Paper to be presented at

DRUID15, Rome, June 15-17, 2015

(Coorganized with LUISS)

Are flexible labor markets innovation-enhancing? Evidence from OECD panel data

Cornelia Storz
Goethe University Frankfurt
Faculty of Economics and Business Administration
storz@wiwi.uni-frankfurt.de

Na Zou
Goethe University Frankfurt am Main
Department of Microeconomics and Management
zou@wiwi.uni-frankfurt.de

Abstract

Structural reforms in labor markets have been launched in most OECD countries in order to create conditions for an innovative economy. The EU, for example, identifies more flexible labor markets as one driver of becoming ?the most dynamic and competitive knowledge-based economy? (Lisbon Strategy 2000, 2005). We observe a gradual change of employment protection legislation which captures the size of dismissal costs since 90s. In a model with a step-by-step innovation process with a technology gap, a higher dismissal cost induces innovation for firms both at the technology frontier (neck-and-neck) and for firms that are far from frontier (technology followers). We test this hypothesis based on panel data from 13 manufacturing industries in 15 OECD countries over the time period of 1990 to 2006. Contrast to the theoretical prediction, our preliminary results show a negative relationship between employment protection legislation/dismissal cost and innovation (which is measured by patent intensity), suggesting that softening employment protection legislation is beneficial for innovation. We are fully aware that patent intensity may include strategic patenting behavior which may not reflect the true level of innovation. We are also aware the potential endogeneity concern with regard to our measurement of technology distance/gap and we are still in the process of addressing the above issues.

Jelcodes:J68,P50

Are flexible labor markets innovation-enhancing? Evidence from OECD panel data.

Paper (Working in Progress) for DRUID15 Conference on the Relevance of Innovation

ABSTRACT

Structural reforms in labor markets have been launched in most OECD countries in order to create conditions for an innovative economy. The EU, for example, identifies more flexible labor markets as one driver of becoming „the most dynamic and competitive knowledge-based economy" (Lisbon Strategy 2000, 2005). We observe a gradual change of employment protection legislation which captures the size of dismissal costs since 90s. In a model with a step-by-step innovation process with a technology gap, a higher dismissal cost induces innovation for firms both at the technology frontier (neck-and-neck) and for firms that are far from frontier (technology followers). We test this hypothesis based on panel data from 13 manufacturing industries in 15 OECD countries over the time period of 1990 to 2006. Contrast to the theoretical prediction, our preliminary results show a negative relationship between employment protection legislation/dismissal cost and innovation (which is measured by patent intensity), suggesting that softening employment protection legislation is beneficial for innovation. We are fully aware that patent intensity may include strategic patenting behavior which may not reflect the true level of innovation. We are also aware the potential endogeneity concern with regard to our measurement of technology distance/gap and we are still in the process of addressing the above issues.

Keywords:

Employment protection legislation; dismissal costs; Technology distance; Innovation

Are flexible labor markets innovation-enhancing? Evidence from OECD panel data.

INTRODUCTION

Market failure motivates policy makers intervening the labor market. Since mid-1990s, European continent has experienced a stronger competition from the US and the fast growing Asia economies. As such, European leaders committed to launch a comprehensive but interdepend series of reform to become "the most dynamic and competitive knowledge-based economy" by 2010 in March 2000, which is known as the Lisbon Strategy (2000). In order to achieve the goal, structural reforms in labor markets, in particular reforms on increasing the flexibility by deregulating the labor markets, have been on the key agenda of leveraging the innovation capacity in the EU (see e.g. Europe 2020).

Most previous research on labor market regulation have been focusing on labor market performance, especially on outcomes such as employment and unemployment (see e.g. Addison, Blackburn & Cotti, 2013; Dube, Lester & Reich 2010; Neumark and Wascher, 1992), earnings and income inequality (see e.g. DiNardo, Fortin, & Lemieux 1996) and productivity (see e.g. Bassanini and Venn, 2007; Hoisl, 2007). The common findings fall into two opposite perspectives, what Freeman (1993) has termed the "institutionalist" view and the "distortionist" view. The "institutionalist" view endorses job security arrangements and collective bargaining as providing social protection for workers and as the best way to determine labor outcome. By contrast, the "distortionist" perspective favors the advantage of market processes over interventions, and is concerned that these institutional forms of regulation impede adjustments to economic shocks and deter investments.

Research on labor market regulations and innovation is rather limited. Nevertheless, several scholars credit its important impact on innovation. Casper, Lehrer and Soskice (1999) show that the coordinated labor market in Germany has successfully promoted innovation in two new industries, particularly in the platform-technology segment of biotechnology and the service segments of software industry. Bassanini and Ernst (2002) demonstrate that countries with a coordinated industrial relations and stricter employment protection tend to express a greater comparative advantage in industries with a cumulative knowledge base. Among labor market regulations, employment protection legislation is the most commonly used measure as it reflects the strictness of dismissals and the use of working contracts (see e.g. Barbosa and Faria, 2011).

In perfect and complete markets, it is very clear that a high dismissal cost is bad for innovation and thus growth. For instance, Bertola (1994) shows that strict employment hinders the efficiency of resource allocation. In the standard Schumpeterian model of creative destruction, a monopoly product market structure and a flexible labor market characterized by a low dismissal/turnover cost is beneficial for innovation growth. However, in a step-by-step innovation process, Aghion et al (2002) shows that firms will innovate more if they are subject to debt pressure or a hard budget constraint. Based on the framework of Aghion et al (2002), Koeniger (2003) extends the model by introducing the possibility of firm exit in the market and also predicts a positive relationship between employment protection legislation and innovation. Empirically, the effect of dismissal cost or strictness of employment protection on innovation is far from conclusive. On the one hand, scholars find a positive effect of a higher dismissal cost on innovation (see e.g. Acemoglu, 1997; Acharya et al 2010). The argument is that a stringent employment protection legislation or a stringent dismissal law may encourage firms to invest more in great trainings on the one aspect and workers do not need to maximize their current wages due to employment insecurities on the other aspect. By contrast, others scholars find a negative effect of employment protection legislation on innovation. The main reasoning falls in argument of the inability of stringent employment protection to adjust to the fast technology adoption process (see e.g. Samaniego, 2008). Additionally, most of the studies have focused on aggregated cross section data (see e.g. Bassanini and Ernst, 2002) or country level panel data with a short time span (see e.g. Koeniger, 2005; Barbosa and Faria, 2011).This paper, thereby, aims at providing empirical evidence based on industry-level panel data in 13 manufacturing industries in 15 OECD countries from 1990 to 2006, in order to better understand the relationship between employment protection legislation/dismissal cost and innovation.

The paper is structured as follows. Section 2 presents the theoretical framework, from which we draw our hypothesis on the effect of dismissal costs or strictness of employment protection legislation on innovation. Section 3 provides the data, model and empirical. Section 4 displays the results and robustness checks followed by a discussion. Section 5 ends with some concluding remarks.

THEORETICAL FRAMEWORK

Our theoretical framework is based on Aghion et al (2001), Aghion et al (2002) and Koeniger (2005). We consider the world consisting of a finite number of economies and each economy has a continuum of production industries and a continuum of consumers.

Consumers

Assume that each customer a utility function:

$$u = \int_0^1 ln x_i \, d_i$$

where each x_i is an aggregate of two goods produced by duopolists in sector i. Defining the substitute function of x_i as:

$$x_i = v(x_{Ai} + x_{Bi}) = ({x_{Ai}}^{\alpha_i} + {x_{Bi}}^{\alpha_i})^{\frac{1}{\alpha_i}},$$

where a larger α_i reflecting a higher substitutability between good A and good B, hence, a higher α_i also reflects a higher competition between these two duopolists. We normalize the total expenditure for each consumer on these goods is 1. As such, a consumer chooses x_{Ai} and x_{Bi} to maximize his/her utility such that $p_{Ai}x_{Ai} + p_{Bi}x_{Bi} = 1$. Therefore, the demand functions of x_{Ai} and x_{Bi} for each consumer are as follows:

$$x_{Ai} = \frac{{p_{Ai}}^{\frac{1}{\alpha_i - 1}}}{{p_{Ai}}^{\frac{\alpha_i}{\alpha_i - 1}} + {p_{Bi}}^{\frac{\alpha_i}{\alpha_i - 1}}} \qquad (1) \qquad\qquad x_{Bi} = \frac{{p_{Bi}}^{\frac{1}{\alpha_i - 1}}}{{p_{Ai}}^{\frac{\alpha_i}{\alpha_i - 1}} + {p_{Bi}}^{\frac{\alpha_i}{\alpha_i - 1}}} \qquad (2)$$

For simplicity, in the rest of the paper, we drop the industry index i in the formula. As documented in Aghion et al (2001), we can easily get the elasticity of demand between these two goods, i.e.

$\eta_g = \frac{1-\alpha\lambda_g}{1-\alpha}$ where g=A, B , and the firm revenue is represented by $\lambda_g = p_g x_g = \frac{{p_g}^{\frac{\alpha}{\alpha-1}}}{{p_A}^{\frac{\alpha}{\alpha-1}} + {p_B}^{\frac{\alpha}{\alpha-1}}}$

The total revenue in each industry is normalized as 1, i.e. $\lambda_A + \lambda_B = 1$.

Firms

Now assume that each firm in each industry uses labor as the only input. In each industry there are only two firms producing the corresponding goods. Firms have a constant return production function and wage is taken as given. Since there are only two firms in each industry, the technology level can be leveled (both firm have the same technology level) and unleveled (one firm is the technology leader and the other is the follower). Following Aghion et al (2002), we denote t as the technology level of duopolist firm g in industry i, as such, the advantage of a firm who innovates to achieve a higher technology level is such that $A_g = \gamma^{-tg}$, where $\gamma > 1$, meaning that it takes only γ^{-tg} units of labor for firm g to produce a unit of output.

Suppose that each firm engages in R&D activity to achieve a higher technology level and innovation is a step-by-step process. Assume that $\theta(q) = \frac{1}{2}q^2$ [1] is the R&D costs in the unit of labor of a firm moving up to a higher technological level with a Poisson hazard rate of q. As instructed by Aghion et al (2002), we also assume that in the unleveled industry, the maximum sustainable technology gap is 1, meaning that once a firm innovates to a step ahead, due to the knowledge externality, the follower will automatically copy the leader's previous technology, as such both firms achieve the technology advancement but the gap remains 1. In this case, the firm profit only depends on the technology gap and hence, the technology leader will not invest in any R&D activity. Based on the above economic environment setting, the expected value of firm g in the steady state can be described as follows:

$$rG_t = \pi_t + q_t(G_{t+1} - G_t) + q_{-t}(G_{t-1} - G_t) - \frac{{q_t}^2}{2}$$

where r is the market interest rate and G_t is the expected market value of a firm and t denotes the firm's current technology level. The intuition is: the expected market value of a firm is the sum of the current profit, the gain from moving one technology step ahead with research effort q_t and the loss of having the rival also moving one step ahead with research effort q_{-t}, minus the cost of engaging R&D activities. In the case of duopoly industry structure and maximum technology gap being 1, the corresponding expected market value of firms in unleveled and leveled industry are as follows:

[1] $The\ R\&D\ cost\ in\ Aghion\ et\ al\ (2002) is\ \theta(q) = \frac{1}{2}\beta w q^2$, for simplicity, it is assumed that $\beta = w = 1$

$$rG_1 = \pi_1 + q_{-1}(G_0 - G_1) \quad (4)$$

$$rG_{-1} = \pi_{-1} + q_{-1}(G_0 - G_{-1}) - \frac{{q_{-1}}^2}{2} \quad (5)$$

$$rG_0 = \pi_0 + q_0(G_1 - G_0) + q_0(G_{-1} - G_0) - \frac{{q_0}^2}{2} \quad (6)$$

Analog to the general case, the intuition is: for the technology leader G_1, the expected value equals to the current profit plus the loss of the follower catching up one step (due to the knowledge externality, the leader would not have any incentive for innovation, resulting 0 research effort); for the technology follower G_{-1}, the expected market value equals to the current profit plus the gain from moving a step ahead and minus the cost of engaging in R&D activity; for the neck-and-neck firm G_0, the expected market value is the sum of the current profit, the gain from moving a step ahead and the loss of rival firm catching up minus the cost of R&D activity.

Solving (4)-(6) we can get:

$$q_0 = -r + \sqrt{r^2 + 2(\pi_1 - \pi_0)} \quad (7)$$

$$q_{-1} = -(r + q_0) + \sqrt{r^2 + 2(\pi_1 - \pi_{-1}) + {q_0}^2} \quad (8)$$

As such, for a given market interest rate, the research effort both in the unleveled and leveled industries depends on the relative profit in a step-by-step innovation process.

Industries with stochastic profit shocks

Assume that each industry is exposed to an exogenous profit shock ξ, which is an i.i.d and is uniformly distributed in the interval $[\underline{\xi}, \bar{\xi}]$ with an expected value of 0. Denote F(ξ) the cumulative distribution function.

Assume that each firm has a critical tolerance point ξ_t to absorb such shocks. If the realization of the profit shock ξ is smaller than the critical value ξ_t, all workers have to be fired and a firm has a total firing cost denoting S, thus S capturing the size of dismissal cost. Therefore, the technology leader will close down if $G_1^{\xi} \leq -S$. This is analogy for the technology follower and the neck-and-neck firm, i.e. closing down if $G_{-1}^{\xi} \leq -S$ and $G_0^{\xi} \leq -S$, respectively.

Note that $\xi_1 < \xi_0 < \xi_{-1} < 0$ because the technology leader would exit only if a big adverse shock happens. As such, the probability of collective dismissal decreases in the relativeness of technology level, i.e. $F(\xi \leq \xi_1) < F(\xi \leq \xi_0) < F(\xi \leq \xi_{-1})$.

Therefore, the expected value of firm G in the three steady states under the profit shock can be modeled as:

$$G_1^{\xi} = \frac{1}{r}\int_{\underline{\xi}}^{\overline{\xi}} \left\{max\left[\pi_1^{\xi} + \xi + (1-p)q_{-1}^{\xi}\left(G_0^{\xi} - G_1^{\xi}\right) + p\left(G_m - G_1^{\xi}\right), -S\right]\right\} dF(\xi) \quad (9)$$

Where p is the probability of the profit shock ξ such that $\xi_1 \leq \xi \leq \xi_{-1}$;

$$G_{-1}^{\xi} = \frac{1}{r}\int_{\underline{\xi}}^{\overline{\xi}} \left\{max\left[\pi_{-1}^{\xi} + \xi + q_{-1}^{\xi}\left(G_0^{\xi} - G_{-1}^{\xi}\right) - \frac{(q_{-1}^{\xi})^2}{2}, -S\right]\right\} dF(\xi) \quad (10)$$

$$G_0^{\xi} = \frac{1}{r}\int_{\underline{\xi}}^{\overline{\xi}} \left\{max\left[\pi_o^{\xi} + \xi + q_0^{\xi}\left(G_1^{\xi} - G_0^{\xi}\right) + q_0^{\xi}\left(G_{-1}^{\xi} - G_0^{\xi}\right) - \frac{(q_0^{\xi})^2}{2}, -S\right]\right\} dF(\xi) \quad (11)$$

As suggested in Koeniger (2002), in the unleveled industry, when $\xi_1 \leq \xi \leq \xi_{-1}$, the technology follower exits and the technology leader become monopoly. As we assume that the industry structure is duopoly, thus once one firm exits, another firm will replace it in the next period. As such, there is a possibility of the technology leader being a monopolist in a relatively short time frame.

We can simplify equation (9) to (10) as following:

$$G_1^{\xi} = F(\xi \leq \xi_1)(-S) + F(\xi > \xi_1)\overline{G_1^{\xi}} \quad (12)$$

$$G_{-1}^{\xi} = F(\xi \leq \xi_{-1})(-S) + F(\xi > \xi_{-1})\overline{G_{-1}^{\xi}} \quad (13)$$

$$G_0^{\xi} = F(\xi \leq \xi_0)(-S) + F(\xi > \xi_0)\overline{G_0^{\xi}} \quad (14)$$

In which

$$\overline{G_1^{\xi}} = \frac{1}{r}\left[\pi_1^{\xi} + \int_{\underline{\xi}}^{\overline{\xi}} \xi dF(\xi) + q_{-1}^{\xi}\left(G_0^{\xi} - G_1^{\xi}\right)\right] \quad (15)$$

$$\overline{G_{-1}^{\xi}} = \frac{1}{r}\left[\pi_{-1}^{\xi} + \int_{\underline{\xi}}^{\overline{\xi}} \xi dF(\xi) + q_{-1}^{\xi}\left(G_0^{\xi} - G_{-1}^{\xi}\right) - \frac{(q_{-1}^{\xi})^2}{2}\right] \quad (16)$$

$$\overline{G_0^{\xi}} = \frac{1}{r}\left[\pi_0^{\xi} + \int_{\underline{\xi}}^{\overline{\xi}} \xi dF(\xi) + q_0^{\xi}\left(G_1^{\xi} - G_0^{\xi}\right) + q_0^{\xi}\left(G_{-1}^{\xi} - G_0^{\xi}\right) - \frac{(q_0^{\xi})^2}{2}\right] \quad (17)$$

As can be derived from equation (4) to (6), the marginal revenue of R&D effort for the technology follower and the neck-and-neck firm are:

$$q_{-1} = G_0 - G_{-1}$$

$$q_0 = G_1 - G_0$$

Therefore, when the firm is exposed to the profit shocks,

$$q_{-1} = G_0^{\xi} - G_{-1}^{\xi} = F(\xi \leq \xi_0)(-S) - F(\xi \leq \xi_{-1})(-S) + F(\xi > \xi_0)\overline{G_0^{\xi}} - F(\xi > \xi_{-1})\overline{G_{-1}^{\xi}}$$

$$= [F(\xi \leq \xi_{-1}) - F(\xi \leq \xi_0)]S + F(\xi > \xi_0)\overline{G_0^{\xi}} - F(\xi > \xi_{-1})\overline{G_{-1}^{\xi}}$$

$$q_0 = G_1^{\xi} - G_0^{\xi} = F(\xi \leq \xi_1)(-S) - F(\xi \leq \xi_0)(-S) + F(\xi > \xi_1)\overline{G_1^{\xi}} - F(\xi > \xi_0)\overline{G_0^{\xi}}$$

$$= [F(\xi \leq \xi_0) - F(\xi \leq \xi_1)]S + F(\xi > \xi_1)\overline{G_1^{\xi}} - F(\xi > \xi_0)\overline{G_0^{\xi}}$$

Applying the envelope theorem, we derive the marginal effect of dismissal cost S on R&D investment as follows:

$$\frac{\partial q_{-1}}{\partial S} = \frac{\partial G_0^{\xi} - G_{-1}^{\xi}}{\partial S} = F(\xi \leq \xi_{-1}) - F(\xi \leq \xi_0) > 0$$

$$\frac{\partial q_0}{\partial S} = \frac{\partial G_1^{\xi} - G_0^{\xi}}{\partial S} = F(\xi \leq \xi_0) - F(\xi \leq \xi_1) > 0$$

As such, when the size of dismissal cost S is very high, no matter whether the firm is a technology follower or the firm is a neck-and-neck firm, it induces firm to exert a higher R&D effort and conduct more innovative activities. For the technology follower, with a relative low ability to absorb the adverse profit shock, a higher dismissal cost incentivizes the firm to conduct more R&D research in order to close the technology gap and get a better market position. For the neck-and-neck firms, as both firms are in a same technology level, a higher dismissal cost incentivizes the firm to exert a higher R&D effort to become the technology leader and a better market position in order to avoid such cost.

To sum up, the theoretical framework provides us a testable hypothesis:

H1: Within an industry, conditional on the technology distance, a higher dismissal cost not only induces firms that are closer to the technology frontier (neck-and-neck) to innovate more, but also induces firms that are far from the technology frontier (technology followers) to innovate more.

DATA AND METHODOLOGY

Data

Our empirical analysis covers 13 manufacturing industries at the two-digit level[2] ISIC-Rev. 3 (see Appendix A) in 15 advanced OECD countries over the period 1990 to 2006, leading to an unbalanced panel data with more than three thousand observations for investigation. The countries are Australia, Austria, Belgium, Denmark, Finland, France, Germany, Ireland, Italy, Japan, Netherlands, Spain, Sweden, the United Kingdom and the United States.

Dependent variable

Innovation: Innovation is measured by patent intensity as patents are featured by knowledge creation, thereby capturing the outcome of “knowledge-based economy”. Patent intensity is the total number of patent application divided by the total number of hours worked by employees in corresponding industries. Patent statistics are patent applications to the European Patent Office (EPO) by sector of economic activity in a panel structure, which are obtained from the EUROSTAT database. Based on the international patent classification (IPC) and NACE classification of economic activity Rev 1.1, one can match the patent statistics classification to the ISIC.Rev.3. Total number of hours worked by employees are also obtained in a panel structure from EU KLEMS database at the Groningen Growth and Development Centre (GGDC).

Independent variables

Dismissal cost: Employment protection legislation (EPL) on regular contracts measures the strictness of regulation on individual dismissals among regular workers and has been widely used in empirical analysis (see e.g. Boeri and Jimeno, 2005; Griffith & Macartney, 2014). This indicator is a weighted index in a scale 0-6 over regulations on procedural inconvenience, notice and severance pay for non-fault individual dismissal and difficulty of dismissal. Data is extracted

[2] See e.g. Aghion et al (2002), Amable et al (2009) and Nicoletti and Scarpetta (2006) are also based on two-digit ISIC industry code.

from the employment protection annual series data (1985-2013) from the OECD Employment database. Although this indicator is country specific other than industry specific, its impact is likely to differ across industries, even if all industries are embedded in a similar institutional environment (see e.g. Bassnini, Nunziata and Venn, 2009)[3]

Technological distance/technological gap: The world technology frontier in this paper, following Aghion (2003), is defined as the most productive available technology in each industry in each year. Total factor productivity level (value added) is used to calculate the distance to the world technology frontier. As there is no data on total factor productivity level in such a panel structure employed in this paper, we followed Amable et al (2014) in which the means of calculating the total factor productivity level is well documented. More specifically, we obtained the data on total factor productivity growth index (with year 1995 as the reference) in 13 manufacturing industries from the EU KLEMS database. In addition, we drew data on the total factor productivity level index in the manufacturing industries from the Productivity Level database (PL), which is also provided by the GGDC. Two features of the latter are worth mentioning: 1) the total factor productivity level in the PL database has been deflated by constructing purchasing power parities (PPP) and offered a double deflation for value added, in order to achieve comparable information across countries and industries; 2) the total factor productivity level is in level relative to that of the US and only available in year 1997. Nevertheless, these two datasets provide the possibility to calculate the total factor productivity level in the full range of time across countries and industries.

[3] Bassanini et al (2008) find that employment protection legislation is more likely to be binding in some industries than others.

For a given country c, industry i and year t, denote $TFPG_{cit}^{r}$ the total factor productivity growth index relative to the reference year r; denote $TFPL_{ci,97}^{US}$ the total factor productivity level index relative to that of the US in the year 1997; denote $TFPL_{cit}$ the total factor productivity level index. Therefore, the two data mentioned in the above can be illustrated by the following formulas:

$$TFPG_{cit}^{95} = \frac{TFPL_{cit}}{TFPL_{ci,95}} \tag{18}$$

$$TFPL_{ci,97}^{US} = \frac{TFPL_{ci,97}}{TFPL_{us,i,97}} \tag{19}$$

Since both data are not in the same reference year, we adjusted the reference year to 1997 in the total factor productivity growth index. As such, the total factor productivity level index relative to that of the US in the full sample range can be derived by the following formula:

$$TFPL_{cit}^{US} = \frac{TFPG_{cit}^{97}}{TFPG_{us,it}^{97}} * TFPL_{ci,97}^{US} = \frac{TFPL_{cit}}{TFPL_{US,it}} \tag{20}$$

Here, as instructed by Amable et al (2014), the world technology frontier in industry i and year t is defined as the country c* that has the highest total factor productivity level index relative to that of the US. Denote WTF_{cit} the world technology frontier, therefore,

$$WTF_{cit} = TFPL_{c*,it}^{US} \text{ , where } c* = \underset{c}{argmax} \left\{TFPL_{cit}^{US}\right\} \tag{21}$$

As such, denote CTF_{cit} the closeness to the technology frontier for a country c in each industry i and in each time period t; it can be easily calculated by its total factor productivity level index relative to that of the US divided by the total factor productivity level index of the world technology frontier:

$$CTF_{cit} = \frac{TFPL_{cit}^{US}}{WTF_{cit}} = \frac{TFPL_{cit}^{US}}{TFPL_{c*,it}^{US}} = \frac{TFPL_{cit}}{TFPL_{us,it}} \Big/ \frac{TFPL_{c*,it}}{TFPL_{us,it}} = \frac{TFPL_{cit}}{TFPL_{c*it}} \tag{22}$$

The technological distance is ranging from 0 to 1; the larger the number of CTF_{cit} is, the closer to the world technology frontier is. Therefore, if one industry has a small value of CTF_{cit}, it is among the technology followers; however, when the industry has a big value of CTF_{cit}, it is among the neck-and-neck firms.

Control variables

This paper controlled for a set of variables which has been proven to affect innovation in innovation research (see e.g. Aghion et al 2009; Amable et al, 2009, Barhosa and Faria, 2011).

Product market regulation is included in the regression analysis as it is a factor that has been widely examined in the empirical analysis and has a strong influence on innovation (see e.g. Aghion, 2003; Amable et al 2009). More precisely, we used the OECD Indicator of regulation impact (total) as the measurement of product market regulation[4]. The set of OECD regulation impact indicators measures the potential costs of anti-competitive regulation in selected non-manufacturing sectors on sectors of the economy that use the output of non-manufacturing sectors as intermediate inputs in the production process. The total regulation impact indicator is particularly of interest as this indicator has been calculated for 38 ISIC Rev.3 sectors in 29 OECD countries over the period 1975-2007, making it a perfect candidate for the panel structure used in this paper. Methodology of the indicator construction is described in Conway and Nicoletti (2006). Additionally, we added import penetration ratio in order to cover the foreign competition pressure which is not captured by the above regulation impact index. Data is extracted from OECD STAN database.

Share of capital input is measured by the ratio of total capital compensation over total labor compensation. Both series are obtained from the EU KLEMS database. This variable is used to control for the effect of overall capital input on innovation. In addition, we included contribution

[4] Amable et al (2014) also use this indicator investigating the relationship between product market regulation and innovation.

of information communication technology (ICT) capital service to value added growth as a control variable. This variable captures how many percentage the use of ICT capital service has contributed to growth and thus innovation activity. Data on this is obtained from EU KLEMS dataset. Employment share in manufacturing measures the employment ratio of each industry on total manufacturing in each year. This indicator is obtained from OECDSTAT and is included to control for the quantity of human resource in the innovation activities. Quality of human resource is of importance to innovation, especially high-skill persons. We extracted the data on the share of hours worked by high-skill workers from the World Input-Output database, and used it as a proxy for skill composition. As the data is only available from 1995 to 2006, it is included as a robustness check. A large body of theoretical and empirical studies has investigated the influence of intellectual property right on innovation (see e.g. Chen and Puttitanun, 2005; Varsakelis, 2001). Although the countries involved in this analysis have a relative strong protection of intellectual property right, it is, nevertheless, included to check its effect over the time as the sample contains a 17-year span. Data is obtained from Park (2008)'s updated index of patent rights protection. This index is the unweighted sum of five separate scores for five domains: intentions that are patentable; membership in the international treaties; duration of protection; enforcement mechanisms and restrictions on patent rights. However, it is still only available in a 5-year interval. As such, index of patent right in 1995 serves as a proxy over the period of 1990-1995; index in 2000 serves as a proxy over 1996-2000 and index in 2005 acts as a proxy over 2001-2006. Methodology of the index can be referred to the Appendix A in Park (2008). We also control for two policies in the macro level which may bias our estimation: one is the social welfare and the other is active labor market program. Social welfare has many dimension but we only consider the social expenditure on unemployment as it is highly relevant in the situation of dismissal. Data of social expenditure on unemployment is extracted from social expenditure series from OECDSTAT and is measured by the percentage of GDP. Since mid-80s, many countries have be involved in the active labor market program. This program covers 8 dimensions such as PES and administration; training, employment incentives and etc. This variable served as a control in order to avoid the overestimation of employment protection legislation on innovation. We used the total public expenditure on active labor market program as a percentage of GDP and the data is from OECDSTAT.

The descriptive statistics of all variables are reported in the Appendix B.

Methodology

Assume that the innovation process X follows a Poisson distribution with parameter λ. Hence, the resulting number of patent applications in any time interval has the probability distribution:

$$f = (\lambda, k) = \Pr(\mathrm{X} = k) = \frac{e^{-\lambda} * \lambda^{k}}{k!}$$

in which $\lambda = e^{g(s)}$ measures the relationship between the strictness of employment protection (which is a proxy of the dismissal cost) s and innovation.

Therefore, the expected number of patent application can be expressed by:

$$\mathrm{E(X)} = \lambda = e^{g(s)}$$

Our data has a panel structure in which the individual is defined as a country-industry unit and the time is measured by year. Denote EPL_{ct} the employment protection legislation in country c and time t and denote PI_{cit} the patent intensity[5] in country c, industry i and time t, then the conditional mean of (23) is expressed as:

[5] It is important to know that our dependent variable is an hour worked weighted number of patent applications in each industry and each country.

$$\mathrm{E}(PI_{cit}|EPL_{ct}) = \lambda = e^{g(EPL_{ct})} \quad (24)$$

in which $g(EPL_{ct}) = \alpha_1 EPL_{ct} + \alpha_2 EPL_{ct} * CTF_{cit}$[6]

Denote X'_{cit} the vector of control variables which capture the Marco institutions and other relevant government policies, and other alternative mechanisms which may explain the patent activities in the industry level. Conditional on the control variables, average patent activity is related to employment protection legislation based on:

$$\mathrm{E}(PI_{cit}|EPL_{ct}, X'_{cit}) = \lambda = e^{g(EPL_{ct})+\beta X'_{cit}} \quad (25)$$

It is very likely that a higher level of patent activity has no directly causal relationship with employment protection legislation but rather reflects the heterogeneity between different industries. As such, country-industry fixed effects are included to control for the individual heterogeneity and time fixed effects are included to control for the common macro shocks. Denote δ_{ci} the country-industry fixed effects and denote μ_t the time fixed effects, the average patent activities is determined by:

$$\mathrm{E}(PI_{cit}|EPL_{ct}, X'_{cit}, \delta_{ci}, \mu_t) = \lambda = e^{g(EPL_{ct})+\beta X'_{cit}+\gamma_1\delta_{ci}+\gamma_2\mu_t} \quad (26)$$

Although Poisson maximum likelihood estimator (MLE) is a consistent estimator, we need to use the heteroskedasticity corrected variance covariance matrix in order to avoid the overdispersion problem associated with the Poisson MLE (see e.g. Blundell et al 2002).

RESULTS AND DISCUSSION

Descriptive statistics

Table 1 displays the correlation matrix of variables used in the empirical analysis. At a first glance, one can find that all explanatory variables are significant correlated with the dependent

[6] Note that parametric models studying count data typically base the specification of Poisson model with a linear form of *g(s).* See e.g. Hausman, Hall and Griliches (1984).

variable at 1% significance level. Among independent variables: employment protection legislation has a positive correlation with patent intensity while the interaction term between employment protection legislation and closeness to technology frontier shows a negative correlation. Among the control variables covering macro-level institutions and policies, i.e. social welfare measured by social expenditure on unemployment, public expenditure on active labor market program, trade union density and protection of patent right, we find a positive correlation between all these variables and patent intensity. Among the control variables capturing alternative mechanisms affecting innovation activities, regulation impact index and employment share in the manufacturing show a negative relationship with patent intensity. However, share of capital input, ICT capital service, import penetration ratio and share of high-skill workers are positively correlated with patent intensity.

Insert Table 1 about here

Results

Table 2 presents our results on employment protection legislation and innovation. We tested the hypotheses with different model specifications by adding additional control variables. In each model specification, conditional fixed effect Poisson regression analysis is employed. Country-industry and time fixed effects were introduced to remove spurious correlation between employment protection legislation and average patent count. Since employment protection legislation is a country-specific index and does not have any variation across industries in each country in a given year, it shows the general effect of dismissal cost on innovation over the time. However, the interaction terms between employment protection legislation and closeness to technology frontier is the variable of key interest. It captures the effect of employment protection legislation on innovation in each industry, conditional on its technology distance to the world frontier.

Insert Table 2 about here

Our results show that after holding macro institutions, policies and other influential factors constant and controlling for the individual and time fixed effect, a higher dismissal cost induced by a stricter employment protection legislation is likely to be beneficial for innovation. However, when conditional on the closeness to technology frontier, a higher dismissal cost induced by a stricter employment protection legislation is likely to exert an adverse effect on innovation; the adverse effect is (the largest) larger when the industry is (at the technology frontier) very close to the frontier.

More specifically, without any control variables, model 1 shows that employment protection legislation is negatively associated with innovation at a 5% significance level. Conditional on the closeness to technology frontier, a strict employment protection legislation is also negatively associated with innovation. However, as can be seen from model 2, once controlling for the time fixed effect, the coefficient of both variables are dropped drastically, yet are no longer significant, suggesting that common macro shocks have a strong impact on innovation. In model 3, variables capturing the macro institutions and other state policies are included, in which public expenditure on active labor market program has a positive effect on innovation at 1% significance level. In model 4, share of capital input and the influence of product market regulations are added as additional controls in order to cover their impact. The coefficients of employment protection legislation and its interaction with technology distance remained similar to previous specification. However, social expenditure on unemployment become significant and has a negative effect on innovation. Public expenditure on active labor market program remains positively affecting the innovation. Regulation impact is found to have a substantial negative impact on innovation, which is also confirmed by many other previous studies (e.g. Amable, et al 2009; Barbosa & Faria, 2011). Competition from foreign countries, measured by import penetration ratio, has a positive effect on innovation at a marginal significance level (see a similar result from Bassanini & Ernst, 2002). Capital input share also exerts a positive effect on innovation. Finally, we control for the human capital in which employment share captures the quantity aspect and skill composition captures the quality aspect. As can be seen from model 5, the coefficient of employment protection legislation becomes positive but not significant, however, conditional on the closeness to the technology frontier, employment protection legislation has a significant negative impact on innovation at a 5% significance level. Among the control variables, social expenditure on unemployment, trade union density, regulation impact and employment share have a negative effect at least at a 5% significance level; on the other hand, public expenditures on active labor market program, share of capital input and skill composition exert a positive effect at 1% significance level.

Summarizing the results: Our hypothesis that conditional on the technology distance, a higher dismissal cost is beneficial for innovation for both neck-and-neck firms and technology followers is not supported by the empirical investigation.

Robustness checks

In order to test for the robustness of the results presented above, we estimated the effect of employment protection legislation on innovation with another model with a form of:

$$Ln(PI_{cit}) = g(EPL_{ct}) + \beta X'_{cit} + \gamma_1 \delta_{ci} + \gamma_2 \mu_t + v_{cit}$$

in which $g(EPL_{ct}) = \alpha_1 EPL_{ct} + \alpha_2 EPL_{ct} * CTF_{cit}$, X'_{cit} is a vector of control variables, δ_{ci} is individual fixed effects, μ_t is time fixed effects and v_{cit} is the error term. Panel fixed effect regression was employed. Table 3 displays the results.

Insert Table 3 about here

As can be seen from table 3, the results are very similar to the previous reported results. Without controlling for the time fixed effect, both employment protection legislation and the interaction term have a large negative effect on innovation at 1% significance level. However, after introducing the time fixed effect (see model 7), the coefficient of independent variables dropped dramatically, yet, the interaction term remains significant at a 5% level. From Model 8 to model 10, additional controls on macro institutions and state policies, product market regulation, capital input and human capital are included. Across those specifications, employment protection legislation resembles the same pattern as previously discussed. Conditional on the technology distance, the significant negative impact of employment protection legislation survived from all model specifications, although the size of the effect decreased. Among control variables, social expenditure on unemployment, trade union density, regulation impact and employment share have a negative effect at least at a 5% significance level; while public expenditures on active labor market program, share of capital input and skill composition exert a positive effect at 1% significance level.

To conclude, the robustness checks confirm that the general results hold.

Discussion

Based on the theoretical framework developed by Aghion et al (2001), Aghion et al (2002) and Koeniger (2002, 2005), we drew our hypothesis on the impact of dismissal cost induced by a strict employment protection legislation on innovation. In the economic environment where firms innovate in a step-by-step process; both technology leaders and the followers are engaging in R&D activities to achieve a higher profit. According to the model prediction, firms may innovate more if they are subject to a high dismissal cost when each industry is exposed to a stochastic profit shock. This may due to the fact that under uncertainties in the market, a higher dismissal cost makes firms bounded by a harder budget constraint and therefore try to innovate more in order to get a better market share and escape from competition. As such, we expect to find a positive effect of employment protection legislation on innovation while conditional on the distance to technology frontier. Analyzing the data on the industry level from 15 OECD countries over the period of 1990 to 2006, contrast to the hypothesis, we find the opposite effect of employment protection legislation on innovation while taking the technology distance into consideration, suggesting that a higher dismissal cost or a stricter employment protection legislation is detrimental to the innovation, and this effect is particularly strong when the technology distance is minimum (neck-and-neck)[7]. This negative effect is robust to an array of control variables and an alternative model specification. If we follow the theoretically prediction and the argument in the sense that under market uncertainties, a higher dismissal cost induces a harder budget constraint and thus leads to innovation, we would also expect that a high trade union density exerts a similar effect as a high trade union density would strengthen employees' bargain power against firms and thus imposes a hard budget constraint. However, this argument is not supported by the data.

[7] Note, the technology distance/technology gap is measured by one industry's TFP growth level relative to the world frontier. As such, it is ranging from 0 to 1 in which 0 is the maximum distance/gap while 1 is the minimum distance/gap.

Though contrast to the theoretical prediction, our results are consistent to many previous studies investigating the relationship between employment protection legislation and innovation. The argument is that stringent employment protection or a high dismissal cost is detrimental to innovation because it makes more difficult for firms to adapt to new technologies which may require staff reallocation or downsizing. This arguments follows what Freeman has termed the "distortionist" view in which stringent employment protection may fail to adjust adequately to the market shocks or technology advancement (Freeman, 1993). Saint-Paul (2002) differentiates innovation between "primary innovation" and "secondary innovation" in which the former introduces new products while the latter improves exiting products. He shows that European countries that characterized by stringent employment protection, tend to specialized in "secondary innovation" while the US which has loose employment protection exerts a comparative advantage on "primary innovation". Gust and Marquez (2004) argue that burdensome labor market practices have an adverse effect on adopting information technologies in many industrial countries. Samaniego (2008) demonstrates that firing costs are particularly detrimental to firm profits in industries in which the rate of technology change is very high. In a more recent study, Barbosa and Faria (2011) use cross section data in the industry level in which innovation is measured by the ratio of firms introduced an innovation in the market over the total number of firms in the industry; their findings suggest a negative impact of stringent employment protection on innovation in several European countries.

CONCLUDING REMARKS

This paper tries to answer whether structural reforms aiming at increasing flexibility in labor markets are beneficial for the EU to achieve the goal of being "the most dynamic and competitive knowledge-based economy" (Lisbon Strategy, 2005). Building up a theoretical framework in which each industry is exposed to a stochastic profit shock and firms are engaging in innovation activities in a step-by-step process, we derived our hypothesis that under the market uncertainty, a higher dismissal cost or a stringent employment protection legislation will induce firms innovate more, regardless whether they are close to the technology frontier or they are simply technology followers. Specifically, we tested on the impact of dismissal cost or the strictness of employment protection legislation on innovation based on panel data from 13 manufacturing industries in 15 OECD countries over the time period of 1990-2006. The results reflect a negative relationship between employment protection legislation and innovation, conditional on the closeness to the technology frontier. The empirical evidence does not support the prediction from the theoretical model. However, our results are consistent to many previous studies, though the data and methods are different (see e.g. Barbosa and Faria, 2011). Based on our analysis, we find that the structure reform in labor markets aiming at introducing flexibility by relaxing the labor market regulations is beneficial for innovation.

Several limitations are need to be mentioned: first, the variables used in the paper are not perfect. Innovation is measured by patent intensity which is exclusively focusing on the patent applications at the EPO. Alternative measurement of innovation, for instance, patent statistics at USPTO and patent citation will need to be included in the future research. Second, we are particularly interested in the effect of dismissal cost or strictness of employment protection legislation on innovation and we observe a gradual deregulation of employment protection legislation within OECD countries. However, change of other policies may also have an effect on innovation. Without concerning sufficiently on this respect, our result would have omitted variable bias. Although we cannot control for all policies, we considered several aspects such as the social expenditure on unemployment, public expenditure on labor market program, product market regulation and import penetration, though which we controlled for the potential bias. Last but not least, we introduced country-industry fixed effects and time fixed effects in order to rule out the spurious correlation between employment protection legislation and innovation. We believe that the index of employment protection legislation is a policy related index which is exogenous, however, we cannot fully rule out the concern on endogeneity issue with regard to our measurement of closeness to the technology frontier which is a relativeness of total factor productivity growth level. However, there is no proper instruments that we could draw from literature and this point is still need to be addressed in the future.

REFERENCES

Acemoglu, D. (1997). Training and innovation in an imperfect labour market. **The Review of Economic Studies**, 64(3), 445-464.

Addison, J. T., Blackburn, M. L., & Cotti, C. D. (2013). Minimum wage increases in a recessionary environment. **Labour Economics**, 23, 30-39.

Aghion, P., Bloom, N., Blundell, R., Griffith, R., & Howitt, P. (2002). **Competition and innovation: An inverted U relationship** (No. w9269). National Bureau of Economic Research.

Aghion, P., Blundell, R., Griffith, R., Howitt, P., & Prantl, S. (2009). The effects of entry on incumbent innovation and productivity. **The Review of Economics and Statistics**, 91(1), 20-32.

Aghion, P., Harris, C., Howitt, P., & Vickers, J. (2001). Competition, imitation and growth with step-by-step innovation. **The Review of Economic Studies**, 68(3), 467-492.

Amable, B., Demmou, L., & Ledezma, I. (2009). Product market regulation, innovation, and distance to frontier. **Industrial and Corporate Change**, 1-43.

Amable, B., Ledezma, I., & Robin, S. (2014). **Product market regulation, innovation and productivity**. CES Working Paper.

Barbosa, N., & Faria, A. P. (2011). Innovation across Europe: How important are institutional differences? **Research Policy**, 40(9), 1157-1169.

Bassanini, A., & Ernst, E. (2002). Labour market regulation, industrial relations and technological regimes: a tale of comparative advantage. **Industrial and Corporate Change**, 11(3), 391-426.

Bassanini, A., Nunziata, L., & Venn, D. (2009). Job protection legislation and productivity growth in OECD countries. **Economic Policy,** 24(58), 349-402.

Bertola, G. (1994). Flexibility, investment, and growth. **Journal of Monetary Economics**, 34(2), 215-238.

Boeri, T., & Jimeno, J. F. (2005). The effects of employment protection: Learning from variable enforcement. **European Economic Review**, 49(8), 2057-2077.

Blundell, R., Griffith, R., & Windmeijer, F. (2002). Individual effects and dynamics in count data models. **Journal of Econometrics,** 108(1), 113-131.

Casper, S, Lehrer, M and Soskice, D. (1999). Can High-technology Industries Prosper in Germany? Institutional Frameworks and the Evolution of the German Software and Biotechnology Industries, **Industry and Innovation**, 6(1), 5-24

Chen, Y., & Puttitanun, T. (2005). Intellectual property rights and innovation in developing countries. **Journal of development economics**, 78(2), 474-493.

Conway, P. and G. Nicoletti (2006). **Product Market Regulation in the Non-Manufacturing Sectors of OECD Countries: Measurement and Highlights**. OECD Economics Department Working Paper, No 530

DiNardo, J., Fortin, N. M., & Lemieux, T. (1996). Labor Market Institutions and the Distribution of Wages, 1973-1992: A Semiparametric Approach. **Econometrica**, 64(5), 1001-1044.

Dube, A., Lester, T. W., & Reich, M. (2010). Minimum wage effects across state borders: Estimates using contiguous counties. **The review of economics and statistics**, 92(4), 945-964.

Freeman, R.B. (1993). "Labor Market Institutions and Policies: Help or Hindrance to Economic Adjustment?" **Proceedings of the World Bank Annual Conference on Development Economics, 1992**. Supplement to the World Bank Economic Review and the World Bank Research Observer.

Griffith, R., & Macartney, G. (2014). Employment Protection Legislation, Multinational Firms, and Innovation. **Review of Economics and Statistics**, 96(1), 135-150.

Gust, C., & Marquez, J. (2004). International comparisons of productivity growth: the role of information technology and regulatory practices. **Labour economics**, 11(1), 33-58.

Hausman, J. A., Hall, B. H., & Griliches, Z. (1984). **Econometric models for count data with an application to the patents-R&D relationship.**

Hoisl, K. (2007). Tracing mobile inventors—the causality between inventor mobility and inventor productivity. **Research Policy**, 36(5), 619-636.

Koeniger, W. (2002). **Employment protection, product market competition and growth**. IZA discussion paper No.554

Koeniger, W. (2005). Dismissal costs and innovation. **Economics Letters**, 88(1), 79-84.

Neumark, D., & Wascher, W. (1992). Employment Effects of Minimum and Subminimum Wages: Panel Data on State Minimum Wage Laws. **Indus. & Lab. Rel. Rev**., 46, 55.

Park, W. G. (2008). International patent protection: 1960–2005. **Research policy**, 37(4), 761-766.

Samaniego, R. M. (2008). Entry, exit and business cycles in a general equilibrium model. Review of Economic Dynamics, 11(3), 529-541.

Varsakelis, N. C. (2001). The impact of patent protection, economy openness and national culture on R&D investment: a cross-country empirical investigation. **Research Policy**, 30(7), 1059-1068.

Table 1: Descriptive statistics – Correlation matrix of key variables

	patent intensity	EPL	EPL*CTF	Soical expenditure on unemployment	Public expenditure on ALMP	Trade union density	Protection of patent right	Regulation impact-total	log (share of capital input)	Contribution of ICT capital service	log of import penetration	Employment share	Share of high-skill workers
patent intensity	1												
EPL	0.13***	1											
EPL*CTF	-0.1372***	0.507***	1										
Soical expenditure on unemployment	0.0457***	0.3598***	0.2304***	1									
Public expenditure on ALMP	0.1087***	0.5745***	0.3629**	0.888***	1								
Trade union density	0.0747***	0.2076***	0.1166***	0.4933***	0.59***	1							
Protection of patent right	0.1281***	-0.3128***	-0.1068***	-0.01187***	-0.1137***	-0.0434**	1						
Regulation impact-total	-0.1606***	0.2481***	0.2490**+	0.095***	0.0014	-0.0921***	-0.2165	1					
log (share of capital input)	0.2663***	-0.0632***	-0.0888***	-0.0618***	-0.1127***	-0.0591***	0.0501***	0.0285	1				
Contribution of ICT capital service	0.1136***	-0.0927***	-0.0773***	0.0959***	0.0793***	0.1241***	0.0316***	-0.092***	0.1175***	1			
log of import penetration	0.3097***	0-1621***	0.017	0-3581***	0.3771***	0.2758***	-0.0278	-0.095***	-0.1639***	0.0734***	1		
Employment share	-0.1252***	-0.0074	0.3104***	-0.0005	0.0004	0.0012	-0.0018	0.0122	-0.1025***	0.0101	-0.0182	1	
Share of high-skill workers	0.1535***	-0.2682***	-0.1330***	0.0416**	-0.0967***	-0.0798***	0.2168***	-0.381***	0.0742***	-0.0795***	-0.089***	0.02	1

Note: EPL: employment protection legislation; CTF: closeness to the technology frontier; ALMP: active labor market program; ICT: information communication technolog

Table 2: Result of EPL and innovation (Conditional fixed effect Poisson regression)

	Dependent variable: Patent intensity				
VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5
EPL	-0.601**	-0.0445	-0.0431	-0.0603	0.0134
	(0.282)	(0.114)	(0.129)	(0.0979)	(-0.143)
EPL*CTF	-0.325**	-0.0696	-0.0735	-0.0710	-0.0738**
	(0.156)	(0.0452)	(0.0479)	(0.0511)	(-0.038)
Social expenditure on unemployment (% GDP)			-0.0781	-0.108**	-0.0773**
			(0.0593)	(0.0510)	(-0.0373)
Trade union density (%)			-0.00701	-0.00969	-0.0237***
			(0.00591)	(0.00633)	(-0.0079)
Public expenditure on labor market program (% GDP)			0.124***	0.127***	0.138***
			(0.0462)	(0.0344)	(-0.0324)
Protection of patent right			0.153	0.101	-0.309*
			(0.138)	(0.167)	(-0.174)
Regulation impact (total)				-4.800**	-5.471***
				(2.135)	(-2.115)
Contribution of ICT capital service (value-added %)				0.0162	0.0173
				(0.0176)	(-0.0149)
Log (share of capital input)				0.0570***	0.0510***
				(0.0186)	(-0.0157)
Log (import penetration)				0.157*	0.105
				(0.0894)	(-0.0815)
Employment share (% of manufacturing)					-0.0535**
					(-0.0261)
Skill composition					1.204***
					(-0.415)
Country-industy fixed effect	YES	YES	YES	YES	YES
Year fixed effect	NO	YES	YES	YES	YES
Log likelihood	-2247.526	-2070.8647	-1967.6252	-1775.8378	-1330.502
Wald Chi2 test (P)	0.0021	0.000	0.000	0.000	0.000
Observations	3,246	3,246	3,064	2,744	2,000
Number of individuals	194	194	194	179	179

Standard errors in parentheses (bootstrap); *** p<0.01, ** p<0.05, * p<0.1; skill composition only has data from 1996 to 2006.

Table 3: Result of EPL and innovation (fixed effect panel regression)

	Dependent variable: Log of Patent intensity				
VARIABLES	Model 6	Model 7	Model 8	Model 9	Model 10
EPL	-0.379***	-0.0632	-0.0668	-0.0426	0.108
	(0.102)	(0.0473)	(0.0547)	(0.0456)	(0.0842)
EPL*CTF	-0.362***	-0.0846**	-0.122***	-0.103***	-0.0873**
	(0.104)	(0.0393)	(0.0375)	(0.0352)	(0.0365)
Social expenditure on unemployment (% GDP)			-0.0208	-0.0452*	-0.0459*
			(0.0307)	(0.0264)	(0.0276)
Public expenditure on labor market program (% GDP)			0.0799***	0.0865***	0.132***
			(0.0251)	(0.0215)	(0.0231)
Trade union density (%)			-0.000872	-0.000447	-0.0202***
			(0.00408)	(0.00386)	(0.00522)
Protection of patent right			0.322**	0.426***	-0.0177
			(0.132)	(0.121)	(0.118)
Regulation impact (total)				-4.858***	-5.405***
				(1.025)	(0.928)
Contribution of ICT capital service (value-added %)				-0.00654	-0.00287
				(0.0134)	(0.0123)
Log (share of capital input)				-0.0772***	-0.0938***
				(0.0202)	(0.0179)
Log (import penetration)				0.0518***	0.0380**
				(0.0181)	(0.0167)
Employment share (% of manufacturing)				0.103**	0.0316
				(0.0426)	(0.0281)
Skill composition					1.151***
					(0.366)
Country-industy fixed effect	YES	YES	YES	YES	YES
Year fixed effect	NO	YES	YES	YES	YES
Constant	0.132	-1.345***	-2.841***	-2.508***	0.270
	(0.152)	(0.0898)	(0.620)	(0.670)	(0.682)
F test (p)	0.000	0.000	0.000	0.000	0.000
R-squared	0.096	0.791	0.793	0.831	0.768
Observations	3,263	3,263	3,081	2,756	2,012
Number of individuals	211	211	211	196	191

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1; skill composition only has data from 1996 to 2006.

Appendix A: list of industries based on two-digit ISIC Rev. 3

15t16	Food Beverages and tobacco
17t19	Textiles, leather and footwear
20	Wood and cork
21t22	Pulp, paper, printing and publishing
23	Coke, refined, petroleum and nuclear fuel
24	Chemicals
25	Rubber and plastic
26	Other non-metallic mineral
27t28	Basic metal and fabricated metal
29	Machinery and e.t.c
30t33	Electrical and optical equipment
34t35	Transport equipment
36t37	Manufacturing, recyclings

Appendix B: descriptive statistics of variables

Variables	Obs	Mean	Std.Dev.	Min	Max
Log of patent intensity	3315	-1.003721	1.620806	-5.870167	2.659116
Log of R&D intensity	2993	0.8104996	1.350056	-4.750954	4.470229
Employment protection legislation on regular workers	3315	2.060015	.7638872	.2566667	3.547619
Closeness to the frontier (0-1)	3263	.497441	.2714339	.0044742	1
EPL*CTF	3263	.9993241	.6832009	.009552	3.547619
Trade Union density	3315	38.12002	22.44471	7.586451	83.86254
Social expenditure on unemployment (%GDP)	3315	1.656078	1.123275	.2	5.3
Public expenditure on active labor market program (% GDP)	3315	2.573112	1.473741	.36	7.19
IPR	3315	4.513412	.1991923	4.14	4.88
Regulation impact total	3298	.0938921	.0361275	.0110167	.2373997
Employment share in Manufacturing (%)	3286	7.7347	4.69773	.1426453	25.36693
Skill composition (share of hours worked by high skill workers)	2340	.1682923	.06928	.0300014	.4591563
Log of capital input share	3257	-.7645281	.7860834	-5.354016	3.15205
Log of import penetration	3068	3.523094	.8383405	.6527318	8.63918
Contribution of ICT capital service to value-added growth	3257	.3632376	.7305868	-5.1	19.37