Employee representation legislations and innovation: Evidence from manufacturing sectors

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Abstract

We analyse how sectoral innovation outcomes are affected by national legislations of worker participation to corporate governance. We develop a model of employee representation laws (ERL) and innovation in the presence of incomplete labour contracts and predict heterogeneous ERL effects across different systems of dismissal regulation. We then perform a panel regression analysis, exploiting panel data for five countries over the 1977-2005 period and 21 two-digit manufacturing sectors. We find that ERL effects on aggregate innovation output are positive, statistically significant and higher in magnitude where national labour laws impose significant firing costs to the firm with respect to institutional settings in which firing costs are low or absent. These results are robust to possible technology selection dynamics, endogeneity and institutional changes in the legal system of patent protection. We also estimate ERL effects on innovation conditional on firing costs at an industry level and show that the impact of ERL is relatively larger in those sectors where the human capital contribution to production is higher. Our results have relevant implications for the optimal design of employee representation legislations.

Keywords: employee representation law, hold-up, innovation, panel data.
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1 Introduction

In recent years, the relationship between labour law and innovation has been the focus of an increasing attention by empirical economists. Existing studies so far have examined this relationship looking at a complex bundle of legal norms commonly referred to as employment protection legislation (EPL), which mainly relates to dismissal restrictions and to the availability of temporary contracts. Among others, Acharya *et al.* (2013; 2014) show that country innovation outcomes are fostered by stringent laws governing dismissal of employees. Griffith and Macartney (2014) find that firms perform more incremental innovation in high-EPL countries.

In this literature the role played by the employee representation legislation (hereafter ERL), that is the sphere of labour law concerning the worker rights to participate in business management, has received very little attention (a notable exception is the study of Kraft *et al.* (2011), focused on the 1976 German Co-determination Act). The consequence is that policy concerns on the optimal design of employee representation regulation still wait for conclusive answers. The aim of this paper is to fill this gap.

Legislations of worker participation to corporate governance – by which a direct voice in management is given to the employee along with some control over the allocation of final returns – are institutional devices that contribute to shape the distribution of control rights among firm members. According to the ownership rights theory (Grossman and Hart, 1986; Hart and Moore, 1990), the allocation of ownership rights (i.e. the right to make residual management decisions and to claim the residual profits) is crucial to firm production activity, because it increases the incentives to invest by the owner whilst reducing those of the other investors who remain exposed to hold-up risks. Innovation productions, in particular, require two fundamental types of investors: employees, who provide human capital, and shareholders, who contribute with financial capital. Using an incomplete contract framework, Aghion and Tirole (1994) show that, when the financial capital is more important to the success of the innovation program than the human capital, the probability of a firm innovating increases if ownership rights are assigned to the shareholder; when the marginal efficiency of the working effort is relatively higher, then ownership rights should be allocated to the workers.

A legislation of employee participation in the firm governance can thus have an impact on innovation output of firms as far as it influences the relative abilities of workers and shareholders to appropriate larger shares of the ex-post surplus. However, in a world of incomplete contracts, ERL alone is not sufficient to define the distribution of control rights between the employee and the shareholder if the latter has an ultimate right to fire the worker without the worker having received his share of the innovation revenues. Phrased differently, if – once a successful innovation has been produced – the shareholder can renegotiate ex-ante agreements in order to extract undue rents at the expenses of the worker by threatening dismissal, stronger ERL is unlikely to spur innovative effort by employees. Incentive effects of ERL on innovation, on the contrary, will be significant only provided that the shareholder cannot threaten to fire the worker after the innovation revenues are realized, i.e. where labour law imposes sufficiently high (monetary or non-monetary) costs of exit on the side of the employer.

The main objective of this paper is to provide empirical evidence on these effects, by employing an index of ERL conditional on firing costs in a cross-country econometric model of innovation production. To motivate our empirical strategy we develop a simple theoretical model that incorporates both positive and negative effects of employee representation laws on innovation incentives for firms. On the one hand, legislations promoting worker participation to corporate governance force the shareholder to negotiate with the employees on revenue sharing, thereby increasing the employee incentive to exert innovative effort, as long as the shareholder is prevented from violating ex-ante agreements by dismissal laws. On the other hand, stronger ERL combined with stricter dismissal regulation should reduce the shareholder incentive to contribute financial capital to the firm. The model suggests that, if on average the working effort is relatively more important than the financial effort to the success of innovation processes, we should observe a positive relationship between ERL and innovation output under a strict regulation of dismissal. We see this basic relationship in the cross-country association between ERL and innovation activity in Figure 1. Figure 1 shows the number of yearly successful business patent applications per-capita of a group of five countries, over the 1977-2005 period, plotted against ERL, where country-year observations for which dismissal laws impose significant firing costs are distinguished from observations for which the dismissal regulation is relatively weaker. Countries that combine a strict ERL with high dismissal costs are shown to have a relatively larger number of patents per-capita.

[insert Figure 1 about here]

This aggregate picture may be masking many other effects. Exploiting panel data for five countries (USA, UK, India, France and Germany) over the 1977-2005 period and 21 two-digit manufacturing sectors, we show that this relationship is statistically robust to controlling for countries' innovative specialization heterogeneity, sectoral innovation time patterns, industry-specific time invariant unobservable factors and to the inclusion of *country* $\times$ *year* fixed effects, which absorb variation at the country-year level, possibly due to other institutional changes, to country-specific business cycles or to any other country-level variable that correlates with ERL. We also show that our estimates are not driven by technology selection effects nor by endogeneity of labour laws. Our results, furthermore, are shown to be unaffected by the legal change in the international system of patent protection due to the 1994 Trade-Related Aspects of Intellectual Property Rights (TRIPs) Agreement. We identify a positive and statistically significant effect of ERL on average industry-level innovation in countries where national labour laws impose significant firing costs to the firm.

Moreover, we estimate sector-specific ERL effects on innovation conditional on firing costs, by running a country-year panel regression sector-by-sector. We find that – consistently with our theoretical prediction – ERL effects are relatively larger in those sectors where the employee effort has a greater impact on innovation outcomes, proxied by the sectoral average of intangible assets per worker, the sectoral average years of schooling and an index of routineness of sectors measuring the importance of the worker ability of "making decisions and solving problems". We find that the estimated effect of our index of ERL conditional on high firing costs in the pharmaceuticals industry (where the intangible capital per worker, on average, is 112.13 thousand euros) is 29.78 times larger than that in the fabricated metals industry (where the intangible capital per worker is 13.76 thousand euros).

The contribution of this study is two-fold. First, we add to previous literature on labour laws and innovation (primarily Acharya *et al.* (2013; 2014) and Griffith and Macartney (2014)), providing the first attempt to measure the impact of employee representation legislations on technological innovation under different schemes of regulation of dismissal. Second, our results may complement very recent empirical research on the relationship between employee voice, hold-up and investments (among others, Card *et al.* (2014), Cardullo *et al.* (2015), Conti and Sulis (2015)). While available studies (in particular, Conti and Sulis (2015)) show that union power has a negative effect on physical investments which is larger in sectors where sunk physical capital intensity is higher, symmetrically we find that laws protecting employee voice tend to stimulate worker innovative effort relatively more in human capital intensive industries.

The remaining of the paper proceeds as follows: section 2 briefly describes how employee representation rights may be structured and implemented; section 3 summarizes existing studies that analyze the effects of labour laws - and ERL in particular - on innovation; section 4 presents a simple model of the relationship between ERL and innovation under different levels of firing costs; section 5 introduces the data used in empirical study and discusses the identification strategy; section 6 presents our estimation results, whose robustness is checked in section 7; section 8 concludes.

2 Structure and implementation of employee representation rights

The law governing employee representation rights concerns those institutional devices that shape the worker participation to the corporate governance. Generally, they are structured into three levels pertaining information, consultation and co-determination. Information rights relate to the employer duty to transmit data to employee representatives. Relevant information may include updates on significant financial and business events (e.g., yearly balance sheets, mergers and takeovers) or more general information on the progress of the company. Consultation rights imply a more significant involvement of workers, as they provide an opportunity for the employees to express an opinion on business matters, like significant changes to the company's business strategies and the introduction of new production technologies. Co-determination, finally, applies where the consent of the employees is a mandatory requirement for undertaking particular decisions. Co-determination rules provide workers with a direct role in the management of the company and may take different forms. In some countries, like the US and UK, the law does not provide for employee directors and no managerial role is given to employees. In some others, co-determination rules are stronger. In France, for instance, since the 1982 "lois Auroux", two members of the enterprise committee have the right to attend board meetings in private-sector companies, but without effective co-management powers. In Germany, co-determination has developed to a wider degree and the employees are given seats in a board of directors or in a supervisory board. According to the 1976 "MitbestG" law, in particular, the employees have the right to a 50% representation on the supervisory board in firms with at least 2000 employees.

Workers may implement their participation rights through two main types of representative organizations: trade unions and works councils. While trade unions are voluntary affiliations that represent the interests of their members and deal with the negotiation of collective labour agreements, works councils represent all employees in the company and generally have participation rights over operational issues at the company level. In both France and Germany the right to unionisation is protected by the Constitution. In Germany, however, employees are mainly represented by the works council ("Betriebsrat"), and the trade union density has been declining over the last decades (OECD, 2015). In the UK, the formation of trade unions is allowed and unions are considered as a matter of public interest, but many companies in which trade unions are absent do not have employee representation. In the US, differently, although the Constitution allows unions to be representatives of workers, the right to form trade unions is not recognised and trade unionism is not encouraged by the law.

The effective implementation of worker representation rights is also affected by the employer duties to bargain or to reach an agreement with unions, works councils or other organizations of employees. On this matter, again, significant differences emerge across national legislations, with Germany having no employer duty to bargain as such in its labour law (however, once collective agreements are reached, generally they are extended to third parties at the national or sectoral level), France having enacted a duty to bargain at workplace level in the 1982 "lois Auroux" (extension of sector-level collective agreements by legislation, moreover, is a practice of long standing in France, dating back to the law of 24.6.1936), and the UK and US laws supplying some employee legal duties to bargain, without providing for collective agreements extension to non-signatory workers or unions. Specifically, in the UK, the employer legal duty to recognise trade unions for the purposes of collective bargaining has been reintroduced from 2001 with the 1999 Employment Relations Act, while fair wages legislations providing for extension of collective agreements mostly ceased to have any effect from 1982. In the USA, employers have a duty to enter into collective bargaining with a certified bargaining agent under the National Labor Relations Act, but only a small percentage of the private sector workforce is currently affected by this obligation and no legal underpinning exists for agreement extension.

3 Previous literature

The empirical literature on the relationship between labour laws and innovation is rather scant. Two small bodies of study can be identified.

A first one (Kraft *et al.*, 2011; Acharya *et al.*, 2013) explicitly refers to employee representation legislations, providing contrasting evidence. In particular, Kraft *et al.* (2011) propose an empirical study focused on the German Co-determination Act of 1976 ("MitbestG"), introducing full parity of labour representation on the supervisory board. Specifically, they compare the patenting activity of 148 German manufacturing firms observed in the years 1971-1976, before the introduction of the co-determination law, with their innovation performance over the period 1981-1990, after the law became effective. Their panel regression results show that co-determination has no negative impact on innovativeness, while, if anything at all, a positive effect can be estimated. More generally, Acharya *et al.* (2013) have analysed the relationship bewteen innovation and a set of labour laws indexes covering the regulation of dismissal, industrial action and a measure of employee representation (which includes the workers' right to collective bargaining, board membership and unionization). They use the labour laws data provided by Deakin *et al.* (2007) and patent data from the USPTO. They analyze the labour laws indexes separately and find that only dismissal laws significantly stimulate employees to engage in more successful innovative pursuits, while employee representation legislations have no effect.

We depart from these studies in two ways. First, we aim at providing more general results than Kraft *et al.* (2011), by exploiting cross-sector country-year panel data and using an ERL index based on a set of legal variables that account for the diversity across systems in the mechanisms providing workers with participation rights. Different countries may indeed adopt different legal mechanisms (such as collective bargaining versus co-determination) to reach the same level of protection of labour interests. Second, unlike Acharya *et al.* (2013), we consider possible interactions between ERL and dismissal laws, by estimating the ERL impact on innovation conditional on firing costs. The connection between different aspects of labour laws may indeed be important to properly measure ERL effects.

A second group of studies (Griffith and Macartney, 2014; Acharya *et al.*, 2014) focuses on discharge laws. Griffith and Macartney (2014) use an overall index of EPL, which is a weighted sum of a set of sub-indicators for regular and temporary contracts and collective dismissals, and innovation data from a sample of around 2200 multinational firms that filed one or more patents in the years 1997 to 2003. They find that EPL does not discourage multinational firms from carrying out innovation activity and may in fact spur incremental patenting activity. They also find that multinational firms do locate radical patenting activity disproportionately in low-EPL countries. Acharya *et al.* (2014) exploit the staggered adoption of wrongful discharge laws (i.e. laws that protect employees against unjust dismissal) across US states in order to measure how these laws impact on firms' innovation performance and find that wrongful discharge laws do spur innovation and new firm creation. In both these last mentioned studies, representation laws are not analyzed.

It is worth mentioning that the empirical results of this second group of works partially contrasts with some previous theoretical works on dismissal costs and innovation, in particular Saint-Paul (2002) and Samaniego (2006). They posit some possible negative effects of more stringent dismissal laws and show, respectively, that higher firing costs stimulate improvements on existing (rather than new) products and that countries with high firing costs specialize in industries in which the rate of technical change is slower.

Finally, our analysis also adds to the long-standing literature on unionism, hold-up and quasi-rent sharing, which studies within-firm bargaining by considering the effect of union power and collective worker actions on the level of investment (Grout, 1984; Connolly *et al.*, 1986; Machin and Wadhwani, 1992; Denny and Nickell, 1992; Addison *et al.*, 2007; Card *et al.*, 2014; Cardullo *et al.*, 2015), including investments in firm-specific skills and training (Booth and Chatterji, 1998;

Acemoglu and Pischke, 1999). More generally, our results may contribute to the discussion on employment protection and productivity (e.g., Autor *et al.* (2007), MacLeod and Nakavachara (2007), Bird and Knopf (2009), Cingano *et al.* (2015) and Conti and Sulis (2015)). In particular, our sectoral estimates suggest that the extent to which employment legislations impact on productivity tends to depend on human capital intensity and that employee protection laws are likely to be more influential in more skill-intensive sectors.

4 Theoretical background

In this section, we motivate our empirical study by developing a simple theoretical model that incorporates both positive and negative effects of employee representation laws on innovation incentives for firms. The underpinnings of this model are based on Aghion and Tirole (1994). They analyze the basic contractual relationship between employees and a financier in an innovative firm. They posit that the exact nature of the innovation is ill-defined ex-ante and that the parties involved cannot contract for delivery of a specific innovation. Based on the allocation of property rights on any forthcoming innovation, Aghion and Tirole distinguish an integrated case, in which the financier owns and freely uses the innovation, from a non-integrated case, in which the employees own the innovation and, once the innovation is made, bargain with the financier over the license fee. The model of Aghion and Tirole shows that giving property rights to the employees is optimal when it is more important to encourage the employee's effort to discover than to boost the employer's financial investment in the research. In addition to this Grossman and Hart-like conclusion, we account for the possibility that negligible firing costs leave an hold-up power to the shareholder even if he does not own the innovation, and show that, in this case, any sharing rule contracted upon ex-ante is irrelevant.

A stylised firm is composed of a worker (w) and a shareholder-entrepreneur (s). Both the worker and the shareholder are concerned with the production of a technological innovation with a market value equal to Ψ (with $\Psi > 0$), which they split ex-post in a quota α to the worker and $1-\alpha$ to the shareholder (with $\alpha \in [0, \frac{1}{2}]$). If $\alpha = 0$, control rights are entirely allocated to the shareholder (shareholder-management case); if $\alpha = \frac{1}{2}$ control rights are jointly assigned to the shareholder and the worker (joint-management case). Both parties can contribute to the innovation process with, respectively, working effort ($\eta_w(\alpha, \tilde{\Psi}_w) \in [0, \overline{\eta}_w]$) and financial effort ($\varphi_s(\alpha, \tilde{\Psi}_s) \in [0, \overline{\varphi}_s]$), where $\tilde{\Psi}$ (with $\tilde{\Psi} > 0$) is the expected value of the innovation. The financial effort encompasses both the investment in physical assets and the finance of firm-specific training for the development of human capital. Let us assume that the worker and the shareholder have the same expectation on Ψ (i.e. $\tilde{\Psi}_w = \tilde{\Psi}_s = \tilde{\Psi}$). Both $\eta_w(\alpha, \tilde{\Psi})$ and $\varphi_s(\alpha, \tilde{\Psi})$ are strictly convex and increasing in the share of Ψ they expect to get at the end of the production process, i.e. respectively α and $1-\alpha$. The working effort is verifiable and contractible only up to the level $\underline{\eta}_w$ (with $\underline{\eta}_w > 0$), while effort exterted above $\underline{\eta}_w$ is not verifiable and so cannot be part of an explicit contractual agreement. The working effort has an upper limit $\overline{\eta}_w$, due to physical costraints. On the other hand, the financial effort of the shareholder is constrained between 0 and a level $\overline{\varphi}_s$ due to financial constraints. Assume further that φ_s is sunk and not contractible, i.e. the worker cannot force the shareholder to contribute finance to the firm, and that the worker cannot raise finance on the capital market. The success of the innovation process is uncertain and is described by the probability function $\varrho(\eta_w(\alpha, \tilde{\Psi}), \varphi_s(\alpha, \tilde{\Psi}))$, that is increasing in $\{\eta_w(\alpha, \tilde{\Psi}), \varphi_s(\alpha, \tilde{\Psi})\}$. Let us also assume that the technology has a separable form (this is not crucial for the argument) as follows: $\varrho(\eta_w(\alpha, \tilde{\Psi}), \varphi_s(\alpha, \tilde{\Psi})) = \zeta(\eta_w) \cdot \xi(\varphi_s)$, where $\zeta(\eta_w)$ and $\xi(\varphi_s)$ are functions relating innovation outcomes to working and financial efforts respectively. This latter property means that financial effort and worker effort are complementary.

As for the timing, we consider a three-period setting. In t_1, both the worker and the shareholder take their investment decisions. In t_2, the production process takes place. In t_3, the output is realized, the shareholder collects the revenues, pays the employee and gets the residual profits.[1]

In order to properly analyze the effects of different worker representation regimes, we need to examine separately the case in which dismissal laws impose significant (monetary and non-monetary) costs on firing decisions, therefore locking parties into a bilateral relationship until payoffs are paid, from the situation in which labour laws make employee dismissal costless for the shareholder, so that the latter can threaten to fire (i.e. hold-up) the worker after the output is produced without the worker having received his share of the innovation revenues.

Prohibitively costly firing.

Assume first that, having hired a worker, it is prohibitively costly to fire – i.e. to hold-up – him (we will specify the threshold level of firing costs more precisely later). In this environment, the investment decisions of both the worker and the shareholder and the probability of innovating depend crucially on the worker capability to stipulate ex-ante agreements with the shareholder upon sharing the innovation revenues.

Shareholder-management (SM) case. If no voice in management is given to the employee by ERL and therefore the employer entirely holds the control rights, then the shareholder retains all of the revenues ($\alpha = 0$). In this case, the worker has no incentive to exert any additional effort above $\underline{\eta}_w$ and gets a baseline fixed compensation ω_w (with $\underline{\eta}_w \leq \omega_w < \frac{1}{2}\tilde{\Psi}$), while the shareholder acts in order to solve the problem:

$$\max_{\varphi_s} \quad \pi_s = \varrho(\underline{\eta}_w, \varphi_s(\tilde{\Psi})) \cdot \tilde{\Psi} - \varphi_s - \omega_w \tag{1}$$

and chooses a level of financial effort equal to $\varphi_s^*(\tilde{\Psi})$. Final payoffs υ_w^{SM} and π_s^{SM} to, respectively,

[1]To keep things simple, we exclude the possibility of repeated games and do not consider reputational constraints.

worker and shareholder will be:

$$\upsilon_w^{SM} = \omega_w - \underline{\eta}_w \tag{2}$$

and

$$\pi_s^{SM} = \varrho(\underline{\eta}_w, \varphi_s^*(\tilde{\Psi})) \cdot \Psi - \varphi_s^*(\tilde{\Psi}) - \omega_w. \tag{3}$$

The probability of observing a successful innovation in this case is $\varrho(\underline{\eta}_w, \varphi_s^*(\tilde{\Psi}))$.

Joint-management (JM) case. Under a labour regulation scheme imposing joint-management, the two parties jointly hold profit rights over the innovation revenues. If ERL is strong enough as to give workers and shareholders the same bargaining power, a Nash equilibrium on revenue sharing leads to $\alpha = \frac{1}{2}$.

In this case, the worker will solve the problem:

$$\max_{\eta_w} \quad \upsilon_w = \frac{\varrho(\eta_w(\frac{1}{2}\tilde{\Psi}), \varphi_s(\frac{1}{2}\tilde{\Psi})) \cdot \tilde{\Psi}}{2} - \eta_w, \tag{4}$$

will choose a level of working effort equal to $\eta_w^{**}(\frac{1}{2}\tilde{\Psi})$ and will obtain a payoff equal to:

$$\upsilon_w^{JM} = \frac{\varrho(\eta_w^{**}(\frac{1}{2}\tilde{\Psi}), \varphi_s^{**}(\frac{1}{2}\tilde{\Psi})) \cdot \Psi}{2} - \eta_w^{**}(\frac{1}{2}\tilde{\Psi}) \tag{5}$$

where $\eta_w^{**}(\frac{1}{2}\tilde{\Psi}) > \underline{\eta}_w$.[2] On the other hand, the shareholder solves:

$$\max_{\varphi_s} \quad \pi_s = \frac{\varrho(\eta_w(\frac{1}{2}\tilde{\Psi}), \varphi_s(\frac{1}{2}\tilde{\Psi})) \cdot \tilde{\Psi}}{2} - \varphi_s, \tag{6}$$

[2] The extent to which $\eta_w^{**}(\frac{1}{2}\tilde{\Psi})$ is greater than $\underline{\eta}_w$ depends also on possible shirking (see, e.g., Bradely *et al.* (2016)).

chooses $\varphi_s^{**}(\frac{1}{2}\tilde{\Psi})$ and gets:

$$\pi_s^{JM} = \frac{\varrho(\eta_w^{**}(\frac{1}{2}\tilde{\Psi}), \varphi_s^{**}(\frac{1}{2}\tilde{\Psi})) \cdot \Psi}{2} - \varphi_s^{**}(\frac{1}{2}\tilde{\Psi}) \tag{7}$$

where $\varphi_s^{**}(\frac{1}{2}\tilde{\Psi}) < \varphi_s^{*}(\tilde{\Psi})$.

Here, the probability of observing a successful innovation is $\varrho(\eta_w^{**}(\frac{1}{2}\tilde{\Psi}), \varphi_s^{**}(\frac{1}{2}\tilde{\Psi}))$. The shareholder is prevented from violating the ex-ante agreement to the extent that firing costs χ are greater than $\varrho(\eta_w^{**}(\frac{1}{2}\tilde{\Psi}), \varphi_s^{\delta}(\tilde{\Psi})) \cdot \Psi - \varphi_s^{\delta}(\tilde{\Psi}) - \omega_w - \pi_s^{JM}$, where φ_s^{δ} is the shareholder's optimal level of financial effort under a hold-up strategy.[3]

Costless firing.

If the employee dismissal is costless for the shareholder (i.e. $\chi < \varrho(\eta_w^{**}(\frac{1}{2}\tilde{\Psi}), \varphi_s^{\delta}(\tilde{\Psi})) \cdot \Psi - \varphi_s^{\delta}(\tilde{\Psi}) - \omega_w - \pi_s^{JM}$), the latter can hold-up the worker after the output is produced, i.e. the shareholder can refuse to make payments above the contractible level ω_w and can retain all of the innovation revenues Ψ. In this environment, even if $\alpha > 0$, the worker has no incentive to exert any additional effort above $\underline{\eta}_w$, to the extent he anticipates the opportunistic behavior of the shareholder. The shareholder, on the other hand, will solve the problem:

$$\max_{\varphi_s} \quad \pi_s = \varrho(\underline{\eta}_w, \varphi_s(\tilde{\Psi})) \cdot \tilde{\Psi} - \varphi_s - \omega_w \tag{8}$$

and will choose a level of financial effort equal to $\varphi_s^{*}(\tilde{\Psi})$, giving rise to a probability of innovation

[3]If the shareholder chooses a hold-up strategy, he solves the problem:

$$\max_{\varphi_s} \quad \pi_s = \varrho(\eta_w(\frac{1}{2}\tilde{\Psi}), \varphi_s(\tilde{\Psi})) \cdot \tilde{\Psi} - \varphi_s - \omega_w - \chi,$$

exerts a financial effort equal to $\varphi_s^{\delta}(\tilde{\Psi})$ and obtains:

$$\pi_s^{\delta} = \varrho(\eta_w^{**}(\frac{1}{2}\tilde{\Psi}), \varphi_s^{\delta}(\tilde{\Psi})) \cdot \Psi - \varphi_s^{\delta}(\tilde{\Psi}) - \omega_w - \chi;$$

while, if he did not hold-up, he would have obtained π_s^{JM}. Therefore, hold-up is prevented if $\chi > \varrho(\eta_w^{**}(\frac{1}{2}\tilde{\Psi}), \varphi_s^{\delta}(\tilde{\Psi}))\cdot \Psi - \varphi_s^{\delta}(\tilde{\Psi}) - \omega_w - \pi_s^{JM}$.

equal to $\varrho(\underline{\eta}_w, \varphi_s^*(\tilde{\Psi}))$ (that is the same of the shareholder-management case under prohibitively costly firing).

We summarize these results in Table 1 (while alternative cases are discontinuous and well defined in the Table, they may partially overlap in reality).

[insert Table 1 about here]

To the extent that the explicit form of the two components of ϱ (i.e. $\zeta(\eta_w)$ and $\xi(\varphi_s)$) is unknown, it remains an empirical question as to whether the probability of innovation is relatively higher where $\alpha > 0$ and firing is prohibitively costly. The theoretical discussion only suggests that, under dismissal laws imposing costly firing, a binding worker participation regulation increases, on average, the probability of a firm's innovating when the working effort is relatively more important to the success of the innovation process than the financial effort, that is, formally, when $|\partial\zeta(\eta_w)/\partial\alpha| > |\partial\xi(\varphi_s)/\partial\alpha|$.

5 Empirical strategy

The purpose of our empirical study is to estimate the effect of employment representation legislations on innovation activity under different schemes of dismissal law. To this aim, we conduct our econometric investigation by means of a cross-country-industry panel regression analysis, in which a sectoral measure of innovation output is allowed to react to ERL changes. We next describe the data and then present the identification strategy and the model specification.

5.1 Data

5.1.1 Measuring labour laws

As for labour regulation, we use the labour laws data provided by Deakin *et al.* (2007). The data cover UK, USA, Germany, France and India for the period 1970-2005. Although only five countries are considered, they represent significant national economies as three of them are "parent" systems, one is the world's largest economy, and the other is the largest democracy. Deakin *et al.*'s legal coding is based one the "functional equivalents" concept. According to this approach, the relative importance of a given legal variable may differ across countries, while, on the other hand, different legal mechanisms (such as legal versus non-legal sources of norms) may play a functionally similar role in different systems. Consistently with the theory of functional equivalents, Deakin *et al.*'s data encompass several aspects of labour institutions, by taking into account both positive law and self-regulatory mechanisms, including collective agreements, which may achieve the same effect as a rule of law in certain countries. Moreover, these data take into account differences between formally binding or mandatory laws and default rules.

In particular, in our analysis, we employ an indicator of ERL which measures the strength of employee representation as proxied by a set of 7 sub-indicators covering the right to form trade unions, the right to collective bargaining, the employer's duty to bargain with unions, the extension of collective agreements to third parties at the national or sectoral level, the regulation of closed shops entrance, the workers' right to nominate board level directors, and the legal power of co-decision making given to works council. It is worth emphasizing that these participation rights, generally, do not cover the decision to fire workers. The overall ERL index is calculated as the average of these 7 sub-indicators and ranges from 0 (weakest regulation) to 1 (most stringent regulation). In our econometric analysis, we refer to the ERL index with $ERL_{c,t}$ at a country-year level, c being the country and t the year.

In order to measure ERL effects conditional on firing costs, we use also Deakin *et al.*'s index of regulation of dismissal (referred to as $DC_{c,t}$ in our empirical study), constructed by combining a set of variables on legally mandated notice period and redundancy compensation, minimum qualifying period of service for normal case of unjust dismissal, procedural constraints on dismissal, remedies for unjust dismissal, notification of dismissal, rules of redundancy selection and of priority in re-employment.

Moreover, as controls for the larger labour law environment, we also include in the regression analysis a set of three indicators, measuring, respectively, the regulation of alternative contracts ($AC_{c,t}$), the regulation of working time ($WT_{c,t}$) and the regulation of industrial action ($IA_{c,t}$), again obtained from Deakin *et al.* (2007).[4]

5.1.2 Measuring innovation

We measure economy-wide innovation outcomes at a country-sector level by means of the yearly number of successful patent applications (business enterprise sector) to the European Patent Office (EPO). Patent applications filed at the EPO are an attractive measure of innovative activity because they provide information with administrative nature under well-defined rules that are independent of the location of the patent applicant. Patent data, moreover, have been widely used by related studies (Kraft *et al.*, 2011; Acharya *et al.*, 2013, 2014; Griffith and Macartney, 2014).

EPO data are available for a large sample of countries and industries starting from 1977. In our empirical study, we match EPO data with Deakin *et al.*'s labour laws data and obtain a final sample of five countries (UK, USA, Germany, France and India) over the 1977-2005 period and 21 two-digit manufacturing sectors. Our final innovation outcome variable is the standardized per-capita number of yearly manufacturing business patent applications (i.e. the one-year difference

[4]See Table 7 and Table 8 in Appendix A for a detailed description of the variables.

of total patent levels) measured at a country-sector-year level and denoted by $I_{c,m,t}$, with c being the country, m the sector and t the year.[5]

In Table 2, we report basic descriptive statistics of the labour law and innovation indicators.

[insert Table 2 about here]

5.2 Identification

The key idea of our theoretical discussion is that ERL effects on innovation output are conditional on the level of firing costs. Thus, if the average innovation probability reacts more intensively to working effort than to the financial effort, the effect of ERL will be positive and significant only when firing costs are high. Under costless firing, the impact of ERL is expected to be low or insignificant. As the centerpiece of our identification strategy, this motivates the estimation of ERL effects by means of an explanatory variable that measures the strength of ERL conditionally on the level of the firing costs. Specifically, we first construct three dummy variables measuring alternative dismissal regulation regimes, according to $DC_{c,t} \gtreqless q_\tau$, where q_τ is τth quantile of the $DC_{c,t}$ distribution. In particular, we consider the following three dummies: $DC^{low}_{c,t-1}$ (dismissal costs are low or absent) which equals 0 if $DC_{c,t} > q_{25}$ and equals 1 if $DC_{c,t} \leq q_{25}$, $DC^{med}_{c,t-1}$ (dismissal costs are medium) which equals 0 if $DC_{c,t} \leq q_{25}$ or $DC_{c,t} > q_{75}$ and equals 1 if $q_{25} < DC_{c,t} \leq q_{75}$, and $DC^{high}_{c,t-1}$ (dismissal costs are high) which equals 0 if $DC_{c,t} \leq q_{75}$ and equals 1 if $DC_{c,t} > q_{75}$. Then we construct three variables measuring ERL conditional on dismissal costs – $ERL^{DC_{low}}_{c,t}$, $ERL^{DC_{med}}_{c,t}$ and $ERL^{DC_{high}}_{c,t}$ –, given by the product between our basic $ERL_{c,t}$ indicator and, respectively, $DC^{low}_{c,t-1}$, $DC^{med}_{c,t-1}$ and $DC^{high}_{c,t-1}$.

The three variables $ERL^{DC_{low}}_{c,t}$, $ERL^{DC_{med}}_{c,t}$ and $ERL^{DC_{high}}_{c,t}$ ($ERL^{DC_{low}}_{c,t}$ being the benchmark) will be employed as the main regressors of interest in our cross-country estimation analysis.

[5]See Table 10 in Appendix B for a description of the sectors considered in our empirical study.

A second issue we must deal with is the very large number of country-level variables that may affect innovation while being correlated with ERL, many of which are unlikely to be observable or measurable. Examples include country business cycles, firm demography, quality of physical and institutional infrastructures, higher education levels and capital market development. The presence of unobservable time-varying country-level omitted variables correlated with changes in ERL may be a source of endogeneity and may confound our results. To address this endogeneity concern, in some model specifications, we exploit the country-sector-year level variation of the data, so as to be able to include *country* $\times$ *year* fixed effects. These fixed effects absorb variation at the country-year level and allow us to account for sources of omitted variables for each country-year pair in our sample. While the country-sector-year level specification allows us to circumvent a source of possible endogeneity, it also introduces sectoral heterogeneity in the model. In our context, sectoral heterogeneity may be relevant to the extent that countries show a different propensity to innovate across sectors. As Acharya *et al.* (2014) show, indeed, labour laws may have a relatively larger impact on innovation in industries that exhibit a greater propensity to innovate (because, in such industries, incomplete contracting problems are relatively more intense). We takle this issue, by measuring the one-year lagged sectoral innovative specialization of countries ($S_{c,m,t-1}$) and interacting it with our one-year lagged $ERL_{c,t-1}^{DC_{low}}$, $ERL_{c,t-1}^{DC_{med}}$ and $ERL_{c,t-1}^{DC_{high}}$ variables. Specifically, $S_{c,m,t-1}$ is measured as the ratio between the country-sector-year innovation outcome and the total country-year innovation, as follows: $S_{c,m,t-1} = I_{c,m,t-1} / \sum_{m=1}^{M} I_{c,m,t-1}$, where $S_{c,m,t-1}$ indicates the sectoral specialization level for country c and sector m in the year $t-1$, with $m = 1, ..., M$ and M denoting the number of sectors, and where $I_{c,m,t-1}$ is the country innovation outcome at a sector-year level. All the explanatory variables are one-year lagged in order to avoid reverse causality. Note that, although the interaction of the ERL indicators with $S_{c,m,t-1}$, in the model specifications where it is included, allows us to specify the regression equation at a country-sector-year level so as to circumvent the possible omitted variable bias, it is however not compelling to obtain identification (through alternative empirical models, we will also show that the estimated ERL effects are not driven by the interaction with $S_{c,m,t-1}$).

Moreover, sectors may be characterized by industry-specific time invariant unobservable factors and by different time variant innovation patterns (possibly due to sector-specific technological shocks). We capture time variant sectoral innovation patterns by using a first-order autoregressive component, that is, $I_{c,m,t-1}$, and, finally, we introduce sectoral fixed effects in order to absorb time-constant sector-specific heterogeneity.

The final baseline regression model we implement is:

$$\begin{aligned} I_{c,m,t} = \beta_0 + \beta_1 \cdot ERL_{c,t-1}^{DC_{low}}[\cdot S_{c,m,t-1}] + \beta_2 \cdot ERL_{c,t-1}^{DC_{med}}[\cdot S_{c,m,t-1}] + \beta_3 \cdot ERL_{c,t-1}^{DC_{high}}[\cdot S_{c,m,t-1}]+ \\ +\beta_4 \cdot S_{c,m,t-1} + \beta_5 \cdot I_{c,m,t-1}[+\mathbf{b} \cdot \mathbf{X}_{c,t-1}] + \beta_c + \beta_m + \beta_t[+\beta_{c,t}] + \varepsilon_{c,m,t} \end{aligned} \tag{9}$$

where β_0 is the model constant, β_c, β_m, β_t and $\beta_{c,t}$ are country, sector, time and *country* $\times$ *year* fixed effects respectively, $\varepsilon_{c,m,t}$ are the residuals, and β_2 and β_3 ($ERL_{c,t-1}^{DC_{low}}$ being the benchmark) are the parameters of interest. $\mathbf{X}_{c,t-1}$ is a vector of covariates, including the basic (non-interacted) labour regulation indicators ($ERL_{c,t-1}$, $DC_{c,t-1}^{low}$, $DC_{c,t-1}^{med}$, $DC_{c,t-1}^{high}$), the labour regulation controls ($AC_{c,t-1}$, $WT_{c,t-1}$, $IA_{c,t-1}$) and, where it is required by the triple interaction nature of the model specification, the interactions between these indicators and $S_{c,m,t-1}$.

6 Econometric results

6.1 Basic results

Basic results are collected in Table 3. In column [1], we report the simplest version of the empirical model, in which both the original ERL and dismissal regulation indicators are included as separate regressors. Here, we obtain the baseline result of Acharya *et al.* (2013), who show that employee representation legislations do not have a statistically significant impact on innovation when their effects are studied independently of dismissal costs. In column [2], we introduce a simple interaction term between the two basic $ERL_{c,t-1}$ and $DC_{c,t-1}$ variables, and detect positive and statistically significant complementarities between ERL and dismissal regulation. In column [3], we study ERL effects under different levels of dismissal costs, by distinguishing weak, medium and stringent dismissal regulations, and find that ERL effects on innovation are positive and statistically significant only under relatively strict regulations of dismissal. In column [4], we employ our full country-sector-year version of the regression model, with the sectoral interaction terms and both $I_{c,m,t-1}$ and $S_{c,m,t-1}$, and confirm the statistical significance of ERL effects conditional on high firing costs also in the presence of *country* × *year* fixed effects. Since lags of the dependent variable may be correlated with the residuals in a standard FE model, in column [5] we implement a generalized method-of-moments (GMM) estimator in an Arellano-Bond estimation (Arellano and Bond, 1991), which uses moment conditions in which lags of the dependent variable and first differences of the exogenous variables are instruments for the first-differenced equation, and show that auto-correlation of patent outcomes, if present, does not drive our findings.[6]

Consistently with our theoretical background, we find that ERL effects are positive and statistically significant when firing costs are high. In particular, according to column [4] of Table 3, one-point increase in $ERL_{c,t-1}^{DC_{high}} \cdot S_{c,m,t-1}$ is associated to an increase in $I_{c,m,t}$ equal to 0.234 (and statistically significant at a 5% level) with respect to the benchmark ERL variable (which refers to the group of observations with $DC_{c,t-1} \leq q_{25}$). Following our theoretical framework, we interpret this result, arguing that – on average – an increased ERL under high firing costs stimulates workers' motivation to a greater extent than it reduces the financial and physical capital contribution to innovation programs, and that this effect is relatively larger in industries that

[6] An unreported Arellano-Bover/Blundell-Bond estimation, which uses moment conditions in which lagged first differences of the dependent variable are instruments for the level equation, produced results virtually similar to those obtained by using a standard Arellano-Bond estimator.

exhibit a greater share of patents within country.

In columns [4] and [5], moreover, we find that the two control variables $S_{c,m,t-1}$ (the sectoral specialization regressor) and $I_{c,m,t-1}$ (the first-order autoregressive term) both have a positive and statistically significant impact on innovation outcomes. Nonetheless, they do not significantly absorb the estimated impact of ERL effects.[7]

[insert Table 3 about here]

6.2 Cross-sector human capital heterogeneity

If our theoretical intuition is correct, we should also observe a relatively greater impact of ERL in those sectors where the human capital is relatively more important. This is what we try to investigate in this sub-section, by exploiting the industry-level dimension of the patent data and estimating sectoral ERL effects in the presence of high firing costs. In particular, we run a sector-level country-year panel regression version of model (9) sector-by-sector (here, the model being at a sectoral-level, we exclude interactions with $S_{c,m,t-1}$) and compare the sectoral coefficients of $ERL^{DC_{high}}_{c,t-1}$ with an industry-specific measure of the potential efficiency of the working effort. To this aim, we use three alternative proxies. First, the level of intangible assets per worker. By including the quality of management, information infrastructure, trade secrets, research and development and, more generally, a company's intellectual capital, intangible assets form the knowledge base of a firm and provide a measure of the human capital contribution to production (Battisti *et al.*, 2015). In particular, we consider the sectoral average of intangible capital per worker (in thousand of euro), calculated as the sectoral average of the ratio IK/L (with IK being

[7]In unreported estimations, we have also checked whether our results are driven by sectoral outlier values by means of a jackknife variance estimation procedure. The original sample is divided in M sub-samples, each of them excluding the observations of a different sector and where M is the number of sectors. The estimation of each model's parameter is computed M times, once for each sub-group. The final parameter estimates are then calculated as the average of the M parameters obtained in each regression round. The estimates from the jackknife procedure are substantially similar to those of our baseline model. The table of results is available upon request.

the firm-level amount of intangible assets and L the firm-level number of employees, both obtained from balance sheet data of a sample of 45168 firms from UK, USA, India, France and Germany included in the ORBIS database (Bureau van Dijk, 2013)). Second, we consider the sectoral level of average years of schooling in 1980 ($SchoolYears$), calculated by Ciccone and Papaioannou (2009) for the USA, properly re-classified in order to match our sectoral data. Third, we use the reverse of the Costinot *et al.* (2011)'s index of routineness of sectors ($LowRoutine$), originally calculated for the USA from the 2007 version of the Occupational Information Network database covering more than 200 occupational characteristics in about 800 tasks, which measures the importance of the worker ability of "making decisions and solving problems" at an industry level, re-classified in order to match our EPO patent data ($LowRoutine$ ranges from 0 to 1, with higher values indicating lower routineness and higher importance of worker decision-making).[8]

The main estimation results are collected in Table 4.[9]

[insert Table 4 about here]

We find that ERL effects are relatively larger in those sectors where the employee effort has a greater impact on innovation outcomes, as measured by means of the sectoral average of intangible assets per worker, the Ciccone and Papaioannou (2009)'s indicator of human capital intensity and the reverse Costinot *et al.* (2011)'s index of routineness of sectors. As an example, notice that the estimated effect of our index of ERL conditional on high firing costs in a human capital intensive industry such as the pharmaceuticals (where the intangible capital per worker is 112.13 thousand

[8]Sectoral heterogeneity as measured through proxies of human capital intensity does not necessarily overlap with the traditional distinction between incremental and radical innovation sectors. See Table 9 in Appendix A for a detailed description of these variables.

[9]Regressions are run for 18 manufacturing sectors separately, food and beverages, tobacco, and the group of other n.e.c. (not elsewhere classified) manufacturing activities being excluded, due to unclear matching between the Ciccone and Papaioannou (2009)'s measure of years of schooling, the Costinot *et al.* (2011)'s index of routineness and the EPO patent data. Notice that the variable $ERL_{c,t-1}^{DC_{high}}$ has the same distribution (mean and variance) across sectors, since it is measured at a country-year level; therefore, the corresponding coefficients obtained through separate sector-by-sector regressions can be compared.

euro) is 29.78 times the effect of the same variable in a physical capital intensive industry such as the fabricated metals (where the intangible capital per worker is only 13.76 thousand euro). For the sake of semplicity, in Figure 3 we plot sectoral ERL effects versus the two proxies of the sectoral importance of human capital. In all the three cases, it emerges a linear positive relationship, corresponding to a positive correlation coefficient statistically significant at a 1% level ($Corr$ (ERL coeffs., IK/L) = 0.789 [p-value = 0.000]; $Corr$ (ERL coeffs., $SchoolYears$)= 0.582 [p-value = 0.008]; $Corr$ (ERL coeffs., $LowRoutine$)= 0.606 [p-value = 0.007]).

[insert Figure 3 about here]

7 Robustness

7.1 Technology selection

It might be argued that the positive relationship between innovation outcomes and our index of ERL conditional on firing costs is spurious, to the extent that stronger ERL rules induce firms to substitute labour with capital by adopting more advanced capital-intensive technologies. If capital-intensive technologies are also more innovative, we may then observe a positive relationship between ERL and innovation, even if ERL has no direct impact on employees' motivation and working effort.[10]

In order to check whether such technology selection effect drives our findings, we run a modified version of our baseline model and estimate the impact of a ERL increase on innovation also controlling for physical capital deepening. We use two different measures of capital intensification: the ratio of gross fixed capital formation to value added (PK/VA) and the ratio of gross fixed capital formation to the number of employees (PK/L). Both measures are extracted from the

[10] The idea that labour regulations induce labour saving technical change is widespread in the literature. Among others, see Alesina *et al.* (2015) and Cingano *et al.* (2015).

STAN Database (OECD, 2015) and are provided as aggregate values at a sector-country-year level.[11]

The results of this robustness check are presented in column [6] of Table 5. Analogously to our basic estimation, we find that increases in ERL have a positive and statistically significant (at a 5% level) impact on innovation only when firing costs are high. Regression results from column [6] of Table 5 show this relationship controlling for possible technology selection effects as measured by PK/L and PK/VA respectively. Interestingly enough, while fixed capital formation per worker is associated to a statistically significant parameter, the fixed capital formation to value added ratio is uncorrelated with innovation.[12]

7.2 Endogeneity of labour laws

Account should also be taken of the extent to which labour laws may be implemented with the aim of affecting industrial performance and long-run firms' outcomes (such as innovation output), thus raising reverse causality concerns in our econometric analysis. While in our basic model specifications we use one-year lagged explanatory variables to circumvent possible reverse causality, here we further check the robustness of our findings by running an instrumental variable regression.

It is widely acknowledged that local political and institutional contexts are a main driver of labour law reforms (see, e.g., Botero *et al.* (2004) and Deakin *et al.* (2007)). This is documented by the modern comparative legal research (Roe, 2003) and the varieties of capitalism approach in the contemporary political science literature (Hall and Soskice, 2001). Accordingly, we use two instruments for our ERL variables: an index of governments' orientation with respect to economic policy and an index of institutional separation between ownership from control. Specifically,

[11]See Table 8 in Appendix A for a detailed description of these additional variables.

[12]Notice, however, that in the following robustness checks the sign of the coefficient of PK/L will show not to be robust.

following Botero *et al.* (2004) and Fiori *et al.* (2012), we measure the political determinants of labour law by means of an indicator (called PO, in our econometric study) computed as the interaction between two sub-indicators measuring a government's political orientation (from conservative to socialist) and the total vote share of all government parties, at a country- and year-level; both these sub-indicators are extracted from the Database of Political Institutions (Beck *et al.*, 2001). On the other hand, we measure the institutional drivers of labour legislations through an index (called SP, in our analysis) of shareholder protection against directors, managers and other shareholders, at a country- and year-level, provided by Lele and Siems (2007); as Roe (2003) argues, the evolution of the worker rights to voice has been deeply influenced by the evolution of corporate law.

We run a two-stage instrumental variable (IV) procedure, in which our ERL indicators conditional on firing costs are regressed on $PO_{c,t-2}$, $SP_{c,t-2}$ and the included instruments, in the first stage, while $I_{c,m,t}$ is regressed on the instrumented ERL variables and the full set of controls, including both $(PK/VA)_{c,m,t}$ and $(PK/L)_{c,m,t}$, in the second stage.

The IV results are presented in column [7] Table 5.[13] Reassuringly, our results remain substantially unchanged. We find that the instrumented indicator of ERL effects conditional on high dismissal laws is associated to a positive and statistically significant (at a 5% level) parameter in the II-stage regression (ERL effects conditional on low dismissal laws being the benchmark). We can thus conclude that endogeneity, if present, does not drive our findings.

7.3 The TRIPs Agreement and legal change in patent protection

An additional concern on the robustness of our econometric results might be due to the change in the international patent protection system following the 1994 Agreement on Trade-Related

[13]Note that $\widehat{ERL}_{c,t-1}^{DC_{low}}$ is the benchmark category in the II-stage equation and it does not need to be instrumented in the I-stage. Consequently, we end up with two endogenous variables and two excluded instruments in the I-stage regression and the model is identified.

Aspects of Intellectual Property Rights (TRIPs), signed by 128 countries (including USA, UK, India, France and Germany) within the Marrakesh Agreement establishing the World Trade Organization, that has strengthened the international legal protection of intellectual property rights.

A number of studies, beginning with Scotchmer (1991) and Green and Scotchmer (1995), have stressed the possible negative effects of stronger patent protection in industries characterized by cumulative or sequential technological progress. In particular, the larger scope of patent claims after the TRIPs may have increased contracting costs on sub-pieces of proprietary knowledge for industries with very complex technologies (Mazzoleni and Nelson, 1998) consistently with the "tragedy of anti-commons problem" highlighted by Heller and Eisenberg (1998). If this change in the international patent protection system has induced countries to innovate relatively less in bottom-up innovation activities and relatively more in top-down systems, then it may have also affected the relationship between sectoral innovation output and labour laws as far as different degrees of flexibility in labour regulation may be better at supporting innovation in different types of sectors. In our econometric model, we therefore need to control for the TRIPs Agreement, by including a TRIPs dummy variable (T_t, which equals 0 for $t \leq 1994$ and 1 for $t > 1994$) in our regression equation.

The results are presented in column [8] of Table 5. Again, our estimates are shown to be stable. Once the TRIPs dummy T_t is included, ERL effects are shown positive and statistically significant where dismissal regulations are stricter (the low firing costs group of observations being the benchmark).

[insert Table 5 about here]

7.4 Alternative modelling of cross-sector human capital heterogeneity

Finally, we have also checked whether our results are robust to a different modelling of the cross-sector human capital heterogeneity. We consider different versions of the baseline model (9), in which we interact the indicators of ERL conditional on firing costs with our proxies of the human capital contribution to innovation. A positive effect of these interaction terms (low firing costs environments being the benchmark) would indicate that an increase of ERL in those labour systems where dismissal regulations are relatively strict tends to have a stronger impact on innovation in more human capital intensive sectors and, therefore, that ERL effects conditional on high firing costs are disproportionately larger in industries where the marginal contribution of the working effort to production is higher. In order to control for possible mis-measurement of the human capital contribution to production, we measure human capital by using the sectoral average of the intangible assets to employees ratio ($(IK/L)_m$), obtained from elaboration of ORBIS firm-level data (Bureau van Dijk, 2013), the sectoral level of average years of schooling ($SchoolYears_m$), calculated by Ciccone and Papaioannou (2009), and the reverse of the Costinot *et al.* (2011)'s index of routineness of sectors, which measures the importance of the worker ability of "making decisions and solving problems" at an industry level ($LowRoutine_m$). Results are presented in Table 6.

[insert Table 6 about here]

In Table 6, we show estimates from our model specified at country-sector-year level, where both sectoral human capital proxies and $country \times year$ fixed effects are included. In particular, we interact our ERL variables with $(IK/L)_m$ in column [9], with $SchoolYears_m$ in column [10] and with $LowRoutine_m$ in column [11]. The parameter associated to ERL conditional on high dismissal costs is always positive, statistically significant and stable across model specifications, when the human capital is measured by means of $(IK/L)_m$ and when $SchoolYears_m$ and $LowRoutine_m$ are used.[14]

8 Conclusions

In this paper, we have analysed how innovation outcomes of countries are influenced by employee representation laws. We developed a model of ERL and innovation in the presence of incomplete labour contracts and predicted heterogenous effects across different systems of regulation of dismissal. We then performed a panel country-sector-year regression analysis, exploiting panel data for 21 two-digit manufacturing sectors in USA, UK, India, France and Germany over the 1977-2005 period. Although the variables' construction strategy does not allow us to measure the economic magnitude of the regression parameters, our estimates show a positive and statistically significant effect of ERL on average industry-level innovation in countries where national labour laws impose significant firing costs to the firm, so ruling out that an increase in ERL may depress aggregate patenting activity. Our results are suggestive and consistent with the Grossman-Hart-Moore–style model of Aghion and Tirole (1994).

We interpret our estimation findings, arguing that only where dismissal law is sufficiently stringent ERL effects can be expected to reduce hold-up risks for the employees and to stimulate innovative working effort. Crucial to this intepretation is the legal coding strategy of the ERL index used in the econometric study. This index measures the strength of the employee representation rights from zero (i.e. the firm is fully shareholder-controlled) to a level imposing a joint-management scheme to the corporation's governance. Labour-controlled corporate structures, with shareholders having no voice in management, are outside the scope of the coding.

[14] In unreported estimations, we also run a country-sector-year level version of the model excluding country-year FE and including both the ERL triple interactions with $SchoolYears_m$ and $LowRoutine_m$ and the simple interactions between $ERL_{c,t-1}$ and, respectively, $DC^{low}_{c,t-1}$, $DC^{med}_{c,t-1}$ and $DC^{high}_{c,t-1}$. We find that $ERL^{DC_{high}}_{c,t-1}$ has a positive and statistically significant effect on innovation both when interacted with $SchoolYears_m$ and $LowRoutine_m$ and when considered in isolation. This confirms that ERL effects are significant only provided that dismissal regulation is sufficiently strict and that such effects are not driven by the interaction with sector-level terms.

This implies that our estimates nothing say on the relative relevance of working and financial effort effects for labour-biased management shemes (i.e., according to the notation of the model of section 4, power sharing cases for which $\alpha > \frac{1}{2}$). Given (and, perhaps, thanks to) this limitation, we are able to detect a positive and statistically significant impact of ERL improvements in all the manufacturing sectors considered, with some differences in magnitude across industries. ERL effects are shown relatively larger in those sectors where the employee effort is likely to have a greater impact on innovation outcomes, measured by means of the sectoral average of intangible assets per worker, the Ciccone and Papaioannou (2009)'s index of human capital intensity and the reverse Costinot *et al.* (2011)'s index of routineness of sectors, which measures the importance of the worker ability of "making decisions and solving problems". In particular, we find that an increase in employee representation rights is expected to spur innovation in sectors like chemicals and pharmaceuticals to a larger extent than in the transports, motor vehicles and fabricated metal products industries.

Our findings have relevant implications for the optimal design of employee representation legislations. While previous empirical studies have examined only the relationship between innovation and more general measures of labour laws – commonly referred to as employment protection legislation – (Griffith and Macartney, 2014) or have focused on different aspects of labour laws separately (Acharya *et al.*, 2013, 2014) or on a single country's experience (Kraft *et al.*, 2011), our study permits a more thoughtful and general evaluation of the innovation effects of possibile complementarities between ERL and dismissal regulation. In light of the functional equivalents approach based on which the ERL data used in this paper are coded, our result leaves room for exploration and implementation of different policy strategies, consistently, in each country, with its own institutional pattern. Board membership codetermination, works councils' rights, the extension of collective agreements and the right to unionisation, among others, all are institutional devices for employee representation and participation at the governance level of the company.

There is, therefore, no best practice or solution that can be transplanted, as such, from a country into another. Rather, functional continuity can be obtained also through formally diverse systems of ERL.

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A Description of variables

[insert Table 7 about here]

[insert Table 8 about here]

[insert Table 9 about here]

B List of sectors considered in the empirical study

[insert Table 10 about here]

Table 1: Innovation probabilities under complementary labour laws.

	Shareholder-management (weak ERL, i.e. $\alpha = 0$)	Joint-management (strict ERL, i.e. $\alpha = \frac{1}{2}$)
Firing is prohibitively costly (strict dismissal regulation)	$\zeta(\underline{\eta}_w) \cdot \xi(\varphi_s^*(\tilde{\Psi}))$	$\zeta(\eta_w^{**}(\frac{1}{2}\tilde{\Psi})) \cdot \xi(\varphi_s^{**}(\frac{1}{2}\tilde{\Psi}))$
Firing is costless (weak dismissal regulation)	$\zeta(\underline{\eta}_w) \cdot \xi(\varphi_s^*(\tilde{\Psi}))$	$\zeta(\underline{\eta}_w) \cdot \xi(\varphi_s^*(\tilde{\Psi}))$

Table 2: Descriptive statistics of the main variables (1977-2005 averages).

	US	UK	DE	FR	IN
Deakin *et al.*'s (2007) ERL indicator	0.035	0.221	0.685	0.569	0.256
Deakin *et al.*'s (2007) dismissal law indicator	0.098	0.411	0.442	0.756	0.796
2-digit NACE	Per-capita number of yearly patents (per million inh.)				
10-11	1.741	1.810	3.146	1.829	0.004
12	0.114	0.140	0.236	0.090	0.001
13	0.273	0.255	0.697	0.328	0.001
14-15	0.116	0.136	0.393	0.233	0.000
16	0.046	0.071	0.206	0.093	0.000
17	0.709	0.684	1.651	0.796	0.001
18	0.215	0.201	0.389	0.207	0.001
19	1.409	1.217	3.104	1.434	0.002
20	11.960	11.093	27.388	12.461	0.022
21	9.997	8.315	13.872	7.680	0.032
22	1.183	1.459	3.986	2.044	0.001
23	1.117	1.127	3.198	1.533	0.001
24	1.330	1.379	4.097	1.986	0.001
25	1.298	1.766	5.611	2.692	0.001
26	10.441	9.047	18.900	11.281	0.007
27	2.521	2.587	7.667	3.917	0.001
28	13.332	12.724	33.499	16.692	0.008
29	6.726	7.178	23.626	11.101	0.003
30	1.738	1.926	5.446	2.940	0.001
31	4.038	0.781	2.482	1.633	0.001
32	3.411	2.115	4.038	2.202	0.001

Table 3: Basic results.

	[1]	[2]	[3]	[4]	[5] - GMM†
	DEP.VAR.: $I_{c,m,t}$	DEP.VAR.: $I_{c,m,t}$	DEP.VAR.: $I_{c,m,t}$	DEP.VAR.: $I_{c,m,t}$	DEP.VAR.: $I_{c,m,t}$
$ERL_{c,t-1}$	0.585 (0.518)	0.429 (0.375)			
$DC_{c,t-1}$	1.477* (0.648)	2.873*** (0.568)			
$ERL_{c,t-1} \cdot DC_{c,t-1}$		1.430** (0.440)			
$ERL_{c,t-1}^{DC_{low}}$			benchmark		
$ERL_{c,t-1}^{DC_{med}}$			-0.013 (0.058)		
$ERL_{c,t-1}^{DC_{high}}$			0.032*** (0.000)		
$ERL_{c,t-1}^{DC_{low}} \cdot S_{c,m,t-1}$				benchmark	benchmark
$ERL_{c,t-1}^{DC_{med}} \cdot S_{c,m,t-1}$				0.029 (0.153)	1.218** (0.476)
$ERL_{c,t-1}^{DC_{high}} \cdot S_{c,m,t-1}$				0.234** (0.110)	1.777** (0.814)
$S_{c,m,t-1}$			0.058 (0.146)	0.345** (0.141)	-1.398 (0.869)
$I_{c,m,t-1}$			0.944*** (0.015)	0.920*** (0.020)	0.938*** (0.011)
$\sum_{1}^{3} \mathbf{LabReg\_Controls}_{c,t-1}$	included	included	excluded	excluded	included
$\sum_{1}^{4} \mathbf{LabReg\_Indicators}_{c,t-1}$	excluded	excluded	included	excluded	included
$\sum_{1}^{4} \mathbf{LabReg\_Indicators}_{c,t-1} \cdot S_{c,m,t-1}$	excluded	excluded	excluded	included	included
$\sum_{1}^{3} \mathbf{LabReg\_Controls}_{c,t-1} \cdot S_{c,m,t-1}$	excluded	excluded	excluded	included	included
Constant	0.049 (0.120)	-0.593* (0.244)	0.065** (0.018)	0.383*** (0.082)	0.118*** (0.034)
Country FE	yes	yes	yes	no	no
Year FE	yes	yes	yes	no	no
Sector FE	yes	yes	yes	yes	no
Country-year FE	no	no	no	yes	no
F	2316.91	4876.89	4987.06	5846.27	(Wald $\chi 2$: 48368.21)
Prob > F	0.000	0.000	0.000	0.000	(Prob > $\chi 2$: 0.000)
N. of years	29	29	29	29	29
N. of countries	5	5	5	5	5
N. of sectors	21	21	21	21	21
N. of obs.	2940	2940	2940	2940	2835

Statistical significance: * =10%, ** =5%, *** =1%. Standard errors (in parenthesis) are heteroskedasticity robust. The vector $\mathbf{LabReg\_Indicators}_{c,t-1}$ includes $ERL_{c,t-1}$, $DC_{c,t-1}^{low}$, $DC_{c,t-1}^{med}$ and $DC_{c,t-1}^{high}$. The vector $\mathbf{LabReg\_Controls}_{c,t-1}$ includes $AC_{c,t-1}$, $WT_{c,t-1}$ and $IA_{c,t-1}$. †Arellano-Bond dynamic panel generalized method-of-moments (GMM) estimator.

Table 4: Sectoral effects.

	Coeff. of the var. of interest:					Coeff. of the var. of interest:			
Sector	$ERL_{c,t-1}^{DC_{high}}$	$[IK/L]$	$[SchoolYears]$	$[LowRoutine]$	Sector	$ERL_{c,t-1}^{DC_{high}}$	$[IK/L]$	$[SchoolYears]$	$[LowRoutine]$
NM	0.0008*** (0.000)	[73.388]	[11.655]	[0.530]	PL	0.0006*** (0.000)	[21.699]	[11.704]	[0.520]
TE	0.0009*** (0.000)	[4.487]	[10.397]	[0.490]	BM	0.0007*** (0.000)	[27.491]	[11.486]	[0.518]
WL	0.0003*** (0.000)	[9.378]	[10.196]	[0.464]	FM	0.0001*** (0.000)	[13.760]	[11.577]	[0.525]
WO	0.0006*** (0.000)	[7.607]	[10.787]	[0.560]	EO	0.0009*** (0.000)	[67.293]	[12.518]	[0.635]
PA	0.0008*** (0.000)	[19.507]	[11.693]	[0.647]	EL	0.0005*** (0.000)	[53.147]	[12.357]	[0.588]
PR	0.0025*** (0.000)	[63.792]	[12.792]	[n.a.]	MA	0.0007*** (0.000)	[14.599]	[12.266]	[0.568]
CP	0.0022*** (0.000)	[62.138]	[12.562]	[0.602]	MV	0.0004*** (0.000)	[24.874]	[12.346]	[0.523]
CH	0.0024*** (0.000)	[113.360]	[12.704]	[0.644]	OT	0.0002*** (0.000)	[30.916]	[12.346]	[0.540]
PH	0.0047*** (0.000)	[112.132]	[13.031]	[0.660]	FU	0.0002*** (0.000)	[7.006]	[10.760]	[0.547]

Legend: CH = chemicals, CP = coke and petroleum, PA = paper, PH = pharmaceuticals, PR = printing, TE = textile, WL = wearing and leather, WO = wood, BM = basic metals, CH = chemicals, EL = electrical products, FM = fabricated metals, FU = furniture, MA = machinery, MV = motor vehicles, NM = non-metallic minerals, OT = other transports, PL = plastic and rubber. Statistical significance: * =10%, ** =5%, *** =1%. Standard errors (in parenthesis) are heteroskedasticity robust. Parameters' estimates are obtained by running a sectoral version of model (9) sector-by-sector. Full estimation results are not reported for reasons of space but are available upon request. IK/L indicates the sectoral average of intangible capital per worker (in thousand of euro). IK/L values are calculated at a sectoral level from balance sheet data of a sample of 45168 firms from UK, USA, India, France and Germany included in the ORBIS database (Bureau van Dijk, 2013). The Ciccone and Papaioannou (2009)'s index of human capital ($SchoolYears$) is calculated as the sectoral level of average years of schooling in 1980 for the USA. The reverse Costinot *et al.* (2011)'s index of routineness of sectors ($LowRoutine_m$) is calculated for the USA from the 2007 version of the Occupational Information Network database and measures the importance of "making decisions and solving problems" (from 0 to 1; higher values of indicate lower routineness and higher importance of worker decision-making).

Table 5: Robustness checks: basic specifications.

	[6] Technology selection dep.var.: $I_{c,m,t}$		[7] Endogeneity dep.var.: $I_{c,m,t}$		[8] TRIPs legal change dep.var.: $I_{c,m,t}$
$ERL^{DC_{low}}_{c,t-1} \cdot S_{c,m,t-1}$	benchmark				benchmark
$ERL^{DC_{med}}_{c,t-1} \cdot S_{c,m,t-1}$	0.029 (0.153)				0.029 (0.153)
$ERL^{DC_{high}}_{c,t-1} \cdot S_{c,m,t-1}$	0.234** (0.110)				0.234** (0.110)
$\widehat{ERL}^{DC_{low}}_{c,t-1}$			benchmark		
$\widehat{ERL}^{DC_{med}}_{c,t-1}$			0.703 (0.538)		
$\widehat{ERL}^{DC_{high}}_{c,t-1}$			2.122** (1.051)		
$S_{c,m,t-1}$	0.345** (0.141)		0.015 (0.064)		0.345** (0.141)
$I_{c,m,t-1}$	0.920*** (0.020)		1.030*** (0.045)		0.920*** (0.020)
$(PK/VA)_{c,m,t}$	0.003 (0.006)		-0.636 (0.588)		0.004 (0.006)
$(PK/L)_{c,m,t}$	0.106*** (0.015)		-0.434** (0.204)		0.115*** (0.016)
T_t					-0.020 (0.019)
$\sum_1^3$ **LabReg_Controls**$_{c,t-1}$	excluded		included		excluded
$\sum_1^4$ **LabReg_Indicators**$_{c,t-1} \cdot S_{c,m,t-1}$	included		excluded		included
$\sum_1^3$ **LabReg_Controls**$_{c,t-1} \cdot S_{c,m,t-1}$	included		excluded		included
Constant	-0.033 (0.033)		-0.602 (0.682)		-0.023 (0.046)
		I-stage (a)		I-stage (b)	
Endogenous variable		$ERL^{DC_{med}}_{c,t-1}$		$ERL^{DC_{high}}_{c,t-1}$	
Excl. instrument: $PO_{c,t-2}$		-0.020*** (0.005)		0.009*** (0.002)	
Excl. instrument: $SP_{c,t-2}$		-0.002 (0.001)		-0.001*** (0.000)	
F (Prob > F)		2252.67 (0.000)		1293.53 (0.000)	
Full set of included instruments		included		included	
I-stage R2		0.980		0.966	
Overidentification test			eq. exactly identified		
Country FE	no		yes		no
Year FE	no		yes		no
Sector FE	yes		yes		yes
Country-year FE	yes		no		yes
F	5846.27		3228.62		5846-27
Prob > F	0.000		0.000		0.000
N. of years	29		29		29
N. of countries	5		5		5
N. of sectors	21		21		21
N. of obs.	2940		2835		2940

Statistical significance: * =10%, ** =5%, *** =1%. Standard errors (in parenthesis) are heteroskedasticity robust. The vector **LabReg_Indicators**$_{c,t-1}$ includes $ERL_{c,t-1}$, $DC^{low}_{c,t-1}$, $DC^{med}_{c,t-1}$ and $DC^{high}_{c,t-1}$. The vector **LabReg_Controls**$_{c,t-1}$ includes $AC_{c,t-1}$, $WT_{c,t-1}$ and $IA_{c,t-1}$.

Table 6: Robustness checks: sectoral heterogeneity.

	[9]	[10]	[11]
	DEP.VAR.: $I_{c,m,t}$	DEP.VAR.: $I_{c,m,t}$	DEP.VAR.: $I_{c,m,t}$
$ERL^{DC_{low}}_{c,t-1} \cdot (IK/L)_m$	benchmark		
$ERL^{DC_{med}}_{c,t-1} \cdot (IK/L)_m$	0.001 (0.001)		
$ERL^{DC_{high}}_{c,t-1} \cdot (IK/L)_m$	0.001* (0.000)		
$ERL^{DC_{low}}_{c,t-1} \cdot SchoolYears_m$		benchmark	
$ERL^{DC_{med}}_{c,t-1} \cdot SchoolYears_m$		0.001 (0.010)	
$ERL^{DC_{high}}_{c,t-1} \cdot SchoolYears_m$		0.018* (0.009)	
$ERL^{DC_{low}}_{c,t-1} \cdot LowRoutine_m$			benchmark
$ERL^{DC_{med}}_{c,t-1} \cdot LowRoutine_m$			0.091 (0.130)
$ERL^{DC_{high}}_{c,t-1} \cdot LowRoutine_m$			0.448*** (0.171)
$S_{c,m,t-1}$	0.170*** (0.047)	0.151*** (0.037)	0.135*** (0.038)
$I_{c,m,t-1}$	0.852*** (0.024)	0.918*** (0.020)	0.874*** (0.023)
$(PK/VA)_{c,m,t}$	-0.006 (0.010)	-0.000 (0.001)	-0.003 (0.008)
$(PK/L)_{c,m,t}$	-0.004 (0.008)	-0.000 (0.001)	-0.002 (0.006)
T_t	-0.174*** (0.040)	-0.139 (0.221)	-0.285** (0.144)
$\sum_1^3 \mathbf{LabReg\_Controls}_{c,t-1}$	excluded	excluded	excluded
$\sum_1^4 \mathbf{LabReg\_Indicators}_{c,t-1} \cdot (IK/L)_m$	included	excluded	excluded
$\sum_1^4 \mathbf{LabReg\_Indicators}_{c,t-1} \cdot SchoolYears_m$	excluded	included	excluded
$\sum_1^4 \mathbf{LabReg\_Indicators}_{c,t-1} \cdot LowRoutine_m$	excluded	excluded	included
$\sum_1^3 \mathbf{LabReg\_Controls}_{c,t-1} \cdot S_{c,m,t-1}$	included	included	included
Constant	0.061 (0.040)	0.149* (0.082)	0.170*** (0.062)
Country FE	no	no	no
Year FE	no	no	no
Sector FE	yes	yes	yes
Country-year FE	yes	yes	yes
F	5069.78	6052.30	5536.07
Prob > F	0.000	0.000	0.000
N. of years	29	29	29
N. of countries	5	5	5
N. of sectors	21	21	20
N. of obs.	2800	2940	2660

Statistical significance: * =10%, ** =5%, *** =1%. Standard errors (in parenthesis) are heteroskedasticity robust. The vector $\mathbf{LabReg\_Indicators}_{c,t-1}$ includes $ERL_{c,t-1}$, $DC^{low}_{c,t-1}$, $DC^{med}_{c,t-1}$ and $DC^{high}_{c,t-1}$. The vector $\mathbf{LabReg\_Controls}_{c,t-1}$ includes $AC_{c,t-1}$, $WT_{c,t-1}$ and $IA_{c,t-1}$.

Table 7: Basic variables' description.

Variable	Description	Source of the data
$ERL_{c,t}$	It measures the strength of employee representation, calculated as the average of 7 sub-indicators, each of them ranging from 0 (no protection) to 1 (max protection): [*i*] right to unionisation, [*ii*] right to collective bargaining, [*iii*] duty to bargain, [*iv*] extension of collective agreements, [*v*] closed shops, [*vi*] board membership, [*vii*] codetermination and consultation of workers. Standardized values.	Deakin *et al.* (2007)
$DC_{c,t}$	It measures the regulation of dismissal (i.e. dismissal costs), calculated as the average of 9 sub-indicators, each of them ranging from 0 (no protection) to 1 (max protection): [*i*] legally mandated notice period, [*ii*] legally mandated redundancy compensation, [*iii*] minimum qualifying period of service for normal case of unjust dismissal, [*iv*] law imposes procedural constraints on dismissal, [*v*] law imposes substantive constraints on dismissal, [*vi*] reinstatement normal remedy for unfair dismissal, [*vii*] notification of dismissal, [*viii*] redundancy selection, [*ix*] priority in re-employment. Standardized values.	Deakin *et al.* (2007)
$ERL_{c,t}^{DC_{low}}$	$ERL_{c,t} \cdot DC_{c,t-1}^{low}$, with $DC_{c,t-1}^{low} = 0$ if $DC_{c,t} > q_{25}$, $DC_{c,t-1}^{low} = 1$ if $DC_{c,t} \leq q_{25}$ (where q_{25} is the 25th quantile of $DC_{c,t}$)	Author's own calculation on Deakin *et al.*'s (2007) data
$ERL_{c,t}^{DC_{med}}$	$ERL_{c,t} \cdot DC_{c,t-1}^{med}$, with $DC_{c,t-1}^{med} = 0$ if $DC_{c,t} \leq q_{25}$ or $DC_{c,t} > q_{75}$, $DC_{c,t-1}^{med} = 1$ if $q_{25} < DC_{c,t} \leq q_{75}$ (where q_{25} and q_{75} are, respectively, the 25th and 75th quantiles of $DC_{c,t}$)	Author's own calculation on Deakin *et al.*'s (2007) data
$ERL_{c,t}^{DC_{high}}$	$ERL_{c,t} \cdot DC_{c,t-1}^{high}$, with $DC_{c,t-1}^{high} = 0$ if $DC_{c,t} \leq q_{75}$, $DC_{c,t-1}^{high} = 1$ if $DC_{c,t} > q_{75}$ (where q_{75} is the 75th quantiles of $DC_{c,t}$)	Author's own calculation on Deakin *et al.*'s (2007) data
$I_{c,m,t}$	Standardized per-capita (per million inh.) number of yearly successful patent applications filed at the EPO (business enterprise sector).	Eurostat (2014)
$S_{c,m,t-1}$	$S_{c,m,t-1} = I_{c,m,t-1} / \sum_{m=1}^{M} I_{c,m,t-1}$ (with $m = 1, ..., M$ and M denoting the number of sectors)	Author's own calculation on Eurostat's (2014) data

Table 8: Additional variables' description.

Variable	Description	Source of the data
$AC_{c,t}$	It measures the strength of the regulation of alternative contracts, calculated as the average of 8 sub-indicators, covering part-time, fixed time and agency contracts, each of them ranging from 0 (no protection) to 1 (max protection). Standardized values.	Deakin *et al.* (2007)
$WT_{c,t}$	It measures the strength of the regulation of working time, calculated as the average of 7 sub-indicators, covering weekly and daily working time, overtime working, annual leave and holidays, each of them ranging from 0 (no protection) to 1 (max protection). Standardized values.	Deakin *et al.* (2007)
$IA_{c,t}$	It measures the strength of the regulation of industrial action, calculated as the average of 9 sub-indicators, covering unofficial, political and secondary industrial action, industrial action rights, lockouts, compulsory conciliation and the replacement of striking workers, each of them ranging from 0 (no protection) to 1 (max protection). Standardized values.	Deakin *et al.* (2007)
$(PK/VA)_{c,m,t}$	Gross fixed capital formation to value added ratio. Standardized values.	OECD (2015)
$(PK/L)_{c,m,t}$	Gross fixed capital formation to the number of employees ratio. Standardized values.	Author's own calculation on OECD's (2015) data
$PO_{c,t}$	Government's political orientation (from -1, conservative, to 1, socialist) times the total vote share of all government parties.	Beck *et al.* (2001)
$SP_{c,t}$	It measures the strength of shareholder protection, calculated as the sum of 60 sub-indicators, each of them ranging from 0 (no protection) to 1 (max protection), covering protection against board and management (including powers of the general meeting, board composition rules and directors' duties) and protection against other shareholders (including cumulative voting, right to exit and oppressed minority norms).	Lele and Siems (2007)
T_t	Dummy variable. It equals 0 for $t \leq 1994$ and 1 for $t > 1994$.	Author's own coding

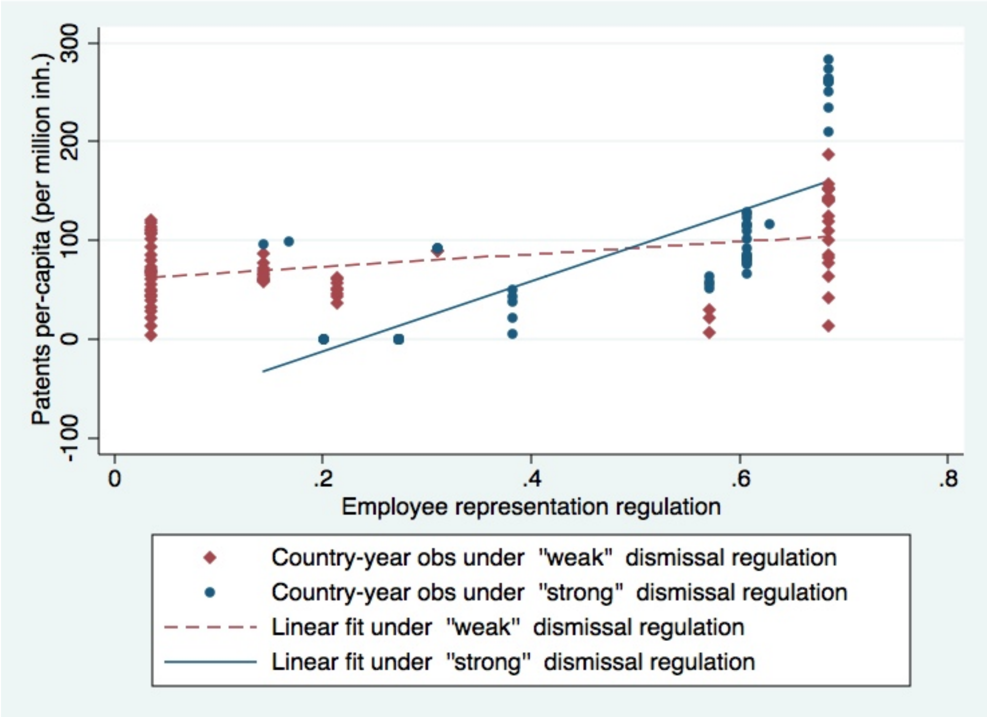
Table 9: Description of alternative proxies of the human capital contribution to innovation.

Variable	Description	Source of the data
$(IK/L)_m$	Sectoral average of intangible capital per worker (in thousand of euro), calculated as the sectoral average of the ratio IK/L (with IK being the firm-level amount of intangible assets and L the firm-level number of employees, both obtained from balance sheet data of a sample of 45168 firms from UK, USA, India, France and Germany included in the ORBIS database (Bureau van Dijk, 2013)).	Author's own calculation on balance sheet data of a sample of 45168 firms from UK, USA, India, France and Germany included in the ORBIS database (Bureau van Dijk, 2013)
$SchoolYears_m$	Sectoral level of average years of schooling in 1980 calculated for the USA, re-classified in order to match EPO patent data.	Ciccone and Papaioannou (2009)
$LowRoutine_m$	Reverse of the Costinot *et al.* (2011)'s index of routineness of sectors, originally calculated for the USA from the 2007 version of the Occupational Information Network database; it measures the importance of "making decisions and solving problems" (from 0 to 1; higher values of $LowRoutine_m$ indicate lower routineness and higher importance of worker decision-making), re-classified in order to match EPO patent data.	Costinot *et al.* (2011)

Table 10: Industry classification (manufacturing).

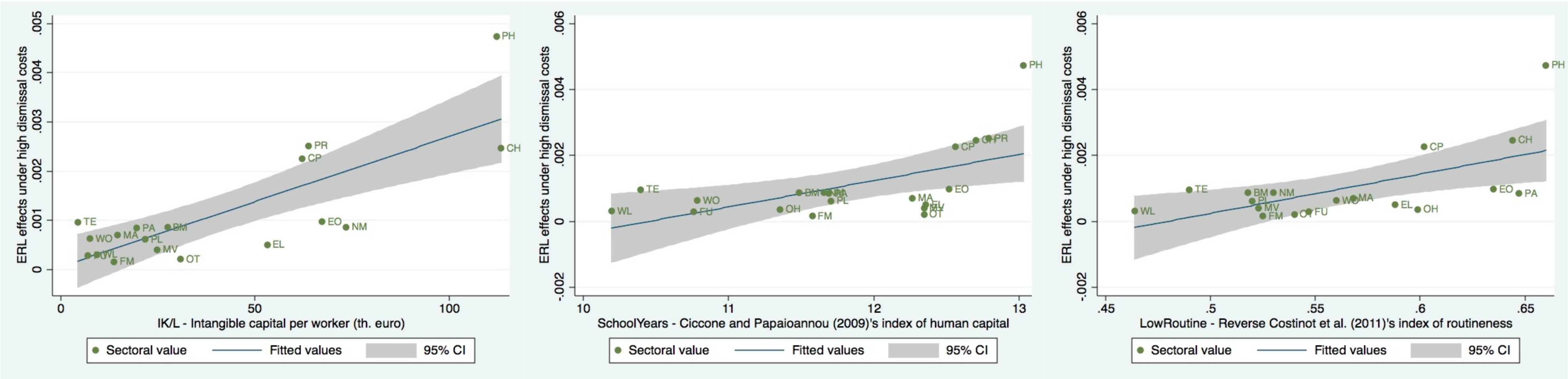
2-digit NACE	Description
10-11	Manufacture of food products and beverages
12	Manufacture of tobacco products
13	Manufacture of textiles
14-15	Manufacture of wearing apparel and manufacture of leather and related products
16	Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials
17	Manufacture of paper and paper products
18	Printing and reproduction of recorded media
19	Manufacture of coke and refined petroleum products
20	Manufacture of chemicals and chemical products
21	Manufacture of basic pharmaceutical products and pharmaceutical preparations
22	Manufacture of rubber and plastic products
23	Manufacture of other non-metallic mineral products
24	Manufacture of basic metals
25	Manufacture of fabricated metal products, except machinery and equipment
26	Manufacture of computer, electronic and optical products
27	Manufacture of electrical equipment
28	Manufacture of machinery and equipment n.e.c.
29	Manufacture of motor vehicles, trailers and semi-trailers
30	Manufacture of other transport equipment
31	Manufacture of furniture
32	Other manufacturing

Figure 1: Innovation and ERL under heterogeneous dismissal laws.



The graph shows the relationship between yearly manufacturing patents filed at the EPO and ERL for France, Germany, India, UK and USA, over the period 1977 to 2005. The x-axis shows the country-year ERL level. The y-axis shows for each country and year the number of patents per-capita (per million inhabitants). Country-year dismissal regulations are considered "weak" if the value of an index of regulation of dismissal is below the median of the sample, they are considered "strong" if the value of an index of regulation of dismissal is above the median of the sample. See section 5 for details of the data used.

Figure 2: Sectoral ERL effects versus sectoral human capital intensity.



Legend: BM = basic metals, CH = chemicals, CP = coke and petroleum, EL = electrical products, EO = electronic and optical, FM = fabricated metals, FU = furniture, MA = machinery, MV = motor vehicles, NM = non-metallic minerals, OT = other transports, PA = paper, PH = pharmaceuticals, PL = plastic and rubber, PR = printing, TE = textile, WL = wearing and leather, WO = wood. ERL parameters' estimates (reported in the Figure and listed in Table 4) are obtained by running a sectoral version of model (9) sector-by-sector and are statistically significant at a 1% level. IK/L values are calculated at a sectoral level from balance sheet data of a sample of 45168 firms from UK, USA, India, France and Germany included in the ORBIS database (Bureau van Dijk, 2013). The Ciccone and Papaioannou (2009)'s index of human capital ($SchoolYears$) is calculated as the sectoral level of average years of schooling in 1980 for the USA. The reverse Costinot *et al.* (2011)'s index of routineness of sectors ($LowRoutine_m$) is calculated for the USA from the 2007 version of the Occupational Information Network database and measures the importance of "making decisions and solving problems" (from 0 to 1; higher values of indicate lower routineness and higher importance of worker decision-making). *Corr* (ERL coeffs., IK/L) = 0.789 [p-value = 0.000]; *Corr* (ERL coeffs., $SchoolYears$)= 0.582 [p-value = 0.008]; *Corr* (ERL coeffs., $LowRoutine$)= 0.606 [p-value = 0.007].