remedy for unfair dismissal	Equals 1 if reinstatement is the normal remedy for unjust dismissal and is regularly enforced. Equals 0.67 if reinstatement and compensation are, de jure and da facto, alternative remedies. Equals 0.33 if compensation is the normal remedy. Equals 0 if no remedy is available as of right. Further gradations between 0 and 1 reflect changes in the strength of the law.
Notification of dismissal	Equals 1 if, by law or binding collective agreement, the employer has to obtain the permission of a state body or third party prior to an individual dismissal. Equals 0.67 if a state body or third party has to be notified prior to the dismissal. Equals 0.33 if the employer has to give the worker written reasons for the dismissal. Equals 0 if an oral statement of dismissal to the worker suffices. Further gradations between 0 and 1 reflect changes in the strength of the law.
Redundancy selection	Equals 1 if, by law or binding collective agreement, the employer must follow priority rules based on seniority, marital status, number or dependants, etc., prior to dismissing an employee for redundancy. Equals 0 otherwise. Gradations between 0 and 1 reflect changes in the strength of the law.
Priority in re-employment	Equals 1 if, by law or binding collective agreement, the employer must follow priority rules relating to the re-employment of former workers. Equals 0 otherwise. Gradations between 0 and 1 reflect changes in the strength of the law.

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Figure 1: Dismissal laws, GDP growth, and business cycle troughs.

The figure shows the strength of the "Regulation of Dismissal" (solid line) plotted against the rate of real GDP growth (dashed line) for a given country and year. The vertical dotted lines denote business cycle troughs. Higher values of the dismissal law index indicate more employment protection, i.e., stricter laws. The dismissal law index data is from Deakin et al. (2007). Data on GDP growth is from the Penn World Table. Country-specific business cycle data is from the Economic Cycle Research Institute (ECRI).

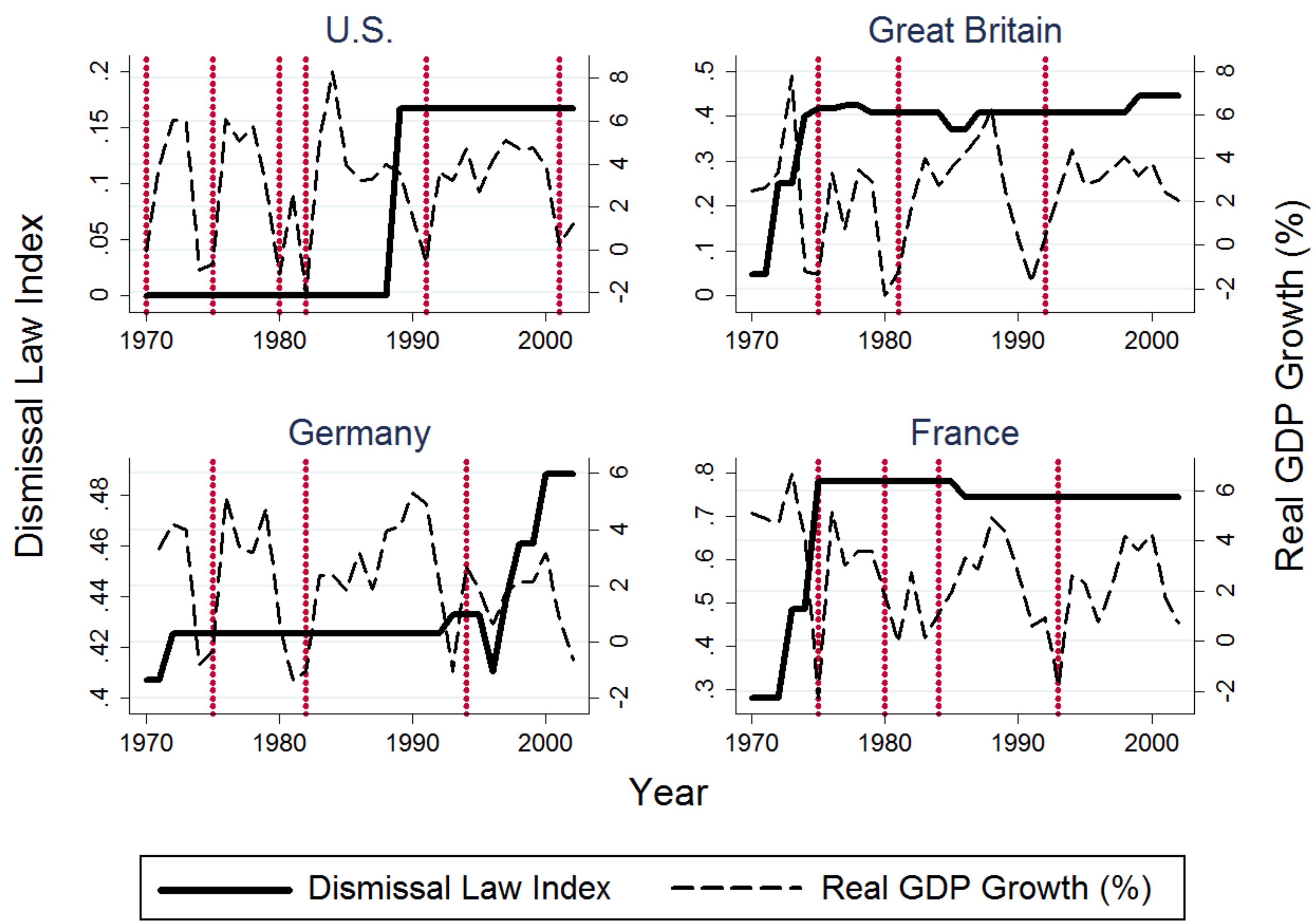

Figure 2: Innovation and dismissal laws: U.S. vs Germany.

This figure shows a plot across time of the *ratio* of the realized number of patents in a particular year to that in 1989, the year the U.S. WARN Act became effective. The continuous line shows the ratio for the U.S. while the discontinuous line shows the same for Germany. The index data is from Deakin et al. (2007).

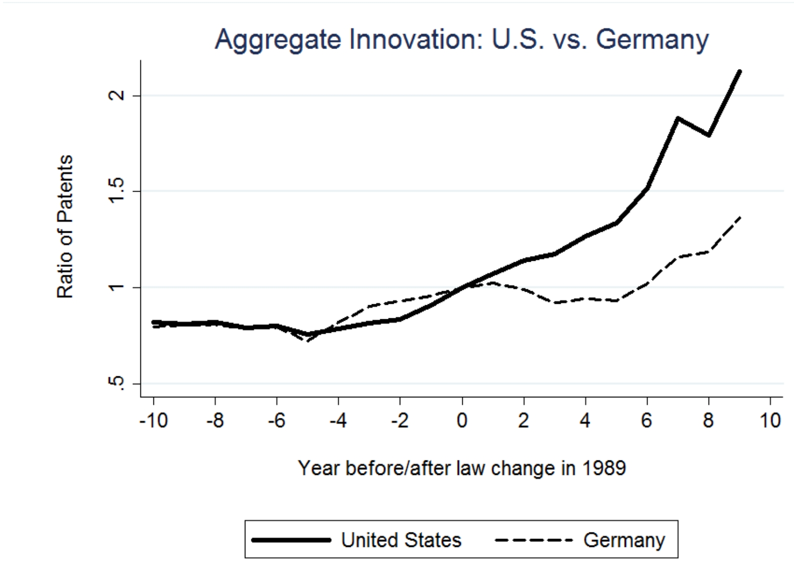

Table 1: Dismissal law changes - detailed description

This table shows the sub-components of the Deakin et al. (2007) dismissal law index and discusses the *changes* that the dismissal laws underwent in the respective countries and years. For more details see Deakin et al. (2007); cited passages are taken from the index description in the latter source.

Law	**F**rance	**G**ermany	**U**.K.	**U**.S.
Legally mandated notice period for all dismissals	No change	No change	No change	Before 1989, there was no notice period required. In 1989, the notice period was increased to 60 days
Legally mandated redundancy compensation	No change	No change	No change	No change
Minimum qualifying period of service for normal case of unjust dismissal	No change	No change	Before 1972, only workers with $\geq$ 3 years of service qualified for general protection against unjust dismissal. This qualification was progressively reduced to 2 years in 1972, to 1 year in 1974 and 6 months in 1975. Then, this qualification was progressively increased to 1 year in 1979 and to 2 years in 1985. However, it was brought back to 1 year in 1999.	No change
Law imposes procedural constraints on dismissal	Before 1973, there were no procedural constraints on dismissal. In 1973, this law was strengthened to "if the procedural requirements were not followed, the dismissal would be found to be unjust."	Before 2000, there were no procedural constraints on dismissal. Since 2000, dismissal has to be in writing, otherwise the dismissal is void. Failure to follow procedural requirements is one of the factors taken into account in determining whether the dismissal is unjust or not.	Before 1972, there were no procedural constraints on dismissal. In 1972, this law was strengthened to "failure to follow procedural requirement was one of the factors taken into account in determining whether the dismissal was unjust or not." In 1987, the law was further strengthened to "if the procedural requirements were not followed, the dismissal would be found to be unjust."	No change
Law imposes substantive constraints on dismissal	Before 1973, dismissal was permissible if it is 'just' or 'fair' as defined by case law. After 1973, dismissal is justified only in the case of serious misconduct or fault of the employee	No change	Before 1972, there were no substantive constraints on dismissal. After 1972, dismissal is justified only in the case of misconduct, lack of capability, redundancy, etc.	No change
	(continued)	*(continued)*	*(continued)*	*(continued)*

Table 1: *—continued*

Law	**F**rance	**G**ermany	**U**.K.	**U**.S.
Notification of dismissal	Before 1973, the law did not require the employer to notify the employee for dismissal. In 1973, the law was strengthened by requiring the employer to provide the employee written reasons for the dismissal. In 1975, the law was further strengthened by requiring the employer to obtain the permission of a state/local body prior to any individual dismissal. In 1986, the law was weakened; now the employer had to only notify the state/ local body prior to an individual dismissal (in contrast to requiring their permission earlier)	Before 1972, the law required the employer to provide the employee written reasons for the dismissal. In 1972, the law was strengthened by requiring the employer to notify the state/ local body prior to an individual dismissal	Before 1972, the law did not require the employer to notify the employee for dismissal. After 1972, the law requires the employer to provide the employee with written reasons for the dismissal	Before 1989, no notification of dismissal was required. In 1989, the law was strengthened to require notification to the state/ local body prior to mass dismissals in the case of firms with more than 100 full-time employees.
Redundancy selection	Before 1975, the law did not require the employer to follow any priority rules in dismissing an employee on grounds of redundancy. After 1975, the law requires the employer to follow priority rules based on seniority, marital status, number or dependants, etc., prior to dismissing an employee for reasons of redundancy.	No change	Before 1974, the law did not require the employer to follow any priority rules in dismissing an employee on grounds of redundancy. After 1974, the law requires the employer to follow priority rules based on seniority, marital status, number or dependants, etc., prior to dismissing an employee for reasons of redundancy	No change
Priority in re-employment	Before 1975, the law did not require the employer to follow any priority rules in re-employing a dismissed employee. After 1975, the law requires the employer to follow priority rules based on seniority, marital status, number or dependants, etc., when re-employing a dismissed employee.	Before 1997, the employer did not have to follow any priority rules in re-employing a dismissed employee. After 1997, the law required the employer to follow priority rules based on seniority when re-employing a dismissed employee.	No change	No change

Table 2: Summary statistics

This table shows summary statistics for the dependent variables employed in the empirical tests, as well as for the dismissal law index; summary statistics are reported separately for each sample country. For the country-level and industry-level tests, we report the number of observations, mean, median, standard deviation, minimum and maximum of the following variables: number of patents, number of citations, standard deviation of citations, and the dismissal law index; the data span the years 1970–2002 for the country-level sample, and the years 1978–2002 for the industry-level sample. For the firm-level sample, we report summary statistics for the ratio of R&D expenses to total assets, the ratio of capital expenditures to total assets, as well as the dismissal law index; the data span the years 1989–2006.
Patent data is from the NBER Patents File (Hall, Jaffe and Trajtenberg, 2001). The labor law index data is from Deakin et al. (2007). Firm-level data is from Compustat.

			United States				
Sample	*Variable*	*Obns.*	*Mean*	*Median*	*Std. Devn.*	*Min.*	*Max.*
Country-level	Number of patents	33	36409.300	30736	15421.220	647	72309
	Number of citations	33	259106.400	264072	116381.500	4	411595
	Standard deviation of citations	33	195.661	221.858	83.794	0.121	307.078
	Dismissal Law Index	33	0.071	0	0.084	0	0.167
Industry-level	Number of patents	9869	96.759	46	160.345	1	2879
	Number of citations	9869	664.485	223	1213.845	0	12116
	Standard deviation of citations	9470	18.756	9.669	27.781	0	319.853
	Dismissal Law Index	9869	0.093	0.167	0.083	0	0.167
Firm-level	CAPEX/Assets	107969	0.064	0.040	0.075	0	0.424
	R&D/Assets	109884	0.071	0	0.160	0	0.949
	Dismissal Law Index	118860	0.167	0.167	0	0.167	0.167
			United Kingdom				
Sample	*Variable*	*Obns.*	*Mean*	*Median*	*Std. Devn.*	*Min.*	*Max.*
Country-level	Number of patents	33	2239.182	2257	643.208	23	3468
	Number of citations	33	12200.970	14333	5578.060	0	17535
	Standard deviation of citations	33	45.479	52.854	24.394	0	84.478
	Dismissal Law Index	33	0.379	0.407	0.095	0.049	0.444
Industry-level	Number of patents	7330	7.548	4	13.174	1	286
	Number of citations	7330	38.348	15	70.408	0	1145
	Standard deviation of citations	5647	7.277	4.359	9.323	0	106.196
	Dismissal Law Index	7330	0.409	0.407	0.017	0.369	0.444
Firm-level	CAPEX/Assets	17534	0.060	0.040	0.068	0	0.424
	R&D/Assets	20118	0.021	0	0.082	0	0.949
	Dismissal Law Index	20161	0.419	0.407	0.018	0.407	0.444
			Germany				
Sample	*Variable*	*Obns.*	*Mean*	*Median*	*Std. Devn.*	*Min.*	*Max.*
Country-level	Number of patents	33	5950	5601	1889.322	83	9881
	Number of citations	33	26377.520	30457	12040.700	0	39107
	Standard deviation of citations	33	98.644	120.443	47.630	0	157.478
	Dismissal Law Index	33	0.433	0.425	0.021	0.407	0.488
Industry-level	Number of patents	8615	18.384	10	24.941	1	349
	Number of citations	8615	75.245	32	116.419	0	1313
	Standard deviation of citations	7616	9.248	5.378	12.483	0	174.062
	Dismissal Law Index	8615	0.434	0.425	0.019	0.411	0.488
Firm-level	CAPEX/Assets	5681	0.065	0.045	0.070	0	0.424
	R&D/Assets	8183	0.016	0	0.049	0	0.949
	Dismissal Law Index	8193	0.481	0.488	0.045	0.411	0.549
			France				
Sample	*Variable*	*Obns.*	*Mean*	*Median*	*Std. Devn.*	*Min.*	*Max.*
Country-level	Number of patents	33	2128.970	1841	787.877	17	3732
	Number of citations	33	9741.061	11354	4367.941	0	14649
	Standard deviation of citations	33	42.195	49.572	19.850	0	74.540
	Dismissal Law Index	33	0.700	0.746	0.151	0.281	0.782
Industry-level	Number of patents	7293	7.791	5	12.125	1	250
	Number of citations	7293	33.020	14	53.694	0	747
	Standard deviation of citations	5639	7.096	4	10.377	0	163.613
	Dismissal Law Index	7293	0.758	0.746	0.017	0.746	0.782
Firm-level	CAPEX/Assets	5868	0.056	0.039	0.060	0	0.424
	R&D/Assets	8159	0.010	0	0.043	0	0.949
	Dismissal Law Index	8218	0.746	0.746	0	0.746	0.746

Table 3: Country-level fixed effects panel regressions

The OLS regressions in the table below implement the following model:
$y_{ct} = \beta_c + \beta_t + \beta_1 * DismissalLaws_{c,t-l} + \beta X_{ct} + \varepsilon_{ct}$
where y_{ct} is the natural logarithm of a measure of innovation from country c in year t. β_c and β_t denote country and application year fixed effects, respectively. $DismissalLaws_{c,t-l}$ denotes the l^{th} lag of the dismissal law index for country c (from Deakin et al., 2007). X_{ct} denotes the set of control variables. The sample spans the years 1970–2002. Heteroskedasticity-consistent standard errors are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A

Dependent Variable is Nat. Logarithm of	(1) Number of Patents	(2) Number of Citations	(3) Std. Dev. of Citations	(4) Number of Patents	(5) Number of Citations	(6) Std. Dev. of Citations
Dismissal Law Index(t-1)	0.349**	0.430**	0.567**			
	(0.168)	(0.182)	(0.225)			
Dismissal Law Index(t-2)				0.335**	0.314*	0.393*
				(0.159)	(0.185)	(0.225)
Country and Year FE	X	X	X	X	X	X
Observations	128	128	128	124	124	124
Adjusted R-squared	0.992	0.993	0.971	0.992	0.993	0.971

Panel B

Dependent Variable is Nat. Logarithm of	(1) Number of Patents	(2) Number of Citations	(3) Std. Dev. of Citations	(4) Number of Patents	(5) Number of Citations	(6) Std. Dev. of Citations
Dismissal Law Index(t-1)	0.364**	0.453**	0.608***			
	(0.175)	(0.189)	(0.210)			
Dismissal Law Index(t-2)				0.353**	0.338*	0.447**
				(0.165)	(0.200)	(0.223)
Creditor Rights Index(t-1)	-0.020***	-0.034***	-0.051***	-0.021**	-0.034***	-0.051***
	(0.008)	(0.008)	(0.009)	(0.008)	(0.009)	(0.010)
Log of per capita GDP	-0.208	-0.392	-0.165	-0.130	-0.323	-0.075
	(0.436)	(0.897)	(0.904)	(0.452)	(0.942)	(0.951)
Country and Year FE	X	X	X	X	X	X
Observations	128	128	128	124	124	124
Adjusted R-squared	0.993	0.993	0.974	0.993	0.993	0.973

Table 4: Dynamic effects

The OLS regressions in the table below implement the following model:

$$y_{ct} = \beta_c + \beta_t + \sum_{k=0}^{6} \beta_k * DismissalLaws_{c,t+3-k} + \beta_7 * DismissalLaws_{c,t-6} + \beta X_{ct} + \varepsilon_{ct}$$

where y_{ct} is the natural logarithm of a measure of innovation from country c in year t. β_c and β_t denote country and application year fixed effects, respectively. $DismissalLaws_{c,t-l}$ denotes the l^{th} lag of the dismissal law index for country c (from Deakin et al., 2007). X_{ct} denotes the set of control variables. Heteroskedasticity-consistent standard errors are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable is Nat. Logarithm of	(1) Number of Patents	(2) Number of Citations	(3) Std. Dev. of Citations
Dismissal Law Index(t+3)	-0.684*	0.384	0.222
	(0.406)	(0.371)	(0.860)
Dismissal Law Index(t+2)	-0.114	0.038	0.303
	(0.458)	(0.464)	(0.894)
Dismissal Law Index(t+1)	0.435	0.676	0.857
	(0.387)	(0.509)	(0.631)
Dismissal Law Index(t)	0.244	-0.129	-0.333
	(0.308)	(0.592)	(0.736)
Dismissal Law Index(t-1)	1.188***	1.970***	2.027***
	(0.442)	(0.613)	(0.655)
Dismissal Law Index(t-2)	0.146	-0.291	-0.014
	(0.344)	(0.385)	(0.306)
Dismissal Law Index(t-3)	0.415*	0.611**	0.828***
	(0.234)	(0.258)	(0.288)
Dismissal Law Index(t-6)	-0.037	-0.014	-0.153
	(0.113)	(0.107)	(0.169)
Creditor Rights Index(t-1)	-0.024***	-0.034***	-0.038***
	(0.007)	(0.007)	(0.009)
Log of per capita GDP	-0.707**	-1.224***	-1.772***
	(0.281)	(0.364)	(0.561)
Country and Year FE	X	X	X
Observations	96	96	96
Adjusted R-squared	0.997	0.997	0.986

Table 5: Industry-level fixed effects panel regressions

The OLS regressions in the table below implement the following model:
$y_{ict} = t\beta_{j\leftarrow i} + t\beta_c + \beta_i + \beta_c + \beta_t + \beta_1 * DismissalLaws_{c,t-l} + \beta X_{ict} + \varepsilon_{ict}$ where y_{ict} is the natural logarithm of a measure of innovation for the USPTO patent class i from country c in year t. $t\beta_{j\leftarrow i}$ denotes a time trend for the industry (patent category) j to which patent class i belongs; $t\beta_c$ denotes a time trend for country c. $\beta_i, \beta_c, \beta_t$ denote patent class, country and application year fixed effects. X_{ict} denotes the set of control variables. The sample spans 1978–2002. Robust standard errors (clustered by country-year) are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable is Nat. Logarithm of	(1) Number of Patents	(2) Number of Citations	(3) Std. Dev. of Citations	(4) Number of Patents	(5) Number of Citations	(6) Std. Dev. of Citations
Dismissal Law Index(t-1)	1.981***	5.054***	1.213**			
	(0.375)	(1.378)	(0.467)			
Dismissal Law Index(t-2)				1.803***	4.063***	1.011**
				(0.465)	(1.489)	(0.452)
Creditor Rights Index(t-1)	-0.010*	-0.029*	-0.011	-0.014**	-0.034*	-0.013
	(0.006)	(0.018)	(0.007)	(0.007)	(0.020)	(0.008)
Log of per capita GDP	0.159	1.614	-0.493	-0.078	0.819	-0.695*
	(0.333)	(1.049)	(0.419)	(0.381)	(1.038)	(0.372)
Log(Imports)	0.004	0.022*	0.000	0.005	0.024*	0.001
	(0.007)	(0.012)	(0.009)	(0.007)	(0.012)	(0.009)
Log(Exports)	-0.053***	-0.072***	-0.042***	-0.054***	-0.073***	-0.042***
	(0.008)	(0.015)	(0.009)	(0.008)	(0.015)	(0.009)
Ratio of Value Added	1.955***	1.598	1.386**	1.811***	1.194	1.289**
	(0.644)	(1.018)	(0.636)	(0.659)	(1.091)	(0.646)
Patent Class, Country, Year FE	X	X	X	X	X	X
Patent Category and Country-Specific Trends	X	X	X	X	X	X
Observations	23,385	23,385	20,194	23,385	23,385	20,194
Adjusted R-squared	0.836	0.825	0.679	0.836	0.825	0.679

Table 6: Changes in governments and in dismissal laws

This table documents significant changes in the composition of government and changes in dismissal laws; the information is based on the Armingeon et al. (2008) government index and the Deakin et al. (2007) dismissal law index. In the column labeled *Government (index changes)*, changes in elected government are documented and how they correspond to changes in the government index. The index ranges from *1* to *5*, with *1* denoting a hegemony of right-wing (and center) parties, and *5* denoting a hegemony of social-democratic and other left parties. Not all changes in elected government result in changes in the balance of power between left- and right-leaning parties in a given country's parliament. The column labeled *Dismissal law (index changes)* documents the years of major dismissal law changes, along with the corresponding index magnitudes.
The government index is from the Comparative Political Data Set by Armingeon et al. (2008) (variable "govparty" in Armingeon et al., 2008). The labor law index data is from Deakin et al. (2007).

Country	Government (index changes)	Dismissal law (index changes)
U.S.	No index changes; index value is 1 throughout sample period	1989 (index changes from 0 to 0.17)
France	Election in 1973 (index changes from 1 in 1972 to 2 in 1974)	1973 (from 0.28 to 0.49)
		1975 (from 0.49 to 0.78)
	Election in 1978 (index changes from 2 in 1977 to 1 in 1979)	
	1981 (from 1 to 5)	
	1986 (from 5 to 1)	1986 (from 0.78 to 0.75)
	1988 (from 1 to 4)	
	1993 (from 4 to 1)	
	1997 (from 1 to 5)	
	2002 (from 5 to 1)	
Germany		1972 (from 0.41 to 0.43)
	1982 (from 3 to 1)	
		1996 (from 0.43 to 0.41)
		1997 (from 0.41 to 0.44)
	1998 (from 1 to 5)	1998 (from 0.44 to 0.46)
		2000 (from 0.46 to 0.49)
		2004 (from 0.49 to 0.55)
	2005 (from 5 to 3)	
U.K.	1970 (from 5 to 1)	
		1972 (from 0.05 to 0.25)
	1974 (from 1 to 5)	1974 (from 0.25 to 0.40)
		1975 (from 0.40 to 0.42)
	1979 (from 5 to 1)	1979 (from 0.42 to 0.41)
		1985 (from 0.41 to 0.37)
		1987 (from 0.37 to 0.41)
	1997 (from 1 to 5)	
		1999 (from 0.41 to 0.44)
		2004 (from 0.44 to 0.41)

Table 7: Tests addressing the potential endogeneity of dismissal laws

The OLS regressions in **Columns 1–3** implement the following model:
$y_{ct} = \beta_c + \beta_t + \beta_1 * DismissalLaws_{c,t-1} + \beta X_{ct} + \varepsilon_{ct}$
where y_{ct} is the natural logarithm of a measure of innovation from country c in year t. β_c and β_t denote country and application year fixed effects. $DismissalLaws_{c,t-1}$ denotes the 1^{st} lag of the dismissal law index for country c. X_{ct} denotes the control variables. The sample covers the years 1970–2002. Heteroskedasticity-consistent standard errors are reported in parentheses below the coefficients.
The OLS regressions in **Columns 4–6** implement the following model:
$y_{ict} = t\beta_{j\leftarrow i} + t\beta_c + \beta_i + \beta_c + \beta_t + \beta_1 * DismissalLaws_{c,t-1} + \beta X_{ict} + \varepsilon_{ict}$
where y_{ict} is the natural logarithm of a measure of innovation for the USPTO patent class i from country c in year t. $t\beta_{j\leftarrow i}$ denotes a time trend for the industry (patent category) j to which patent class i belongs; $t\beta_c$ denotes a time trend for country c. $\beta_i, \beta_c, \beta_t$ denote patent class, country and application year fixed effects. X_{ict} denotes the control variables. The sample covers the years 1978–2002. Robust standard errors (clustered by country-year) are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Sample:		Country-level			Industry-level	
Dependent Variable is Nat. Logarithm of	Number of Patents	Number of Citations	Std. Dev. of Citations	Number of Patents	Number of Citations	Std. Dev. of Citations
Dismissal Law Index(t-1)	0.444**	0.522**	0.598**	1.883***	4.656***	0.892**
	(0.180)	(0.250)	(0.272)	(0.346)	(1.248)	(0.373)
Creditor Rights Index(t-1)	-0.022***	-0.037***	-0.048***	-0.009*	-0.025	-0.006
	(0.008)	(0.011)	(0.013)	(0.006)	(0.017)	(0.007)
Log of per capita GDP	-0.082	-0.518	-0.518	0.066	1.267	-0.623
	(0.508)	(1.041)	(1.019)	(0.367)	(1.144)	(0.431)
Government	-0.011	-0.010	0.012	0.005	0.022	0.021***
	(0.011)	(0.022)	(0.024)	(0.005)	(0.016)	(0.006)
Real GDP Growth rate (%)	-0.007	0.008	0.016	0.001	0.001	-0.003
	(0.009)	(0.017)	(0.017)	(0.004)	(0.010)	(0.004)
Recession Dummy	-0.056	0.002	-0.077	-0.044**	-0.143**	-0.072***
	(0.050)	(0.107)	(0.104)	(0.022)	(0.060)	(0.020)
Log(Imports)				0.004	0.022*	0.000
				(0.007)	(0.012)	(0.009)
Log(Exports)				-0.053***	-0.072***	-0.042***
				(0.008)	(0.014)	(0.009)
Ratio of Value Added				1.990***	1.725*	1.468**
				(0.640)	(1.007)	(0.637)
Country and Year FE	X	X	X	X	X	X
Patent Class FE				X	X	X
Patent Category and Country-Specific Trends				X	X	X
Observations	128	128	128	23,385	23,385	20,194
Adjusted R-squared	0.993	0.993	0.974	0.836	0.826	0.680

Table 8:
Triple-difference tests controlling for all sources of omitted variables at the country level

The OLS regressions in **Panels A and B** below implement the following model:
$y_{ict} = \beta_{c,t} + t\beta_{j\leftarrow i} + \beta_i + \beta_1 \cdot \left(DismissalLaws_{c,t-1} * InnovationIntensity_{i,t}^{US}\right) + \beta_2 \cdot InnovationIntensity_{i,t}^{US} + \beta X_{ict} + \varepsilon_{ict}$
where y_{ict} is the natural logarithm of a measure of innovation for the USPTO patent class i from country c in year t. $t\beta_{j\leftarrow i}$ denotes a time trend for industry (patent category) j to which patent class i belongs; $\beta_{c,t}$ denotes country*year fixed effects. β_i denotes patent class fixed effects. $DismissalLaws_{c,t-1}$ denotes the index of laws governing dismissal in country c in year $(t-1)$. An industry's propensity to innovate ($InnovationIntensity_{i,t}^{US}$) is proxied with two alternative measures: in Panel A, we employ the average (over the years 1983–1993) number of R&D scientists and engineers per 1,000 employees in U.S. manufacturing companies for patent class i; this measure exhibits no time-series variation, so β_2 is not identified in Panel A. The second measure, employed in Panel B, is based on firm-level data for the U.S. and proxies innovation intensity as the lagged median of *R&D/Assets* per industry and year; this measure exhibits time-series variation, so β_2 is identified in Panel B. X_{ict} denotes the set of control variables.
The sample period is 1978–2002. Robust standard errors (clustered by country-year) are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A

	(1)	(2)	(3)	(4)	(5)	(6)
					excluding U.S.	
Dependent Variable is Nat. Logarithm of	Nb. of Patents	Nb. of Citations	SD. of Citations	Nb. of Patents	Nb. of Citations	SD. of Citations
Dismissal Law Index(t-1) * InnovationIntensity	0.010***	0.014***	0.004***	0.011***	0.017***	0.008***
	(0.001)	(0.002)	(0.002)	(0.002)	(0.004)	(0.003)
Log(Imports)	0.013	0.023	0.012	0.002	0.022	0.016
	(0.009)	(0.016)	(0.011)	(0.011)	(0.022)	(0.015)
Log(Exports)	-0.073***	-0.101***	-0.069***	-0.033**	-0.040*	-0.029**
	(0.011)	(0.019)	(0.012)	(0.013)	(0.023)	(0.014)
Ratio of Value Added	3.007***	3.523***	1.968***	3.768***	2.759*	0.574
	(0.673)	(1.069)	(0.712)	(0.941)	(1.429)	(0.956)
Country * Year FE	X	X	X	X	X	X
Patent Category Trends	X	X	X	X	X	X
Patent Class FE	X	X	X	X	X	X
Observations	14,631	14,631	12,363	10,465	10,465	8,341
Adjusted R-squared	0.813	0.806	0.638	0.674	0.681	0.528

Panel B

	(1)	(2)	(3)	(4)	(5)	(6)
					excluding U.S.	
Dependent Variable is Nat. Logarithm of	Nb. of Patents	Nb. of Citations	SD. of Citations	Nb. of Patents	Nb. of Citations	SD. of Citations
Dismissal Law Index(t-1) * InnovationIntensity	8.057***	12.616***	4.325**	13.622***	17.984***	6.863**
	(1.273)	(2.463)	(1.684)	(2.315)	(4.139)	(2.922)
InnovationIntensity	-5.441***	-3.052	1.193	-9.230***	-6.856**	-0.268
	(1.181)	(1.892)	(1.251)	(1.615)	(2.860)	(1.996)
Log(Imports)	0.008	0.017	0.008	-0.011	0.007	0.013
	(0.007)	(0.012)	(0.009)	(0.007)	(0.013)	(0.012)
Log(Exports)	-0.042***	-0.055***	-0.037***	-0.017*	-0.032**	-0.026***
	(0.007)	(0.012)	(0.008)	(0.009)	(0.015)	(0.010)
Ratio of Value Added	2.222***	2.843***	1.783***	3.401***	2.920**	1.090
	(0.612)	(0.940)	(0.615)	(0.818)	(1.211)	(0.799)
Country * Year FE	X	X	X	X	X	X
Patent Category Trends	X	X	X	X	X	X
Patent Class FE	X	X	X	X	X	X
Observations	20,355	20,355	17,435	14,539	14,539	11,793
Adjusted R-squared	0.830	0.824	0.664	0.705	0.710	0.562

Table 9: Triple-difference tests accounting for industry-level placebo effects

The OLS regressions below estimate the following regression model:
$Ln(y_{ict,\text{ firms}} - y_{ict,\text{ individuals}}) = t\beta_{j \leftarrow i} + t\beta_c + \beta_i + \beta_c + \beta_t + \beta_1 * DismissalLaws_{c,t-1} + \beta X_{ict} + \varepsilon_{ict}$
where $y_{ict,\text{ firms}}$ and $y_{ict,\text{ individuals}}$ represent measures of innovation by firms and individuals in a patent class i, country c, and year t, respectively. $t\beta_{j \leftarrow i}$ denotes a time trend for the industry (patent category) j to which patent class i belongs; $t\beta_c$ denotes a time trend for country c. $\beta_i, \beta_c, \beta_t$ denote patent class, country and application year fixed effects. X_{ict} denotes the control variables.
The sample period is 1978–2002. Robust standard errors (clustered by country-year) are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)
Dependent Variable is Nat. Logarithm of	Innovation by Firms - Innovation by Individuals	
	Number of Patents	Number of Citations
Dismissal Law Index(t-1)	0.824***	2.583***
	(0.226)	(0.824)
Creditor Rights Index(t-1)	-0.012**	-0.013
	(0.005)	(0.011)
Log of per capita GDP	-0.131	2.037***
	(0.243)	(0.704)
Log(Imports)	-0.011	-0.012
	(0.007)	(0.013)
Log(Exports)	-0.052***	-0.055***
	(0.009)	(0.015)
Ratio of Value Added	2.723***	3.243***
	(0.588)	(0.936)
Country and Year FE	X	X
Country-Specific Trends	X	X
Patent Category Trends	X	X
Patent Class FE	X	X
Observations	23,385	23,385
Adjusted R-squared	0.735	0.641

Table 10: Effect of dismissal laws vis-à-vis other dimensions of labor laws

The OLS regressions below implement the following model:
$y_{ict} = t\beta_{j \leftarrow i} + t\beta_c + \beta_i + \beta_c + \beta_t + \beta_1 * lA_{c,t-1} + \beta_2 * lB_{c,t-1} + \beta_3 * lC_{c,t-1} + \beta_4 * lD_{c,t-1} + \beta_5 * lE_{c,t-1} + \beta X_{ict} + \varepsilon_{ict}$
where y_{ict} is the natural logarithm of a measure of innovation for the USPTO patent class i from country c in year t. $t\beta_{j \leftarrow i}$ denotes a time trend for the industry (patent category) j to which patent class i belongs; $t\beta_c$ denotes a time trend for country c. $\beta_i, \beta_c, \beta_t$ denote patent class, country and application year fixed effects. β_1 - β_5 measure the impact on measures of innovation of the respective labor law for the five components of the Deakin et al. (2007) labor law index: Alternative employment contracts ($lA_{c,t-1}$), Regulation of working time ($lB_{c,t-1}$), Regulation of Dismissal / Dismissal Law Index ($lC_{c,t-1}$), Employee representation ($lD_{c,t-1}$), and Industrial action ($lE_{c,t-1}$). X_{ict} denotes the set of control variables. The sample period is 1978–2002. Robust standard errors (clustered by country-year) are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable is Nat. Logarithm of	(1) Number of Patents	(2) Number of Citations	(3) Std. Dev. of Citations
Dismissal Law Index(t-1)	2.030***	4.971***	1.204***
	(0.380)	(1.213)	(0.431)
Regulation of Working Time(t-1)	-0.264	2.228***	1.069***
	(0.276)	(0.786)	(0.305)
Alternative Employment Contracts(t-1)	-0.222*	0.048	0.049
	(0.125)	(0.322)	(0.149)
Employee Representation(t-1)	0.264	-2.708***	-1.126***
	(0.331)	(0.959)	(0.384)
Industrial Action(t-1)	0.327	1.262	0.051
	(0.427)	(1.368)	(0.406)
Creditor Rights Index(t-1)	-0.009	-0.037**	-0.014**
	(0.006)	(0.016)	(0.006)
Log of per capita GDP	0.248	1.711	-0.535
	(0.341)	(1.061)	(0.381)
Log(Imports)	0.004	0.016	-0.003
	(0.007)	(0.012)	(0.009)
Log(Exports)	-0.053***	-0.070***	-0.040***
	(0.008)	(0.014)	(0.009)
Ratio of Value Added	1.987***	1.958*	1.512**
	(0.643)	(1.009)	(0.647)
Patent Class, Country, Year FE	X	X	X
Patent Category and Country-Specific Trends	X	X	X
Observations	23,385	23,385	20,194
Adjusted R-squared	0.836	0.826	0.679

Table 11: Capital deepening?

The OLS regressions below implement the following model:
$y_{fct} = \beta_f + \beta_t + \beta_1 * lA_{c,t-1} + \beta_2 * lB_{c,t-1} + \beta_3 * lC_{c,t-1} + \beta_4 * lD_{c,t-1} + \beta_5 * lE_{c,t-1} + \beta X_{fct} + \varepsilon_{fct}$
where y_{fct} is the ratio of research and development expenses to assets (Columns 1 and 2) or the ratio of capital expenditures to assets (Columns 3 and 4), both measured at the firm level. β_f and β_t denote firm and year fixed effects, respectively. β_1 - β_5 measure the impact on investment of the respective labor law for the five components of the Deakin et al. (2007) labor law index: Alternative employment contracts ($lA_{c,t-1}$), Regulation of working time ($lB_{c,t-1}$), Regulation of Dismissal / Dismissal Law Index ($lC_{c,t-1}$), Employee representation ($lD_{c,t-1}$), and Industrial action ($lE_{c,t-1}$). X_{fct} denotes the set of control variables. The sample period is 1989–2006. Robust standard errors (clustered by country-year) are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
Dependent Variable is	R&D/Assets		CAPEX/Assets	
Dismissal Law Index(t-1)	0.006	-0.005	0.016	0.005
	(0.016)	(0.013)	(0.035)	(0.037)
Regulation of Working Time(t-1)		0.008		0.036*
		(0.015)		(0.020)
Alternative Employment Contracts(t-1)		0.024		-0.018
		(0.016)		(0.013)
Employee Representation(t-1)		0.026		-0.004
		(0.027)		(0.028)
Industrial Action(t-1)		-0.022		-0.018
		(0.021)		(0.025)
Creditor Rights Index(t-1)	0.001	0.002**	0.003	0.005**
	(0.001)	(0.001)	(0.002)	(0.002)
Log of per capita GDP	0.031	-0.022	0.090***	0.110***
	(0.029)	(0.020)	(0.025)	(0.039)
Debt/Assets	-0.005**	-0.005**	-0.001	-0.001
	(0.002)	(0.002)	(0.001)	(0.001)
RoA	-0.101***	-0.101***	-0.016***	-0.016***
	(0.005)	(0.005)	(0.002)	(0.002)
Market-to-Book	0.000	0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Ln(Market Equity)	-0.003***	-0.003***	0.007***	0.007***
	(0.001)	(0.001)	(0.001)	(0.001)
Firm and Year FE	X	X	X	X
Observations	110,908	110,908	105,221	105,221
Adjusted R-squared	0.734	0.734	0.504	0.504