Employment Protection Legislation, Multinational Firms and Innovation

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Abstract

The theoretical effects of labour regulations, such as employment protection legislation (EPL), on innovation is ambiguous. EPL increases job security, and the greater enforceability of job contracts may increase worker investment in innovative activity. On the other hand EPL increases adjustment costs faced by firms, and this may lead to under-investment in activities that are likely to require adjustment, including technologically advanced innovation. In this paper we find empirical evidence that these effects are at work, in particular a higher share of multinational enterprises innovative activity in countries with high EPL is technologically advanced.

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1 Introduction

Employment protection legislation (EPL) has been a focus of policy concern in the European Union. There is considerable evidence that this type of labour market rigidity is associated with lower worker flows and higher unemployment.[1] More recently attention has focused on the impact of labour regulations on the incentives for firms to invest in productivity enhancing innovation and growth, with a number of papers pointing to a negative effect.[2] However, here the relationship is less clear. Theory suggests that there will be two effects of EPL. First, EPL introduces a firing cost to any adjustment to employment made by the firm. Second, this adjustment cost increases job security for existing workers as it reduces the probability of being fired in response to small fluctuations in demand. Efficiency wage arguments suggest that this increases the value of employment for the worker and increases their (unobservable) effort, which in turn can increase the return to innovation for the firm.[3] On the other hand, where innovation is radically new and requires new skills, and thus a drastic adjustment to employment, EPL may increase the cost of such innovation. Existing models of radical innovation suggest that countries with low EPL have a comparative advantage in radical innovation.[4]

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[1] See, inter alia, Lazear (1990), Blanchard and Wolfers (2000), Nickell, Nunziata and Ochel (2005), and Griffith, Harrison and Macartney (2007).
[2] See, inter alia, Autor et al (2007), Bassanini et al (2009), and Cingano (2010).
[3] See Shapiro and Stiglitz (1984) for the efficiency wage set-up and Boeri and Jimeno (2005) for an application to EPL. Although not its central point, workers invest more in general training in the presence of search frictions in the labour market when they are less likely to be fired by their present employer in Acemoglu (1997). See also Akerloff (1982), Agell (1999) and Chapter 10 of Saint-Paul (1996) for the positive effects of EPL.
[4] See Saint-Paul (1997, 2002) and Samaniego (2006). Also Cunat and Melitz (2007) provide theoretical and empirical evidence that countries with flexible labour markets have a comparative advantage in industries with high demand volatility. Caballero et al. (2004) provide theoretical and empirical evidence that countries with strong EPL are slow to adjust employment, and that this is associated with low productivity growth. Also, Bartelsman et al. (2008).

The main contribution of this paper is to provide empirical evidence on these effects. To motivate our empirical strategy we develop a model that incorporates both positive and negative effects of EPL on innovation incentives for firms. We distinguish between innovations that are near to the science base, and thus more radical in nature, and incremental innovation: radical innovation is potentially more profitable than incremental innovation, but requires a large and drastic employment adjustment, because workers with new skills are needed to implement the innovation (as in Chapter 8 of Aghion-Howitt 1998). EPL increases this cost of adjustment, but it also has positive effects on both types of innovation by increasing workers' effort to further increase the productivity of innovations. The model suggest that, for plausible parameter values, the optimal level of investment in radical innovation decreases with EPL but that the optimal level of investment in incremental innovation increases with EPL.

The paper is related to several literatures. It is directly related to the growing literature on the effects of labour market regulations on productivity and by extension to the papers on cross-country patterns of specialization and national institutions.[5] There is a related literature on the product life-cycle that distinguishes between new product innovation and mature product innovation, where demand is more certain for the latter.[6] It also relates to the endogenous growth literature and the model presented builds heavily on the framework of Aghion-Howitt, where the distinction between radical and incremental innovation is through the employment adjustment that is

[5] In addition to the references in footnote 2 see Nunn (2007), Carlin (2003).
[6] See, inter alia, Klepper (1996) and Breschi et al. (2000), Audretsch (1995), Puga and Trefler (2005), and Saint-Paul (1997, 2002).

required to implement radical innovation.[7] Our paper is also related to the literature on the location of activity by multinational firms. [8]

There is an existing empirical literature on the relationship between labour regulations and productivity and innovation. The recent literature, including Bassanini et al (2009) and Cingano et al (2010), use a difference-in-difference identification strategy and compare the impact of EPL in industries that have a greater tendency to adjust on the external market (measured by US dismissal or job market turnover rates) to those that adjust less. We show results using a similar estimation strategy.[9] Other papers are based mainly on cross-country evidence, with studies finding divergent results.[10] Such studies struggle to deal with two key identification problems. One is that the effect of EPL may depend on the *nature* of innovation, and in most data it is difficult to distinguish between incremental and radical innovation. The other is that in the cross-section labour regulations may be correlated with unobservable characteristics of countries, industries and firms that determine innovation. We deal with the first challenge by using an intuitively appealing measure of radical innovation: the

[7] This is in contrast to the distinction that radical innovation is less likely to succeed than incremental innovation that is made in Saint-Paul (1997, 2002) and Bartelsman et al. (2008). We argue that modelling radical innovation as requiring adjustment to employment is appropriate for our sample of large incumbent firms, whereas modelling radical innovation as more risky with high firing costs arising in the event of failure seemed more appropriate for small firms and considerations of firm entry and exit. If radical innovation were more risky and the cost of failure (exit) increased with EPL then this would enhance our predictions.

[8] See, inter alia, Dunning (1977), Caves(1996), Ekholm and Hakkala (2007), Devereux and Griffith (1998). Haaland and Wooton (2003) show that multi-national enterprises will locate high risk projects in countries with low redundancy costs in the presence of industry or economy wide wage bargaining, and when the risk profile of the MNE is different to that of domestic firms.

[9] We are thankful to an anonymous referee for pointing us to this literature.

[10] Both Storm and Nastepaad (2007) and Buchele and Christiansen (1999) find that high EPL is associated with greater productivity growth. Bassanini and Ernst (2002) find that EPL has a negative effect in less coordinated countries, in higher coordinated countries workers and firms can align their interests better**.** Similarly, Scarpetta and Tressel (2004) find a significant impact of EPL on multi-factor productivity growth when interacted with bargaining coordination, but no linear result. Hall and Soskice (2001) argue that differences in specialisation between Germany and the US are due to the more market orientated financial and labour market institutions in the US. Acharya et al. (2009) find that strong labor laws encourage innovation. Akkermans et al. (2005) support the view that liberal market economies specialise in radical innovation.

proportion of citations on a patent application made to scientific journals (as opposed to other patents). We show that patents that are closer to the scientific literature are associated with more variability in output and employment. We tackle the second challenge by basing our results on an identification strategy that uses variation *within* multinational firms from 12 countries on where they locate different innovative activities. The advantage of this identification strategy is that it controls for unobservable characteristics of the home country, industry and firm that affect the innovation decision. The key assumption of this strategy is that those characteristics dissipate throughout the multinational and that the inherent propensity for a subsidiary to innovate, due to corporate culture or manager motivation, is determined by the multinational firm to which it belongs, rather than the country in which it innovates. It follows from this identification assumption that the regulatory environment in the country where the subsidiary is located has an exogenous effect on its innovation activity. The strength of our strategy over other more aggregate cross-country studies is that, taking our identification assumption as valid, we can disentangle the effects of regulations such as employment protection on innovation, from national cultural effects that may both determine regulation and the propensity to be innovative and take risk through radical innovation. Our strategy's weakness is that it cannot, of course, control for variation in culture and motivation across the subsidiaries within a multinational. Therefore if one were to believe that the management of a subsidiary belonging to a multinational was run along the lines of the management norms of its country of location, rather than the management norms if its parent company, then our strategy may not be satisfactory. We mitigate this, at least in part, by using a difference-in-differences strategy that considers how EPL affects innovation in subsidiaries in industries with a greater tendency to adjust on the external labour market, while controlling for unobserved effects specific to the country where the subsidiary is located. We also investigate how EPL affects the innovation rates in larger subsidiaries compared to smaller ones, again while controlling for unobserved effects specific to the location of the subsidiary.

We find that multinational firms perform more overall innovation in high EPL countries, but that the same multinational firms perform more radical innovation in low EPL countries. In addition, we show that, as expected, the effect of EPL on the share of innovation that is radical is more pronounced in industries with a propensity to hire from the external labour market. Similarly, there is evidence of such an interaction for incremental innovation, although the results are not as strong. Further, there is evidence that EPL increases incremental innovation more in larger subsidiaries than in smaller ones, consistent with the idea that the dominant effect of EPL on incremental innovation is through worker motivation (Boeri and |Jimeno, 2005). We find no such effect for the share of radical innovation.

We see these basic relationships in the cross-country association between EPL and innovation activity. Figure 1 shows the average proportion of citations to the scientific literature plotted against EPL, using data on all firms located in the countries in our sample that applied for patents at the European Patent Office.[11] The downward sloping relationship suggests that a lower proportion of the innovation performed in countries with high EPL is radical. In this paper we focus on multinational firms.[12] Figure 2 shows the same negative association between EPL and radical innovation across these

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[11] This graph is based on patent applications made to the European Patent Office by 38,644 listed and unlisted firms in the private sector, see Macartney (2009). These firms were responsible for the filing of 232,655 patents in the period 1997 to 2003. The country is the country of registration of the applicant firm.

[12] This is a sample of 1,084 subsidiaries of multinational firms, see Section 4 for details of the data used.

firms. In Figure 3, however, we see a positive effect of EPL on overall innovation. These aggregate pictures may be masking many different effects. We show below that these results are robust to controlling for firm fixed effects and for many country level factor endowment characteristics.

This paper proceeds as follows: section 2 presents a simple model of incremental and radical innovation; section 3 discusses our identification strategy; section 4 describes our empirical specification and data, explaining our measure of radical innovation; section 5 presents our results; and a final section concludes.

2 Theoretical Background

The current literature on the effect of EPL on productivity suggests that the nature of innovation has a role to play. The endogenous growth literature (Aghion-Howitt, 1998) emphasize the difference between radical and incremental innovation. Where successful, radical innovation requires a drastic adjustment of employment as the human capital of existing workers is rendered obsolete. EPL increases this cost by way of firing costs. Radical innovation is more valuable than incremental innovation and more costly. If there is uncertainty in future demand then EPL also has a positive effect on the returns to both types of innovation, in that it increases worker commitment and their efforts in making the new technology more productive through learning by doing. EPL will increase incremental innovation effort, but at sufficiently high levels it will decrease radical innovation effort. Thus firms will be more likely to choose to perform radical innovation in low EPL regimes and incremental innovation in high EPL regimes, which is the central prediction tested in this paper.

The underpinnings of this model are based on Aghion-Howitt (1998). Innovation improves the productivity of intermediate goods supplied by a firm for use in the production of a final good. A further improvement on this productivity gain comes via the effort (or learning by doing) of production workers. This effort is higher in the presence of EPL, which takes the form of higher firing costs per worker, as production workers are less likely to be fired and therefore more likely to share in the surplus from increased productivity.

However, EPL can also have negative effects on innovation, depending on whether innovation is radical or incremental. Radical innovation is more productive, but makes existing human capital obsolete. The implementation of a radical innovation requires that all production workers are replaced, at a per worker firing cost. Incremental innovation increases productivity, but to a lesser extent than radical innovation, and existing production workers are retained. EPL's effect on worker effort will have an increasing effect on the returns to both types of innovation, but due to the firing costs it will also have a negative effect on the returns to radical innovation.

In this paper our main interest is in the impact of EPL on innovation incentives, where the main impact of EPL is on costs, and therefore to focus on this effect we assume away any strategic impact of innovation in the product market.

2.1 Model

A final good is produced using a continuum of intermediate goods produced by firms, each one of which is a monopolist in its market, using the technology,

$$y = \int_0^1 \left(Z\left(e_i^j\right) A_i^j \right)^{1-\alpha} x_i^{\alpha} \, di \, , \tag{1}$$

where y is final output, i indexes firms (and intermediate industries, since each firm is a monopolist in its industry), $j = 0, I, R$ indexes innovation type, $Z\left(e_i^j\right)$ is the level of investment in unobservable effort made by production workers, A_i^j is the intermediate producers productivity level, and x is other inputs to production.

Profits of the intermediate firm are given by,

$$\pi_i^j = \delta Z\left(e_i^j\right) A_i^j \ , \tag{2}$$

where π_i^j is profits and δ reflects the extent of competition in the intermediate goods market.

We consider the following timing of events:
Intermediate producers draw an initial productivity level A_i^0. Firms decide whether to invest in radical or incremental innovation, and how much to invest (which determines the probability of success μ_i^R, μ_i^I). If successful, incremental innovation leads to a productivity increase of $\gamma > 1$ and, if radical innovation is successful productivity increases by a factor of γ^2. Innovation incurs a fixed cost.

Productivity is enhanced by the efforts of workers. However, in the case of radical innovation existing workers do not have the required skills to work with the new technology and must be fired and replaced by more skilled workers.[13] Production workers decide the level of investment in unobservable effort e_i^j, which increases

[13] This implies that innovation and production are co-located, so the effect EPL has on worker incentives affects the firm's innovation incentives. Such a co-location is more likely when technology transfer costs are high relative to product transport costs (see Ekholm and Hakkala 2007). This is consistent with a model where location is endogenous and determined by the effect EPL has on the benefits to innovation. That is, if transport costs are low so that production can be located anywhere, firms may choose to locate innovation and production in countries where the labour market environment is conducive to their intended type of innovation.

productivity by a factor $Z(e_i^j)$. A demand shock occurs which leads to the possibility of the worker being fired. We assume that the future uncertainty in demand is small enough to be trivial to the firm, although of importance to the workers.

Intermediate production occurs, if the firm chooses incremental innovation then they use existing workers. If the firm chooses radical innovation then existing production workers are fired at cost φ per worker. They are replaced at zero hiring costs by production workers with more appropriate skills. Output is sold and the surplus shared between the firm and its workers, depending in part on (exogenous) worker bargaining power β. We are interested in the innovation incentives for the intermediate producers.

To solve for the impact of firing costs on firms' incentives to innovate we solve the problem by backward induction:

Output generates surplus for the firm. These are given for each *j* technology by,

$$V_i^0 = (1-\beta)\pi_i^0 \tag{3}$$

$$V_i^I = \mu_i^I (1-\beta)\pi_i^I + (1-\mu_i^I)(1-\beta)\pi_i^0 - c_i^I - F^I \tag{4}$$

$$V_i^R = (\mu_i^R (1-\beta)\pi_i^R - f_i) + (1-\mu_i^R)(1-\beta)\pi_i^0 - c_i^R - F^R \tag{5}$$

where V_i^j is firm *i*'s surplus using technology *j*, μ_i^j is the level of innovation effort by the firm, c_i^j is variable costs of innovation for *j* technology, f_i is firing cost incurred if radical innovation is successful, and F^j is fixed costs of innovation for *j* technology.

Variable costs take the form,

$$c_i^j = \frac{1}{2} A_i^j \left(\mu_i^j\right)^2 . \tag{6}$$

Intermediate production occurs. Output of the intermediate firm is given by equation (2).

If the firm has chosen not to innovate or chosen incremental innovation then it uses existing workers. If the firm choses radical innovation then existing production workers do not have the skills to work with the new technology and are fired by the firm. EPL is modeled as a firing cost of φ per worker (a bureaucratic cost, not a transfer to the worker), that makes employment adjustment costly.[14] These firing costs take the form,

$$f_i = \varphi k Z\left(e_i^0\right) A_i^0 \tag{7}$$

where $kZ\left(e_i^0\right)A_i^0$ is the number of existing workers employed by the firm.[15] New workers are hired at zero hiring costs.

Demand shock occurs. There are shocks to demand which mean that the worker will be fired with probability $s(\varphi)$. This occurs after the worker has committed to an effort level. We assume that the future uncertainty in demand is small enough to be

[14] There are conditions where EPL will be irrelevant to firm location, specifically when EPL takes the form of a redundancy payment rather than a bureaucratic cost to the firm. Pissarides (2001) and Lazear (1990) show that redundancy costs are irrelevant to the firm location decision if wages are determined endogenously. The worker takes into account both the probability of firm bankruptcy and the size of the redundancy payment when bargaining over wages. We have assumed this situation away by interpreting EPL as regulation that results only in a (bureaucratic) firing cost to the firm and not a transfer to the worker. However, EPL as redundancy will affect location decisions if wage bargaining is conducted at the industry level rather than at the firm level and the probability of bankruptcy is private information to the firm and is different to the industry average (Haaland and Wooton 2003). The worker, taking into account the probability of receiving a redundancy payment, accepts a low (high) wage if the industry average riskiness is high (low). Therefore a firm that is more risky than the average is worse off, as it still has to pay the same wage as other firms but has a higher probability of paying a redundancy payment. Therefore risky firms (or firms more likely to make employment adjustments) have an incentive to locate their activities in a low EPL country.

[15] Let $k = \left(\frac{1}{\alpha^2}\right)^{\frac{1}{\alpha - 1}}$. The number of existing workers comes from simple profit maximisation.

trivial to the firm, although of importance to the workers (see Acemoglu 1997, and Boeri and Jimeno 2005). The firing cost of φ per worker makes it more likely that employment adjustment in the face of demand shocks is unprofitable to the firm and, therefore, $s = s(\varphi), s'(\varphi) < 0$. In this way EPL increases workers' job security, and therefore increases their effort.

Production workers decide level of effort. This increases productivity by a factor $Z(e_i^j)$ (where $Z(0)=1, Z'(e_i^j)>0, Z''(e_i^j)<0$). Workers will choose effort to maximise their expected return,

$$\max_{e_i^j}\left[(1-s(\varphi))\beta\pi_i^j + s(\varphi)\cdot 0 - e_i^j\right] \tag{8}$$

We assume Z takes the form $Z(e_i^j)=\sqrt{e_i^j+1}$, so that Z displays diminishing returns to workers effort and is equal to one if workers make zero effort. Using this, substituting equation (2) into (8) and performing the maximization we obtain an expression for the worker's optimal effort, e_i^{j*}:

$$Z(e_i^{j*}) = \frac{(1-s(\varphi))\beta\delta}{2} A_i^j \,. \tag{9}$$

Worker effort for target innovation type j is increasing in the productivity of that innovation, and increasing in EPL,

$$\frac{\partial Z(e_i^{j*})}{\partial\varphi} = -\frac{\partial s(\varphi)}{\partial\varphi}\frac{1}{2}\beta\delta A_i^j > 0\,, \tag{10}$$

since $s'(\varphi)<0$, i.e. the probability of being fired decreases with EPL.

Firm decides level of innovation. The problem facing the firm is to choose the optimal level of innovation effort, conditional on the type of innovation and on worker effort. For incremental innovation the firm chooses innovation effort, μ_i^I, such that (from substitution of equation (2) into equation (4)):

$$\max_{\mu_i^I}\left[\mu_i^I(1-\beta)\delta Z\left(e_i^{I*}\right)A_i^I+\left(1-\mu_i^I\right)(1-\beta)\delta Z\left(e_i^{0*}\right)A_i^0-c_i^I-F^I\right]. \qquad (11)$$

Using equation (6), the fact that $A_i^I=\gamma A_i^0$ and $Z\left(e_i^{I*}\right)=\gamma Z\left(e_i^{0*}\right)$ the firm's optimal innovation effort will be:[16]

$$\mu_i^{I*}=(1-\beta)\left(\gamma-\frac{1}{\gamma}\right)\delta Z\left(e_i^{0*}\right). \qquad (12)$$

This effort is increasing in EPL, since learning-by-doing is increasing in firing costs, as stated in equation (10), and $\gamma>1$.

To investigate how radical innovation varies with firing costs we substitute equations (2), (6) and (7) into equation (5) and, using the fact that $A_i^R=\gamma^2A_i^0$, we obtain:[17]

$$\max_{\mu_i^R}\mu_i^R\left[(1-\beta)\delta Z\left(e_i^{R*}\right)\gamma^2A_i^0-\varphi kZ\left(e_i^{0*}\right)A_i^0\right]+\left(1-\mu_i^R\right)(1-\beta)\delta Z\left(e_i^{0*}\right)A_i^0-\frac{1}{2}\gamma^2A_i^0\left(\mu_i^R\right)^2-F^R. \qquad (13)$$

Solving as before, the firm's optimal radical innovation effort will be:

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[16] Maximisation of equation (11) gives $(1-\beta)\left(\delta Z\left(e_i^{0*}\right)\gamma^2A_i^0-\delta Z\left(e_i^{0*}\right)A_i^0\right)-\gamma A_i^0\mu_i^{I*}=0$, which after rearrangement results in equation (12).

[17] Maximisation of equation (13) gives
$(1-\beta)\left(\delta Z\left(e_i^{0*}\right)\gamma^4A_i^0-\delta Z\left(e_i^{0*}\right)A_i^0\right)-\varphi kZ\left(e_i^{0*}\right)A_i^0-\gamma^2A_i^0\mu^{R*}=0$, which after rearrangement gives equation (14).

$$\mu_i^{R*} = \left[(1-\beta)\left(\delta\gamma^2 - \frac{\delta}{\gamma^2} \right) - \frac{\varphi k}{\gamma^2} \right] Z\left(e_i^{0*}\right). \tag{14}$$

Innovation incentives are increasing in workers' learning-by-doing effort and therefore EPL has an increasing effect for both types of innovation. Due to the large employment adjustment required in the case of radical innovation, firing costs also have a decreasing effect on the incentives for radical innovation.

If we take the ratio of equation (14) to equation (12) we get

$$\frac{\mu_i^{R*}}{\mu_i^{I*}} = \gamma + \frac{1}{\gamma} - \frac{\varphi k}{\gamma^2} \tag{15}$$

which shows that radical innovation is decreasing in firing costs, conditional in incremental innovation. In addition, if we note that

$$\frac{\mu_i^{R*}}{\mu_i^{I*} + \mu_i^{R*}} = \left(\gamma + \frac{1}{\gamma} - \frac{\varphi k}{\gamma^2} \right) \Big/ \left(1 + \gamma + \frac{1}{\gamma} - \frac{\varphi k}{\gamma^2} \right) \tag{16}$$

we can see that the share of radical innovations is decreasing in firing costs.[18] In Appendix X we specify a functional form for the probability of being fired, and

[18] We are grateful to an anonymous referee for pointing out this simplification.

consider how innovation effort variables over reasonable ranges of firing costs. The theoretical discussion suggests two empirical predictions that we can take to the data:

Prediction 1: Overall firm innovation activity could be higher or lower in regimes with higher EPL.

Prediction 2: The proportion of innovation performed by firms that is "radical" (and will likely require significant adjustments in employment) is higher in regimes with low EPL.

2.2 Robustness to assumptions

The idea that EPL increases worker effort in making innovation more productive is robust to changing a number of the assumptions of the model. For instance, we have assumed that the workers' return to learning-by-doing effort is entirely tied to the firm, i.e. their efforts enhance the productivity of the firm's capital but do not enhance their own productivity. However, say the worker gained from their efforts by way of acquiring general skills. Becker (1964) predicts an under-investment in general skills, as workers are credit constrained and firms are reluctant to fund skills that the worker may use elsewhere. As described by Acemoglu (1997) it is likely that a contract could be written to mitigate such a problem (penalties for workers who train and quit) and, for our purposes, it is not initially clear what role EPL has to play: EPL will not stop workers leaving once trained and offered a job elsewhere. Acemoglu (1997) considers a model of training and innovation with job market search frictions, where workers can exogenously lose their job with probability s.[19] Costly job search means that when

[19] Our equation (9) is inspired by equation (2) in Acemoglu (1997).

a worker and firm are matched they bargain over the surplus of the match, and therefore over any increased productivity that the worker has achieved through learning-by-doing effort. This leads to an under-investment in training by workers, as there is a probability of being fired and then, after search, receiving only a part return to their training efforts. Where EPL reduces this probability of being fired, it will mitigate this problem of under-investment, which would be qualitatively consistent with our model.

We have also assumed that the worker's effort is unobservable, otherwise the firm and worker could write a contract specifying e in return for a guaranteed wage in each period. We could relax this assumption and assume that such a contract can be written and that there is a monitoring technology available to the firm so that a worker can be caught shirking with some probability. The efficiency wage paid to the worker so that they do not shirk is increasing in the exogenous probability of spontaneous dismissal in the future ("economic dismissal"), increasing in the exogenous probability of once dismissed getting another job ("flow into employment") and decreasing in the probability of getting caught shirking and subsequently being dismissed ("disciplinary dismissal"), as in Shapiro and Stiglitz (1984). EPL can then have two effects: it will decrease the probability of economic dismissal, but it will also decrease the probability of disciplinary dismissal. Boeri and Jimeno (2005), argue that for large firms (which is what we consider in our empirical application), where monitoring is very difficult, the dominant effect of EPL is that it decreases the probability of economic dismissal and therefore increases the value of employment to the worker and reduces the efficiency wage that the firm must pay. As in our model, EPL will increase the firm's innovative effort, since the lower efficiency wage will increase the return to the firm from innovation.

3 Empirical strategy

In order to investigate the two empirical predictions outlined above we consider the decisions of multinational firms from twelve European countries over where to locate innovative activities. Our main measure of the level of innovative activity is a count of patent applications.

Our identification strategy exploits two features of the data. First, the predictions are distinct for different types of innovation. We consider the impact of EPL on total patenting activity and also on the most technologically new projects or near science patents, which we interpret as being those most associated with employment adjustment and volatility (we show evidence to support this interpretation).

Second, we use variation in the location of patents *within* multinational firms.[20] In contrast to empirical work at the cross-country level this allows us to control for potentially unobservable characteristics at the firm, industry and home country level. However, EPL might be correlated with other institutional variables that also affect innovation incentives. There is not very much time series variation in EPL so we are not able to fully control for omitted country effects. We take a difference-in-difference approach that is now standard in the literature (Rajan and Zingales (1998), Bassanini et al (2009), Cingano et al (2010)) and look at how the impact of EPL varies across industries. The idea is that EPL will have a bigger impact in industries where firms have a higher propensity to adjust on the external labour market. We use information on dismissal rates in US industries to measure the underlying variation across industries. In addition we look at how the impact of EPL varies across firms of

[20] Cingano et al (2010) also use within firm variation to consider the impact of EPL and financial market constraints on productivity.

different sizes, the idea being that workers' motivation to shirk depends on the probability of getting caught, and this probability is expected to be lower in large firms, as monitoring is more difficult. This is implied by the theory and we would expect it to be more important for incremental than for radical innovation. These empirical predictions are consistent with the theoretical model we develop, and have been used in the literature and so provide a useful reference point.

To model the count of patents we follow the literature (Hausman et al (1984), Pakes (1986), Blundell et al (1999)) and use a linear exponential model.

Consider a multinational firm (m), with a number of subsidiaries (s) each of which operates in (a potentially different) industry (i) and is located in country (c). We model the level of inventive activity, measured by patent applications (P_{ms}), in each location as a function of EPL_c, a vector of covariates ($\underline{X}_{ci}$), multinational effects (η_m) and an idiosyncratic error (u_{ms}):

$$P_{ms} = \exp\left(\beta_1 EPL_c + \underline{\alpha}.\underline{X}_{ci} + \eta_m + u_{ms}\right) \tag{19}$$

Our interest is in the sign and magnitude of β_1. Recall from the discussion above that the theoretical literature is ambiguous about what we expect the sign to be - a positive sign would suggest that the dominant effect of EPL is to increase both firms investment in workers and worker commitment, while a negative sign would support the idea that higher EPL makes employment adjustments more costly. To implement the difference-in-difference approach with respect to the propensity to hire from the external labour market we allow $\beta_1 = \beta_{10} + \beta_{1L} Highlayoff_i$, where $Highlayoff_i$ is the layoff rate in the US for industry i between the years 1997 and 2003. Similarly, to investigate if our effect varies by firm size we let $\beta_1 = \beta_{10} + \beta_{1B} Bigfirm_{ms}$ where $Bigfirm_{ms}$ is an indicator variable that is equal to one for firms that are bigger than the median firm size (defined by revenue) for the country in which they are located.

While the theoretical literature is ambiguous about the impact of EPL on the overall level of innovative activity, it clearly points to a detrimental effect of EPL on the share of innovative activity that is more technologically advanced or risky. To empirically investigate this prediction we follow Papke and Wooldridge (1996) and estimate:

$$\frac{NPL}{CIT}_{ms} = G\left(\beta_2 EPL_c + \underline{\alpha}.\underline{X}_{ci} + \eta_m + \nu_{ms}\right) \tag{20}$$

where we assume that G() is the logistic function, NPL_{ms} is a count of the citations made to the non-patent literature, mainly scientific journals (the specific definition is discussed further in the next section) and CIT_{ms} is a count of the total citations made. Our interest is the sign and magnitude of β_2 - a negative sign would indicate that higher technologically advanced patenting, as a proportion of overall patenting, is associated with lower EPL. To implement the difference-in-difference approach with respect to the propensity to adjust on the external labour market we allow $\beta_2 = \beta_{20} + \beta_{2L} Highlayoff_i$, and to investigate if the effect on radical innovation varies by firm size we let $\beta_2 = \beta_{20} + \beta_{2B} Bigfirm_{ms}$.

A concern we might have is that differences in country-industry specialization may influence our results. The trade literature emphasises that countries with a large endowment of capital or skills have an advantage in industries that are capital or skill intensive, which may include high-tech industries. We follow Nunn (2007) and use capital abundance and investment in skills at the country level, interacted with estimates of industry capital and skill intensity. Another concern is that country size may be correlated with EPL, and production activity locates in large countries to access the product market, and where this production is highly skilled it drives up wages for high skilled workers in those countries (e.g. see Ekholm and Hakkala, 2007). As market access is less important for R&D this may crowd out highly skilled innovation to smaller countries. To control for country size we include population.

These considerations lead to the following structure for $\underline{\alpha}.\underline{X}_{ci}$:

$$\begin{aligned}\underline{\alpha}.\underline{X}_{ci} &= \alpha_1 \ln(K/W)_c + \alpha_2 \ln(K/W)_c * (K/Y)_i + \alpha_3 (K/Y)_i \\ &+ \alpha_4 \ln(Educ/GDP)_c + \alpha_5 \ln(Educ/GDP)_c * (SK/W)_i + \alpha_6 (SK/W)_i \\ &+ \alpha_6 Pop_c\end{aligned}$$

(21a)

Where $\ln(K/W)_c$ is the natural log of the capital per worker in country *c*, $(K/Y)_i$ is the capital per unit output in industry *i* based on US data (the US is not in the sample), $\ln(Educ/GDP)_c$ is the natural log of the proportion of GDP spent on higher education in country *c*, $(SK/W)_i$ is the skill intensity of industry *i*, and Pop_c is the working population of country *c* averaged over the sample period.

As a further robustness check we include country and industry effects, in which case

$$\alpha X_{ci} = \eta_c + \eta_i$$

(21b)

4 Data

In order to estimate equations (19) and (20) we need information on the geographic location and level of technological sophistication of multinational firms' innovative activity, along with information on EPL and other country and industry characteristics. We provide a brief description of the data here, with more details available in the Data Appendix.

4.1 *Measuring the innovative activity of multinational firms*

The data on patents come from the European Patent Office PATSTAT dataset, which we have matched to information on corporate ownership structure and financial accounts from BVD Amadeus (these data are constructed on a similar basis to the NBER Patents Data but cover European firms, see Appendix A.3 and Abramovsky et al (2008)). Patent applications filed at the European Patent Office (EPO) are an attractive measure of innovative activity for a number of reasons. The advantage of this measure is that it is administrative in nature with well defined rules that are independent of the location of the patent applicant. Furthermore, it is measured at the firm-location level (in contrast to data on firm level R&D expenditure, which is not widely available for firms in many European countries, and where it is reported it is almost always at the world-wide level). Patents data has been widely used and found to be closely related to R&D expenditure measures (see Griliches et al. 1984 and 1990), and this is also true for our data at the industry level (see Abramovsky et al (2008)). There are of course also drawbacks to using patents as a measure of innovative activity, including that firms in different industries and countries have different propensities to patent, and that the value of a patent is heterogenous across firms. Our identification strategy, of looking *within* the firm, helps to control for many of these potential drawbacks.

In the results section we show that we first estimate equation (19) for a large sample that includes subsidiaries that do not patent. This sample consists of 46,811 subsidiaries of 2,219 multinational firms. Specifically, this large sample represents all multinationals with subsidiaries in at least two locations, at least one of which files a patent(s) in the years 1997-2003, and we include all of the subsidiaries, whether or not they patent.[21] The distribution of the subsidiaries and the patents filed by those subsidiaries is presented in Table 2, columns (1) and (2).

The baseline sample on which we then proceed to estimate both of equations (19) and (20) is presented in Table 2, columns (3) and (4). This sample conditions on subsidiaries that patent and that make a citation. This criteria is necessary for estimating the functional form of equation (20), which includes as the denominator of the dependent variable the log of the total number of citations made by patents filed by each subsidiary. This sample contains 1,084 subsidiaries of 231 multinational firms. The sample includes all patent applications whether or not they have been granted (we show the results are robust to considering only granted patents).

To estimate equation (19) we measure innovative activity as a simple count of patents (P_{ms}). We use simple counts rather than weighting patents by citations *received* as many of the patents are relatively new and therefore citations are severely truncated. However, our key results are robust to using citation weighted patents, suggesting that the effect is significant for economically valuable patents. To estimate equation (20) we measure *radical* innovation activity (NPL_{ms}) as a count of patent citations that refer to the non-patent literature (NPL) for patents filed by subsidiary *s* in multinational firm *m* over the sample time period, divided by the total number of citations made by the same patents of the same subsidiary. This measure is an indicator of the newness of the innovation, since NPL citations are typically citations

[21] MNEs that file no patents whatsoever are excluded from the sample, as with the MNE fixed effects they provide no information for the estimation and their inclusion can cause convergence problems in the maximum likelihood estimation. For similar reasons, MNEs that do not have any variation in the EPL in which their subsidiaries reside (for example, all of their subsidiaries are in one country) are excluded. These criteria are applied to all samples in this paper.

to scientific journals. Table 3 shows how this variable – i.e. the proportion of all citations made to NPL - varies across industries. We can see that industries which we might expect to require highly scientific innovation, such as pharmaceuticals, food production, transport and communications, finance and chemicals have the highest proportion of NPL citations, and industries which we might expect to involve less scientific innovations, such as light manufactures, have the lowest proportion of NPL citations.

Our interest in this paper is on the effect of labour market regulations that affect job security for workers and adjustment costs for employees. Increased job security increases worker incentives to invest in innovation and therefore increases the return to innovation for employers. However, where innovation is uncertain or significantly new, in that it requires an adjustment in the skill mix of employees which may involve the replacement of existing workers with external workers, regulations that protect existing employment increase the cost of innovation. Our expectation is that the second effect will dominate the first when innovation is significantly technologically advanced, as measured by the proportion of patents that make citations to NPL.

The central idea behind using the NPL measure is that for the sort of new, radical innovation that can create wholly new products or processes, the technology is at an early stage of its life-cycle, where there is still a lot of new science involved. This new science is sourced from technical and academic journals. The NPL measure as an indicator of radical innovation has support from the literature. Haupt el al. (2007) hypothesize that early life-cycle technologies often cite NPL for the same reasons that we have just described, and they find empirical support for their hypothesis in the case of pacemaker technology. In Table 4 we show a number of correlations that further support the appropriateness of the NPL measure. We start in column (1) by showing the positive correlation between high NPL citations and the average number of inventors per patent, a possible indicator of the complex nature of the technology. Column (2) shows that NPL innovation is positively correlated with employment adjustment within firms and column (3) that NPL innovation is correlated with country-industry sales volatility, a measure of uncertainty.

4.2 Employment Protection Legislation and Layoff Rates

We use an index of EPL from Venn (2009) that is widely used in the literature on productivity (see, Bassanini et al. 2009). Similar measures are used in the literature on the determinants of unemployment (see, inter alia, Nickell et al. 2005, Nicoletti et al 2000). Our preferred measure is version 2 of Venn's overall summary indicator, which is a weighted sum of sub-indicators for regular and temporary contracts and collective dismissals. Key for our purposes is that there is real variation in this measure across the countries in our sample, as is evident from Figure 1. Although there have been some changes in EPL in our sample of countries over the last 20 years, these changes have been small and some countries have experienced no change. Most importantly the construction of our dataset is such that the matching of firms to patents is most accurate in the time period after 1997 and there have been very few changes in EPL in that time frame. This lack of time variation means that identification of EPL's effects on patenting must be sought from a cross-sectional identification strategy, and we have chosen such a strategy that controls for MNE specific fixed effects.

The danger with using a cross-sectional identification strategy is that EPL may be correlated with unobserved country-characteristics, that also drive a MNE's decision regarding the location of incremental and radical innovation. To mitigate this issue we have followed the differences-in-differences approach described in section 3, based on industry layoff rates. We use information on mass layoffs in the US in order to identify industries that inherently adjust employment levels and access the external labor market frequently. It is in these industries that we expect the effect of EPL on the innovation decision to be more prevalent. Specifically, we construct a dummy variable equal to one if the US layoff rate for each 3-digit NACE industry is higher than the median US layoff rate across the 3-digit NACE industries for which this data is available. The layoff rate for each industry is calculated as the total initial claimants from mass layoff events (defined as events where there were at least 50 initial claims against a firm for unemployment insurance during a 5-week period) in the period 1997 through 2003, divided by the number employed in that industry in 1997. Data on mass layoffs and industry employment levels was taken from the US Bureau of Labour Statistics.

The information on EPL and layoff rates is described more fully in the data appendix, and summary statistics are provided in Table A4.

5 Results

We are interested in the empirical support for the two predictions in Section 2.1: (1) that overall firm innovation activity could be higher or lower in regimes with higher EPL; (2) that the proportion of innovation performed by firms that is "radical" (and will likely require significant adjustments in employment) is higher in regimes with low EPL.

We control for multinational fixed effects, country and industry characteristics. In addition, we investigate whether these effects are more pronounced in industries that inherently rely heavily on the external labour market; in such industries one might expect that the effect of more stringent regulations regarding dismissals may have a stronger effect on workers' incentives. These results help us to identify that the effect is from EPL rather than other country level institutions. We also consider whether the effect of EPL on innovation depends on firm size. As we noted in Section 2.2, workers' motivation to shirk depends on the probability of getting caught, and we expect this probability to be lower in large firms where monitoring is more difficult.

In summary, our results suggest that if anything EPL is associated with higher overall patenting. EPL is associated with a lower share of radical innovation, and the effect is more pronounced in industries that inherently access the external labor market more. The effect of EPL on overall patenting is more pronounced for large firms, which is consistent with expectations that the negative effect of EPL on worker motivation due to a lower likelihood of being fired if caught is lower in big firms, where the probability of getting caught is low. There is no firm size effect with regard to radical innovation, which is consistent with our model, where the dominant dynamic regarding radical innovation is on the ability of the firm to radically adjust its workforce, rather than EPL's effect on worker motivation.

5.1 Main results

The results for total innovation are presented in Table 5. In column (1) we start by showing the correlation between EPL and overall patenting in a large sample that includes all MNEs in our data that perform some patenting in the sample period, and all of their subsidiaries, even those that do not patent. This alleviates, to some extent, sample selection concerns that may arise from conditioning on only firms that patent.[22] Specifically, the sample includes all MNEs with subsidiaries in at least two

[22] We thank an anonymous referee for pointing out that it may be the case that in high EPL countries there may be no patenting at all in traditionally patent-scarce industries, but in low EPL countries some

locations at least one of which files a patent(s) in the years 1997-2003, and we include all of the subsidiaries, whether or not they patent. This sample contains 46,811 subsidiaries in total, owned by 2,219 MNEs. Column (1) shows the result for this sample, with fixed effects for the 2,219 MNEs. The coefficient on EPL is positive and statistically significant, consistent with the idea that EPL encourages more overall innovation. Although not reported in Table 5, we also estimated a zero-inflated Poisson model to account for the large number of observations with zero patents in the sample. Indicator variables for two-digit industry classifications were used as zero-covariates, the idea being that industry of operation determines in part whether subsidiaries choose to innovate or not. These zero covariates were statistically significant, as was the coefficient on EPL which equaled 0.7275.

In column (2) we focus on a sample of multinationals and their subsidiaries that have filed patents that have made citations to either other patents or the non-patent literature. In column (2) the coefficient on EPL is positive and statistically significant, now a similar magnitude to column (1). The positive coefficient on EPL indicates that, within multinational firms, more innovation is performed by subsidiaries in countries with high employment protection for workers.

We might be concerned that the result is driven by patterns of industrial specialization in countries with abundant skills; in column (3) we include as control variables the skill level of the country in which each subsidiary is registered, the skill intensity of each industry in which it operates and the interaction between these two variables. Although the coefficient on this interaction is negative, counter to intuition, column

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patenting in such industries, but less than in traditionally patent-intensive industries. The concern is that excluding zero observations would exclude such industries for high EPL countries and upwardly bias the coefficient on EPL.

(3) shows that our results are not driven by patterns of comparative advantage with relation to skills. We also include the working population of each country to ensure that the result that total patenting occurs more in countries with high EPL is not driven by market size effects that may be correlated with employment regulation.

A further concern might be that patterns of industrial specialization in countries with abundant capital are driving the results; in column (4) we also include as control variables the capital abundance of the country in which each subsidiary is registered, the capital intensity of the industry in which it operates and the interaction between these two variables. The coefficient on the interaction of capital abundance and capital intensity is positive as we would expect, and the coefficient on EPL remains positive and statistically significant.

In order to further investigate the central idea that it is EPL driving these effects and not some other national institution, we explore how the EPL effect varies across industries that inherently rely more heavily on the external labor market (Bassanini et al (2009) and Cingano et al (2010)). These result are presented in columns (5)-(9); country effects are now included, so all country level variables are omitted, and in columns (8) and (9) industry effects are included, so all industry level variables are also omitted.

The coefficient on the interaction of EPL with an indicator variable that is one for industries with a high layoff rate in the US are positive but not statistically significant except in column (8). This is weak evidence that that the motivational effect of EPL on workers through increased job security is stronger when there is a high inherent risk of losing one’s job due to the nature of the industry. The difference between columns (8) and (9) are the weights used, in column (8) patents that make more citations to other patents are more heavily weighted, while in column (9) patents that receive more citations from other patents are more heavily weighted. While these results are not that strong for an overall positive effect, they do not indicate an overall negative effect. In fact column (8) is the specification that best captures the idea we are considering if we think that patents that make a higher number of citations indicate an innovation that is more incremental, that builds more on past innovation; this is exactly where theory suggests that EPL should have a bigger positive impact through increasing worker effort.

Columns (10) - (12) investigate the importance of firm size, as defined by operating revenue. The literature on shirking, as described in section 2.2, suggests that EPL may have a negative effect on worker motivation, which is less pronounced in big firms. Idle workers may see EPL as an insurance against being caught shirking and strong EPL may therefore reduce their effort. Boeri and Jimeno (2005) argue that such an effect is lower in big firms, because there is little chance of getting caught in the first place. Our results are consistent with this idea – in column (10) EPL has a positive effect on innovation in big firms, although it is insignificant. Once we control for industry effects the positive effect in big firms is positive and statistically significant. This is true both when we weight patents that make more citations in column (11) and when we weight patents that receive more citations in column (12).

Table 6 shows the results for the share of innovations in a location that are radical innovations. The specifications in Table 6 follow the structure of columns (2)-(12) in Table 5. In column (1) the negative coefficient on EPL indicates that, within multinational firms, a higher share of the more technologically advanced innovation is performed by subsidiaries in countries with low employment protection for workers. In column (2) we control for industry skill intensity, country skill abundance and their interaction, and in column (3) we control for industry capital intensity, national capital abundance and their interaction. The coefficient on the interaction of capital abundance and capital intensity is positive, as we would expect. The working population of each country is included as a control for market size effects. The coefficient on EPL remains negative but is not statistically significant after including all of these controls.

Columns (4)-(8) present what we see as our main result. We investigate whether the effect of EPL on the share of innovation that is radical is more pronounced in industries with higher inherent layoff rates (the equivalent to column (5)-(9) in Table 5). The coefficient on the interaction of EPL with the high layoff rate variable is negative. It is statistically significant when we control for observed country and industry characteristics (column (6)). When we add industry effects and weight the patents by the number of citations that the patent makes the coefficient on the interaction term reduces and becomes insignificant. However, when we weight by the number of citations that the patent receives we find a negative and significant effect of EPL on the share of patents that are radical. When considering the results in Table 5 we argued that citations made could be seen as indicative of the importance of incremental innovation; when considering radical innovation it is plausible that the number of citations received gives a better indication of the importance of radical innovation.

Columns (9) - (11) consider how the effect of EPL varies with firm size. The effect of EPL on radical innovation is not statistically more important for big firms than for smaller firms. This is consistent with the theory described above, firm size is important for the worker motivation effect – it affects the probability of getting caught shirking – but it is not important for the radical employment adjustment that would result from radical innovation.

5.2 Robustness

The results thus far have relied on patent filings irrespective of whether or not those patents have been granted. The motivation for using all patent filings is that some patents may not have been granted yet, although they will be in the future. Furthermore, the length of time it takes for a patent to be granted may be related to the nature of that innovation, i.e. how radical the innovation is, and therefore conditioning on only granted patents may introduce non-classical measurement error into the dependent variable. Nevertheless, it may be interesting to consider how the results hold up to conditioning on only patents that have been granted. This reduces the sample to 593 observations. The results of these tests are presented in Table 8. The coefficient (standard error) on the EPL variable for the equivalent specification to column (2) of Table 5 when we use only granted patents is shown in column (1) of Table 7 and the equivalent of column (1) in Table 6 in column (2) of Table 7. Due to the reduced sample size we are not able to include other controls.

There are twelve countries in the sample that we have investigated in this paper, and a concern may be that the results are heavily influenced by just one of those countries, particularly the larger economies. We have run the equivalent specifications to column (2) in Table 5 and column (1) in Table 6 on the sample with each of France, Germany and the UK (the three largest countries in our sample) removed. With Germany removed, the coefficient on the EPL variable retains its sign and significance in both the incremental innovation model and the radical innovation model. With France removed, the coefficient on the EPL variable retains its sign and significance in the radical innovation model, but loses both sign and significance in the incremental innovation model. However, when the citations weighting in the regression is removed in the incremental innovation model along with France, the coefficient on the EPL variable is once more strongly positive and significant. With the UK removed, both results become statistically insignificant, but due to an inflation in the standard errors, rather than a reduction in the point estimates. However, keeping the UK removed, we also removed Germany and statistical significance returned to both models. These results are available from the authors upon request.

5.3 Economic Significance

What is the economic significance of these estimates? To consider this we look at the impact of moving each country to the mean EPL index of 2.34. We use our estimated coefficients from column (2) of Table 5 and column (1) of Table 6 to predict the number of patents and the share of patents that are radical for each observation. We report the mean percentage change across observations when we compare the predicted value at the actual level of EPL and when we set EPL equal to the mean of 2.34. These are shown in Table 8 for each country.

Consider a country such as France, which has relatively strong employment protection legislation with an EPL index of 2.87. Reducing their EPL to the mean in our sample of 2.4 would result in an average 38% fall in patenting across firms in France, but an increase in the share of innovations that were radical of around 6.9% (or around 0.8 percentage points, from 11.4% to 12.2% of patents).

On the other hand, consider a country like Denmark with a low amount of employment protection, which has an EPL index of 1.84. Increasing their EPL index to 2.34 would lead to an increase in overall patenting of around 27%, but a fall in radical innovations of around 6.9% (or around 0.8 percentage points, from 14.9% to 14.1% of patents). These are substantial effects.

6 Conclusion

This paper has investigated the relationship between employment protection legislation and innovation activity across twelve European countries. We use new data on the activities of multinational firms operating across different jurisdictions. Our findings suggest that EPL does not discourage multinational firms from carrying out innovation activity, and may in fact spur on incremental patenting activity, but that multinational firms do locate radical patenting activity disproportionately in low EPL countries. This is consistent with a variant of an Aghion-Howitt style growth model that incorporates the two effects of EPL - increases job security for existing workers, and thus increased effort, and increased firing costs leading to higher adjustment costs for the firm.

As a caveat, however, our empirical findings are also consistent with other theoretical models, such as Saint-Paul's model of comparative advantage, and with the ideas put forward in Hall and Soskice. We are not able to empirically distinguish these alternative models. Care must be taken in interpreting these results. While we have attempted to control for a number of other characteristics that vary across countries, and for firm specific characteristics, identification is still from cross-sectional data. We do not observe sufficient time series variation in EPL and our data to identify the effects of changes in labour market regimes. Nonetheless, this evidence is suggestive and appears to be robust to a number of standard concerns put forward in the literature.

How do our results fit in with the existing literature on the effect of EPL on investment, innovation and productivity? Although our results essentially suggest both positive and negative effects of EPL on innovation, we do not see that they are at odds with results in other studies. Using industry level data for OECD countries Bassanini et al. (2009) find that EPL has a decreasing effect on productivity growth and more so in industries that inherently rely more on the external labour market. Cingano et al. (2010) use firm level data to show that EPL reduces firm investment and capital per worker, and therefore value added per worker. Autor et al. (2007) find using variation in the adoption of wrongful discharge protection across US States that, although increased dismissal costs increase labor productivity, they are associated with lower total factor productivity. In sum, the recent literature finds negative effects of EPL on productivity. We note two things in this regard. First, productivity encompasses more than innovation and the allocation and efficiency effects (such as those emphasized by Autor et al. (2007) related to capital deepening in the presence of high EPL) may be more apparent in productivity than innovation. Secondly, the radical innovation that we find is reduced by EPL may be of greater importance to productivity growth than the incremental innovation that we find is increased by EPL. In fact, our intuition tells us that it should be. We hope that future research will more fully explore the links between EPL, radical innovation and incremental innovation, and productivity.

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Appendix A.1 Relevant ranges for firing costs to affect innovation effort

Specifying a functional form for $s(\varphi)$ allows us to infer how optimal innovation effort varies over reasonable ranges of firing costs. In a similar vein to Boeri and Jimeno (2005) consider that there is a small probability p that demand for the final good will drop from high, θ^h, to low, θ^l.[1] For a given level of worker effort output is then given by $y = \theta^S \int_0^1 (ZA_i)^{1-\alpha} x_i^{\alpha} di$, where $S = h, l$.[2] On the realisation of the demand shock the firm will wish to adjust employment from x_i^h to the new optimal level x_i^l by firing workers. The probability of being fired for each worker is then given by:

$$s = p.\left(\frac{x_i^h - x_i^l}{x_i^h} \right). \tag{A1}$$

In the presence of EPL it costs the firm φ per worker to adjust employment downwards. The loss to the firm of a non-optimal level of employment, x_i, is given by:

$$\Delta\pi_i = \left(\theta^l \alpha (ZA_i)^{1-\alpha} x_i^{\alpha-1} - 1\right) x_i - \left(\theta^l \alpha (ZA_i)^{1-\alpha} (x_i^l)^{\alpha-1} - 1\right) x_i^l, \tag{A2}$$

where the first term is the level of profits given low demand but with employment $x_i > x_i^l$ and the second term is the level of profits given low demand and the optimal level of employment. When $x_i = x_i^l$, $\Delta\pi_i = 0$. The firm faces firing costs given by $\varphi(x_i^h - x_i)$. The firm will adjust the employment level until the marginal gain from doing so equals the

[1] This is simpler than Boeri and Jimeno (2005) in that we consider that demand is normally high, but there is a small possibility that it drops. The firm initially chooses employment levels assuming demand will be high.

[2] For simplicity the j superscript and the variable for workers effort, e_i^j, are omitted from the discussion in this section.

marginal cost of firing an employee. The optimal level of employment, $\hat{x}_i$, given firing costs is then given by:

$$\theta^l \alpha^2 (ZA_i)^{1-\alpha} \hat{x}_i^{\alpha-1} - 1 = -\varphi \tag{A3}$$

Therefore,

$$\hat{x}_i = \left(\frac{1-\varphi}{\theta^l \alpha^2}\right)^{\frac{1}{\alpha-1}} ZA_i . \tag{A4}$$

This expression is increasing in φ. Note that it reduces to x_i^l in the absence of firing costs ($\varphi = 0$). There will also exist some level of φ where no adjustment occurs. Substituting this into A1 gives the probability of being fired faced by each worker in the presence of firing costs:

$$s = p.\left(\frac{\left(\frac{1}{\theta^h \alpha^2}\right)^{\frac{1}{\alpha-1}} ZA_i - \left(\frac{1-\varphi}{\theta^l \alpha^2}\right)^{\frac{1}{\alpha-1}} ZA_i}{\left(\frac{1}{\theta^h \alpha^2}\right)^{\frac{1}{\alpha-1}} ZA_i} \right) = p.\left(1 - \left(\frac{\theta^h}{\theta^l}\right)^{\frac{1}{\alpha-1}} (1-\varphi)^{\frac{1}{\alpha-1}} \right). \tag{A5}$$

This probability decreases as $\theta^l \rightarrow \theta^h$ as we would expect.[3] Writing out $s(\varphi)$ followed by its first and second derivatives, gives:

$$s(\varphi) = p.\left(1 - \left(\frac{\theta^h}{\theta^l}\right)^{\frac{1}{\alpha-1}} (1-\varphi)^{\frac{1}{\alpha-1}} \right), \tag{A6}$$

---

[3] The probability of being fired is non-positive when $\theta^l = \theta^h$. Note that $\alpha < 1$.

$$s'(\varphi) = p.\frac{1}{(\alpha-1)}\left(\frac{\theta^h}{\theta^l}\right)^{\frac{1}{\alpha-1}}(1-\varphi)^{\frac{2-\alpha}{\alpha-1}}, \tag{A7}$$

$$s''(\varphi) = -p.\frac{(2-\alpha)}{(\alpha-1)^2}\left(\frac{\theta^h}{\theta^l}\right)^{\frac{1}{\alpha-1}}(1-\varphi)^{\frac{3-2\alpha}{\alpha-1}}. \tag{A8}$$

As $\alpha < 1$ and restricting $\varphi \in [0,1)$ we have $s'(\varphi) < 0, s''(\varphi) < 0$, that is the probability of a worker losing their job is decreasing in φ and at an increasing rate.[4]

Using a Taylor expansion around $\varphi = 0$ we can now write A1 as:

$$s = p.\left(1-\left(\frac{\theta^h}{\theta^l}\right)^{\frac{1}{\alpha-1}}\right) - p.\frac{1}{(1-\alpha)}\left(\frac{\theta^h}{\theta^l}\right)^{\frac{1}{\alpha-1}}\varphi - p.\frac{1}{2}\frac{(2-\alpha)}{(\alpha-1)^2}\left(\frac{\theta^h}{\theta^l}\right)^{\frac{1}{\alpha-1}}\varphi^2.... \tag{A9}$$

Then:

$$s(\varphi) = p.\left(1-\left(\frac{\theta^h}{\theta^l}\right)^{\frac{1}{\alpha-1}}(1-\varphi)^{\frac{1}{\alpha-1}}\right). \tag{A10}$$

This function is decreasing in φ at an increasing rate: $s'(\varphi) < 0, s''(\varphi) < 0$. Using a linear approximation for equation (A10) and, along with equation (9), we note that the expression for radical innovation effort, equation (14), is quadratic in firing costs. Furthermore, radical innovation effort initially increases with φ and then decreases with φ. This functional form

[4] Restricting firing costs to be between zero and one is natural here as the workers reservation wage is normalised to one and it is likely that firing costs will be some proportion of that. *s* tends to negative infinity as firing costs tend to one, but we just exclude this and say that at some point firing costs are so high that the firm does not adjust employment at all.

for $s(\varphi)$ is not necessary for the qualitative predictions of our model, but it will help in discussing the dominant effect of EPL on radical innovation effort for realistic values of φ.

From differentiation of equations (12) and (14) in the main text, incremental innovation and radical innovation effort vary with firing costs as described in A11 and A12.

$$\frac{\partial \mu_i^{I*}}{\partial \varphi} = (1-\beta)\left(\gamma - \frac{1}{\gamma}\right)\delta \frac{\partial Z\left(e_i^{0*}\right)}{\partial \varphi}, \qquad \text{(A11)}$$

$$\frac{\partial \mu_i^{R*}}{\partial \varphi} = (1-\beta)\left(\gamma^2 - \frac{1}{\gamma^2}\right)\delta \frac{\partial Z\left(e_i^{0*}\right)}{\partial \varphi} - \frac{\varphi k}{\gamma^2}\frac{\partial Z\left(e_i^{0*}\right)}{\partial \varphi} - \frac{k}{\gamma^2} Z\left(e_i^{0*}\right). \qquad \text{(A12)}$$

For small φ we can write (from equation A9):

$$s(\varphi) = p.\left(1 - \left(\frac{\theta^h}{\theta^l}\right)^{\frac{1}{\alpha-1}}\right) - p.\frac{1}{(1-\alpha)}\left(\frac{\theta^h}{\theta^l}\right)^{\frac{1}{\alpha-1}}\varphi . \qquad \text{(A13)}$$

Inserting this into equation (9) from the main text and letting $b = \frac{1}{(1-\alpha)}\left(\theta^h/\theta^l\right)^{\frac{1}{\alpha-1}}$ we can write:[5]

$$Z(e_i^{0*}) = \frac{1}{2}\left(1 - p\left(1 - (1-\alpha)b - b\varphi\right)\right)\beta\delta A_i^0 = \frac{1}{2}\left(\left(1 - p + p(1-\alpha)b\right) + pb\varphi\right)\beta\delta A_i^0 . \qquad \text{(A14)}$$

Insertion of expression (A14) into (A11) and (A12), after trivial manipulation results in:

$$\frac{\partial \mu_i^{I*}}{\partial \varphi} = (1-\beta)\left(\gamma - \frac{1}{\gamma}\right)\delta \frac{1}{2} pb\beta\delta A_i^0 \qquad \text{(A15)}$$

[5] Note that *b* is decreasing in the severity of the shock. Its range is between zero and $\frac{1}{1-\alpha}$.

$$\frac{\partial \mu_i^{R*}}{\partial \varphi} = (1-\beta)\left(\gamma^2 - \frac{1}{\gamma^2}\right)\delta \frac{1}{2} pb\beta\delta A_i^0 - \frac{\varphi k}{\gamma^2}\frac{1}{2} pb\beta\delta A_i^0 - \frac{k}{\gamma^2}\frac{1}{2}\left((1-p+p(1-\alpha)b)+pb\varphi\right)\beta\delta A_i^0$$

(A16)

Equation (A15) is strictly positive: higher EPL, modeled as higher firing costs, unambiguously increases optimal incremental innovation effort. In equation (A16) the first term is positive for $\gamma > 1$, and the second two terms are negative and increasingly so in φ. To find the point at which firing costs start to have a negative effect on radical innovation, $\hat{\varphi}^R$, set equation (A16) equal to zero and solve to obtain:[6]

$$2\hat{\varphi}^R = (1-\beta)(\gamma^4 - 1)\left(\frac{1}{\alpha} - 1\right) - \frac{(1-p)}{pb} - (1-\alpha). \tag{18}$$

Therefore, $\hat{\varphi}^R$ is lower when the productivity gains from innovation are low (when γ is smaller), and when the firms gets a low proportion of the return to innovation (worker bargaining power, β, is high). Also, $\hat{\varphi}^R$ is lower when the extent to which φ increases learning-by-doing is lower: that is, when the probability of a negative demand shock, *p*, is low and therefore the relevance of EPL in making workers feel secure in their jobs is lower; and when the elasticity of final good output with respect to intermediate good input is low (i.e. $-(1-\alpha)$ is small) as this reduces the intermediate good adjustment required in the face of a small demand shock and therefore the possibility of getting fired and the relevance of EPL to job security.

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[6] We obtain $2\hat{\varphi}^R = \frac{1}{kpb}\left[(1-\beta)(\gamma^4 - 1)\delta pb - k(1-p+p(1-\alpha)b)\right]$, which using $\frac{\delta}{k} = \left(\frac{1}{\alpha} - 1\right)$ becomes equation (18) after some rearrangement.

We can show that for reasonable values of the parameters in our model we always expect to be in the range where EPL has a negative impact on incentives for radical innovation, that is $\hat{\varphi}^R$ is less than the lower limit of the likely range of φ. The firing cost φ, which is a bureaucratic cost of dismissing a worker, is likely to be no greater than the worker's reservation wage which is normalized at one. Therefore, it is realistic to assume that φ is between zero and one. Setting $\alpha = 1/2, b = 2, p = 0.1, \beta = 1/2$ we can calculate that $\hat{\varphi}^R < 0$ for $\gamma \leq 1.821$ and that for $1.821 < \gamma \leq 1.968$, $0 < \hat{\varphi}^R < 1$.[7] In this second range of γ values, EPL increases the value of radical innovation initially, but will start to decrease it again as the radical firing cost effect starts to outweigh the learning-by-doing effect. Remembering that in this model the productivity gain from an incremental innovation is γ and that for a radical innovation is γ^2, the values just mentioned are very large: $\gamma = 1.821$ corresponds to a productivity gain from incremental innovation of 82.1 percent and from radical innovation of 231.6 percent. Therefore, in this model it is likely that $\hat{\varphi}^R < 0$ and, therefore, firing costs have a strictly decreasing effect on radical innovation incentives. Also, the model predicts that firing costs have a strictly increasing effect on incremental innovation.

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[7] By inserting values into the following expression and solving for γ:
$$\left(\gamma^4 - 1\right) = \frac{1}{(1-\beta)}\left[\left(\frac{1}{\alpha} - 1\right) + \frac{(1-p)}{pb} + (1-\alpha) + 2\hat{\varphi}^{RI}\right].$$

Appendix A.2 Data Appendix

In order to implement our empirical strategy we need information on the geographic location and level of technological sophistication of multinational firms' innovative activity, along with information on Employment Protection Legislation (EPL) and other country and industry characteristics.

We use information on all patent applications made to the European Patent office from PATSTAT. In order to match patents to firms we use information on firm corporate structure from Bureau van Dijk's Amadeus data, as well as information from business registers, firms' websites and other sources, which we match to the PATSTAT data. This creates a dataset that is very similar in structure and nature to the NBER Patents database (http://www.nber.org/patents/), which has been very widely used for economic research. Similar data for UK firms has been used in a number of publications including Blundell et al (1999; Review of Economic Studies), Aghion et al (2005; Quarterly Journal of Economics) and Griffith et al (2006, American Economic Review).

PATSTAT Data

PATSTAT is a dataset that is distributed by the European Patent Office (EPO). It contains information on all patent applications made to the EPO. The information includes the name of the applicant, the address of the applicant, all citations made on the patent application, whether or not the patent application was subsequently granted, along with a large amount of additional information. However, for our purposes, one key piece of information that it does not contain is whether the applicant is a corporate entity, and where it is a corporate entity there is no information on the ownership structure. This information is essential if we want to look at where multinational firms locate innovative activity.

Information on ownership structure

Abramovsky et al (2008) describe the data and the process of matching PATSTAT to Amadeus in detail, and provide a detailed analysis of the match between patents and firms. The process of matching these two datasets involves the following steps:

i. identify all patent applications with at least one corporate applicant

ii. standardise the way that firm names are written so that the names can be matched

iii. use a computer algorithm to match the two data sets based on name and using information on industry and address

iv. manually checking that the observations that have been matched are correctly matched

v. manually checking and matching all corporate applicants that patent frequently (the definition of frequently varies by country and industry)

vi. manually checking and matching that we have a reasonable number of patent applications for all firms that spend large amounts on R&D

The result is a dataset that we believe contains the vast majority of patenting activity by corporate entities in the European countries considered.

The Table below (Table 5 from Abramovsky et al (2008)) shows the match results across countries for the entire time period, 1978-2007, with countries ordered by decreasing overall matching success (the final column).

Abramovsky et al Table 5: Applicants of EPO patents filed between 1978 and 2007 matched to Amadeus firms

Country	The number of applicant/proprietors that we have identified as corporate (not university, individual or government department)	The proportion of corporate applicants which we have matched to one or more entries in Amadeus	The proportion of corporate applicants which we have matched to one or more entries in Amadeus, weighted by the applicant's total number of patents
UK	15,542	0.70	0.88
Germany	28,804	0.55	0.88
Netherlands	5,868	0.45	0.83
Finland	2,168	0.58	0.85
Sweden	5,610	0.49	0.78
Denmark	2,579	0.55	0.77
Belgium	2,323	0.52	0.74
Norway	1,421	0.62	0.73
Spain	2,868	0.52	0.69
France	15,990	0.37	0.65
Italy	13,822	0.52	0.64
Portugal	198	0.35	0.48

Source: Abramovsky et al (2008).

We can see from this that, for example, in the UK we have matched 88% of the patent applications made by corporate applicants. In most countries the % matched is high. In Portugal we do not achieve a high match rate, on the other hand there are very few patents in Portugal so this does not unduly worry us.

Amadeus data from Bureau van Dijk

Versions of Amadeus

An important feature of the Amadeus data is the criteria for dropping firms from the sample over time. As long as a firm continues to file its financial statement it continues to appear in Amadeus. When a firm stops filing its financial statement is kept in the Amadeus data for four years from the last year financial statement. Thus to ensure we have a sample that incorporates firms that subsequently exit we use several versions of Amadeus disks from 2001, 2004 and 2006.

Ownership

Amadeus contains information on subsidiary as well as parent firms. We seek to identify the ultimate corporate owner of each subsidiary. The ultimate owner is defined as the corporate entity that controls over 24.99% of the shares, if more than one entity controls over this amount the ultimate owner is the one with the largest shareholding. We augment the information in Amadeus with information from firms' website and business directories.

We use information on the ownership structure prevailing in 2004. As a result of this we do not account for any mergers or acquisitions that take place either before or after 2004.

Description

Tables A1-A3 below provide some further description of the process of selection in our data. Table A1 shows in column (1) the total number of firms reporting in Amadeus from 1997-2003 and the distribution of median sizes across countries. There are a total of 6,109,381 such firms, the large number reflecting the fact that Amadeus contains data for *all* registered firms - in any country the vast majority of firms are very small (e.g. zero or one employees). Column (2) shows that 611,787 of these firms have ultimate owners identified (as described in our data appendix, see also discussion below under our response to point *ii*) and shows the distribution of median firm size across country. Column (3) shows that 141,613 of these firms are part of multinationals, including multinationals that have just one parent-subsidiary relationship, but where the parent and subsidiary are in different countries. Not surprisingly, as we move from the population of all firms to only those that are part of multinationals, the median firm size for all countries increases.

Table A2 describes how we move from this population of multinationals toward the baseline sample that we use in Tables 5 and 6:

- Sample 1 contains all multinationals with subsidiaries in at least two locations, at least one of which files a patent(s) in the years 1997-2003, and we include all of the subsidiaries, whether or not they patent. Sample 1 constitutes the 46,811 observations used in Table 5 column (1).
- Sample 2 removes the subsidiaries from sample 1 that do not patent (the number of MNEs remains at 2,219, but their non-patenting subsidiaries are removed). This sample is not used in any of our specifications, but is a logically intermediate step between sample 1 and sample 3.
- Sample 3 conditions on patents that make citations and for which there is variation in the EPL variable across the subsidiaries in each multinational. This sample is our baseline sample used in Table 5 columns (2)-(8) and Table 6.

Table A3 shows the distribution of median firm size across countries for each of the three samples shown, and we note that median firm size increases as non-patenting firms are removed.

EPL and Layoff Data

We obtain information on EPL from the OECD, published in Venn (2009), and on other country and industry characteristics from the OECD STAN database and the UK labor force survey. Data on industry mass layoffs and industry employment levels in the US was taken from the Bureau of Labour Statistics. This information is described in Table A4, along with the summary statistics for the key variables used in our analysis.

Table A1: Population of firms in Amadeus, 1997-2003

	(1) All firms active in the period 1997-2003			(2) Firms with an ultimate owner			(3) Firms part of an MNE		
country	No. of firms	Median Operating Revenue ($000s)	Median No. of Employees	No. of firms	Median Operating Revenue ($000s)	Median No. of Employees	No. of firms	Median Operating Revenue ($000s)	Median No. of Employees
Belgium	317,166	221	3	20,111	2,026	10	5,895	4,851	20
Denmark	154,490	230	4	34,435	751	8	6,011	7,566	22
Finland	83,923	258	4	5,377	1,569	14	1,643	5,315	29
France	827,608	335	5	70,147	2,640	21	24,624	5,315	37
Germany	843,830	819	5	78,541	3,296	10	24,185	8,161	17
Italy	441,817	1,659	7	8,248	5,798	23	3,576	10,293	38
Netherlands	345,920	4,071	3	109,356	7,528	6	13,437	22,163	17
Norway	174,400	267	3	26,811	613	6	4,132	2,419	11
Portugal	90,383	304	23	3,883	2,775	50	1,142	7,602	97
Spain	812,651	282	4	35,072	1,565	14	9,554	4,443	28
Sweden	236,837	242	3	38,216	863	7	8,401	3,989	24
United Kingdom	1,780,356	190	14	181,590	2,513	36	39,013	6,534	49
Total	6,109,381			611,787			141,613	5,991	28

Table A2: Sample descriptions

	Sample 1		Sample 2		Sample 3	
Country	No. of Subsids	Patent Applications Filed	No. of Subsids	Patent Applications Filed	No. of Subsids	Patent Applications Filed
Belgium	1,638	1,054	123	1,054	27	433
Denmark	1,556	1,926	220	1,926	24	216
Finland	587	1,085	60	1,085	3	68
France	9,620	17,345	923	17,345	278	10,223
Germany	9,460	24,977	1,544	24,977	357	10,338
Italy	1,499	1,981	230	1,981	77	950
Netherlands	3,331	2,641	301	2,641	53	1,740
Norway	920	158	48	158	5	54
Portugal	321	30	7	30	2	25
Spain	2,852	558	161	558	30	161
Sweden	2,940	3,341	452	3,341	50	2,097
United Kingdom	12,087	7,465	1,158	7,465	178	2,343
Total	*46,811*	*62,561*	*5,227*	*62,561*	*1,084*	*28,648*
No. of MNEs	*2,219*		*2,219*		*231*	

Table A3: Distribution of firm size

	Sample 1		Sample 2		Sample 3	
Country	Median Operating Revenue ($000s)	Median No. of Employees	Median Operating Revenue ($000s)	Median No. of Employees	Median Operating Revenue ($000s)	Median No. of Employees
Belgium	8,392	30	41,519	145	89,852	221
Denmark	18,564	44	39,303	197	58,604	258
Finland	10,175	44	11,290	80	28,275	146
France	8,688	53	50,289	244	88,735	448
Germany	16,835	44	57,045	289	80,357	448
Italy	16,714	59	51,296	231	63,429	355
Netherlands	29,466	24	49,842	91	87,886	200
Norway	5,045	18	17,094	116	73,087	325
Portugal	15,409	134	37,128	384	29,664	384
Spain	10,514	49	42,711	274	68,068	368
Sweden	7,245	40	17,545	99	56,356	307
United Kingdom	13,280	78	41,459	234	68,929	360

Table A4: Summary Statistics of Key Variables

Variable Name	Variable	Description	Source	Mean (s.d.)
P_{ms}	Number of patent applications	Patents filed between 1997 and 2003 by subsidiary.	PATSTAT	26.428 (88.522)
NPL_{ms}	Number of citations to NPL	Number of citations made between 1997 and 2003 by subsidiary's patent filings to non-patent literature (i.e. to scientific literature).	PATSTAT	9.631 (38.489)
$CiteMade_{ms}$	Citations made	Total citations made between 1997 and 2003 by subsidiary's patent filings to patents and to non-patent literature.	PATSTAT	71.218 (222.229)
$(NPL/CiteMade)_{ms}$	Number of citations to NPL / Citations made	-	PATSTAT	0.123 (0.164)
$CiteReceived_{ms}$	Citations received	Total citations received between 1997 and 2003 by subsidiary's patent filings in that time range.	PATSTAT	4.077 (14.334)
EPL_c	Employment Protection Legislation (Regular Contracts)	Version 2 of Venn's overall summary indicator, which is a weighted sum of sub-indicators for regular and temporary contracts and collective dismissals, averaged over the years 1998-2003.	Venn (2009)	2.443 (0.595)
	Union Density - Average 1997-2003	Actual union members as percentage of employees.	OECD Labour Force Statistics.	42.108 (25.387)
	Collective Bargaining Coverage	Percentage of employees covered by collective bargaining, whether they are union members or not.	Nickell (2003)	79.667 (15.692)
	Employment Tax Wedge - Average 1997-2003	Average of the tax wedge for one-earner family with two children and single persons without children.	OECD, Taxing Wages (2003).	38.748 (6.951)
	Bargaining Coordination	The degree of coordination of bargaining at the industry level.	Nickell (2003), originally obtained from Wolfgang Ochel	2.083 (0.515)
	OECD Product Market Regulations 1998&2003 Average	Top level indicator capturing extent of state control of product markets, barriers to entrepreneurship and trade and investment.	OECD International Regulation Database.	1.701 (0.354)
	Credit Institutions per Capita - Average 1997-	Credit institutions are defined by the European Central Bank as any institution covered by the definition contained in Article 1(1)	CESIfo Dataset, see http://www.cesifo.de. For	0.040 (0.026)

	2002	of Directive 2000/12/EC, as amended. Accordingly, a credit institution is "(i) an undertaking whose business is to receive deposits or other repayable funds from the public and to grant credits for its own account; or (ii) an undertaking or any other legal person, other than those under (i), which issues means of payment in the form of electronic money."	Norway, from Eitrheim et al. (2003).	
	% of Claim Spent in Court and Attorney Fees (where mandatory)	The estimated cost of suing for breach of contract in a hypothetical case as a percentage of the claim amount. See http://www.doingbusiness.org/ExploreTopics/EnforcingContracts/ for data and exact methodology.	Doing Business Report	19.442 (7.114)
$Highlayoff_i$	High Industry LayOff Rate (US - 1997-2003)	Dummy variable equal to one if US layoff rate for that 3-digit NACE industry is higher than the median US layoff rate for 3-digit NACE industries for which this data is available. The layoff rate for each industry is calculated as the total initial claimants from mass layoff events (defined as events where there were at least 50 initial claims against a firm for unemployment insurance during a 5-week period) in the period 1997 through 2003, divided by the number employed in that industry in 1997.	Bureau of Labour Statistics, Mass Layoff Statistics (www.bls.gov/mls/), Series 005 – Total Initial Claimants; Bureau of Labour Statistics, Current Employment Statistics (www.bls.gov/ces/), Number Employed.	0.680 (0.467)
Big $firm_{ms}$	Big firm dummy variable	Dummy variable equal to one if operating revenue for that subsidiary is greater than the median for subsidiaries in that country.	Amadeus	0.499 (0.500)
Pop_c	Population	Average working population (mil.) 1997-2003.	OECD	39.112 (15.908)
$\ln(K/W)_c$	Log of Real Capital per thousand workers, 2000 USD, 1995 prices, in year 1997	For total economy, averaged over sample period. Calculated using a permanent inventory method using gross fixed capital formation. In units of 2000 USD at 1995 prices.	OECD STAN	4.620 (0.303)

$(K/Y)_i$	Industry Capital Intensity	Capital divided by output for each industry using US data, average over the sample period.	OECD STAN	1.192 (0.486)
$\ln(Educ/GDP)_c$	Log of Share of GDP Spent on Higher Education	As a proportion of GDP. Averaged over 1991-1995, making it pre-sample period.	OECD	-1.063 (0.244)
$(SK/W)_i$	Industry Skill Intensity	Proportion of workers in each two digit industry in the United Kingdom in 2000 with degree or other higher education.	UK Labour Force Survey	0.251 (0.107)

Notes: means for labour institutional variables, product market institutional variables and legal institutional variables are the simple averages across the countries in the sample. The means for the other variables are the averages across the baseline sample and are therefore weighted by the number of observations for each country in that sample.