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The distribution of unemployment risks: Employment Protection Legislation and Skill-biased Technological Change

Jenny Bennett

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ISG – Institut für Sozialforschung
und Gesellschaftspolitik GmbH
Barbarossaplatz 2
50674 Köln

Abstract

This article focuses on the relationship between employment protection legislation (EPL) and skill-specific unemployment risks. It is expected that this relationship is moderated by the level of technological progress, which is linked to the specific requirements of functional and numeric flexibility. The analysis is based on data from the Labour Force Survey from the year 2008. The results show that EPL is positively related to unemployment risks for all skill groups. However, for the medium- and highly skilled, the effects are moderated by the level of technological progress: the higher the share of employment in (medium-) high-tech manufacturing and knowledge-intensive services, the lower this relation will be. In countries with very large employment shares in both sectors, the relationship between EPL and unemployment can even be negative. One striking result of the analysis is that there is no robust relationship between EPL and the risk of long-term unemployment.

1. Introduction

A lack of numerical flexibility in the hiring and firing decisions of employers is generally regarded as a main reason for high and persistent unemployment rates in many European countries (Addison and Teixeira, 2001; OECD, 2004; Skedinger, 2010; Walwei, 1996, 2002). The relaxation of employment protection legislation (EPL) is believed to improve employment chances, particularly for people that are disadvantaged in the labour market; for example, the low skilled, who often appear to be the losers of technological progress. Due to structural change, jobs offered in the primary and secondary sector have decreased. Achieved knowledge on these fields has become obsolete. At the same time, new skills are needed to fulfill the requirements in the service sector and new established branches. These new jobs mainly demand rather higher levels of qualification (Iversen and Cusack, 2000). In this context, the enhancement of labour market flexibility – particularly by facilitating the use of temporary employment – has been one of the main targets of the European Union's current and future employment strategies (Council of Europe, 2005; European Commission, 2012), which aims to reduce the degree of social exclusion and improve social cohesion. The easing of dismissal rules is expected to simplify access to the labour market by retrenching employment barriers.

Empirically, however, there is no clear evidence of a relationship between the relaxation of EPL and a reduction in the unemployment rate in general (for an overview, see Addison and Teixeira, 2001; Skedinger, 2010). Moreover, specific effects of EPL on different skill groups have only been of minor interest in the past. The OECD (1999) and Oesch (2010) both concentrated on the effects that EPL has on the low skilled unemployment rate, but were unable to show any significant relation. Esping-Andersen (2000) identified a significant and positive relationship between the long-term unemployment rate of less-educated workers and EPL, but again not with the low skilled unemployment rate in general. The first insights into skill-specific labour market outcomes for differently educated workers were provided by Gebel and Giesecke (2011). The authors concentrated on the relative differences between skill groups in temporary employment and unemployment. Their results show that deregulating restrictions on temporary employment increases the relative share of low skilled workers in temporary employment in comparison to better skilled workers; however, there was no effect concerning the distribution of unemployment risks. In their study, the easing of dismissal rules for regular employment decreased the relative unemployment risks for the low skilled. Bennett (2012) could only confirm these results relating to differences between individuals with medium and high levels of qualification, while also facilitating the possibility that employing workers on a temporary contract has no influence on the distribution of unemployment risks at all. However, the author shows that an increase in the level of EPL leads to bigger differences in the employment rates between the low and highly skilled, whereas differences in employment rates between the medium- and highly skilled are strengthened only by an increase in the regulation of temporary employment.

The following analysis aims to provide more insights into the interplay between EPL and skill-specific unemployment risks. In contrast to previous studies, it does not concentrate on changes in EPL, but on the level of EPL that is implemented at a specific point in time. Previous studies mostly focused on the effects of a reform only by neglecting the base level of EPL. By taking a cross-sectional perspective, the existing differences between countries concerning the currently implemented levels of dismissal rules ant their relation to individual unemployment risks are highlighted. Therewith, the general effects that are related to differences in the level of EPL can be captured. In addition, the article also deals with the likelihood that the observed unemployment status is permanent.

Furthermore, this article contributes to the literature by taking technological progress into account. In the course of an explorative analysis, the article tries to answer the question whether the relation between EPL and unemployment risks for different skill groups might be moderated by the level of technical progress that can be observed in a country. Since technological advancements are considered to be skill-biased (as will be outlined later), they might produce different flexibility requirements on varying skill groups.

The analysis is based on data from the Labour Force Survey (wave 2008) and captures 21 European countries. In order to account for compositional effects, hierarchical models are used.

The paper is structured as follows: Chapter 2 deals with skill-specific unemployment risks; potential positive and negative employment effects of EPL are initially described, before the role of technological progress and its possible interplay with EPL for different skill groups are discussed. Chapter 3 describes the data, variables and methods that have been used. In Chapter 4, the descriptive, bivariate and multivariate results are presented. The paper ends with a discussion of the results.

2. Skill-specific unemployment risks

2.1. Employment protection legislation

Generally, EPL can be described 'as restrictions placed on the ability of the employer to utilize labor' (Addison and Teixeira, 2001: 2), or according to the OECD, as 'rules governing the hiring and firing process' (OECD, 2004: 64). Actually, EPL is the sum of a rather complex system of rules that vary from country to country.

From an economic perspective, the strictness of EPL is determined by the costs related to the dismissal of an employee. One can distinguish between costs directly associated with a lay-off – i.e. quantifiable and already known before the employment relation starts, e.g. severance payments – and indirect costs arising from procedural inconveniences and difficulties to enforce a dismissal.

Given that the flexibility of wages is somehow restricted, the literature argues that strict EPL has both negative and positive employment effects that determine the probability of unemployment (Addison and Teixeira, 2001; Skedinger, 2010). Negative employment effects might result from high labour costs and restrictions on the flexibility of entrepreneurial activity. Dismissal regulations increase separation costs, for example by severance payments, and delay the optimal moment of a dismissal in a company. As neoclassical employment theory states, high labour costs are generally related to a reduction in labour demand so as to reach an optimal amount of labour. Furthermore, by limiting the freedom of action, appropriate responses to economic changes are constrained. Compared to labour markets with low requirements on firing rules, employers in strictly regulated markets are restricted in their competitiveness. Rigid EPL might thus result in recruitment freezes or shifts in foreign markets. By creating employment barriers, strict dismissal rules are specifically expected to increase the probability of being long-term unemployed.

However, hiring and firing decisions depend on the employer's expectation to what extent the additional labour costs will be compensated in the future (OECD, 2004).

Redundancies often result from a decrease in demand (Nolte, 2001). In this regard, labour demand for simple activities is more price elastic. According to Davis and Reeve (1997), the more easily input factors are substitutable, the more they respond to price fluctuations (here: in terms of decreasing marginal labour productivity). In the case of highly skilled workers, the elasticity of labour demand is, therefore, rather low. Future replacement of highly skilled workers in times of increasing demand is expensive. Moreover, highly skilled employees can even become indispensable as important service providers for the production process of the company. For the highly skilled, there is generally a greater need for functional flexibility. Functional flexibility describes the ability to redeploy workers from one task to another. These workers often participate in decision-making, work in teams, and their wages are often determined by the organizational performance of the company. Therefore, layoffs due to declines in consumer demand affect, at least in the short run, mainly low skilled workers.

However, the literature also gives some reason to suspect that there are positive employment effects resulting from strict dismissal rules (see, in particular, Belot et al., 2002; Storm, 2007). First of all, those being employed profit from a high level of job protection, and consequently the frequency to become unemployed should be lowered. Through the establishment of specific dismissal laws, long contract negotiations at the beginning of the employment relationship can be avoided and thus reduce transaction costs. Moreover, job security afforded by EPL increases the extent of human capital investments by workers. Increases in productivity could compensate for high labour costs. In order to obtain investment incentives, workers have to be provided with an appropriate employment guarantee, which protects them against the opportunistic behaviour of the employer so that, at the very least, the investment costs can be amortized (OECD, 2004). Because productivity rates increase in relation with the skill level acquired, dismissal risks - for the same seniority – decrease more for highly skilled than for low skilled workers (Layte et al., 2002; Nolte, 2001). Strict EPL also tends to improve the extent of cooperation by increasing job security. According to Walwei (1996) it promotes the identification with operational objectives, in-house mobility and the acceptance of technological progress. A lack of EPL might, in contrast, result in more frequent strikes, a reduced willingness to make concessions by workers' representatives and an increased amount of shirking (Walwei, 1996).

However, the added value for the company resulting from an increased level of cooperation depends on how important cooperation in the production process is. The more ambiguous and unstructured the task is and the higher the required skill levels are, the more difficult the monitoring of performance is (Jones, 1984). Productivity benefits from strict firing rules, therefore, derive priory for highly skilled workers.

Whether the detrimental or beneficial effects prevail is unclear. Unemployment risks are determined by both the frequency of unemployment periods and their duration. On the one hand, strict EPL can mutate into an employment barrier for those searching for a job by reducing hiring incentives to high labour costs; on the other hand, workers that are already employed profit from low dismissal risks because they are protected by legislation. Both effects might compensate for each other, so that the net effect is zero. Since the actual employment effects depend on the employers' expectations as to what extent labour costs will be compensated and which productivity gains will be met in the future (OECD, 2004), the negative effects should decrease with the skill levels acquired.

2.2. The relation between EPL, skills and technological change

Differences in unemployment risks between skill groups can partly be explained by technological progress. The question that shall be answered within this study is whether technological progress also moderates the relation between EPL and unemployment risks. This would be the case if technological progress alters flexibility demands.

In the past, technological progress has led to skill-biased technological change, with different effects on the working conditions and labour market chances for differently skilled workers. There are two reasons for this development. One is the increase in the proportion of skilled workers in the labour force (Acemoglu, 1999, 2002; Autor et al., 1998; Berman et al., 1997). Increases in skilled labour usually lead to decreases in the wage premium for in investments in education. However, if a certain threshold is reached, it becomes more beneficial for employers to create jobs targeted specifically at highly qualified workers; this also results in higher returns to education. Thus the key determinant of skilled-biased technological change has been the market size of skilled labour. The second reason is that increases in skill supply have been accompanied by technological progress, thereby reducing the optimal amount of labour by increasing the factor productivity at the same time. Technological change has resulted in a qualitative change in the composition of jobs. It has been associated with changes in production techniques, but also with organizational changes and capital deepening (Autor et al., 1998). The developments observable in the labour market confirm the existence of skill-biased technological change, and the formation of two separate job markets for skilled and unskilled workers (Acemoglu, 1999). Furthermore, the highly skilled are encouraged to match with other highly skilled workers through positive wage effects, rather than working as managers in companies employing mostly low skilled workers. The positive wage effects result from increases in productivity that can be realised in this context (Acemoglu, 2002). The diffusion of computers and telecommunication technologies in the 1980s and early 1990s has largely contributed to this development. For both the manufacturing and non-manufacturing sector, the increase in demand for highly skilled individuals has been greatest in the most computer-intensive industries. In particular, the simple and repetitive tasks of white collar workers have been rationalized by computerization rather than complex and specific tasks. Many production processes have also been substituted. While many clerical and production jobs have been displaced from the labour market, workers with managerial and professional jobs have benefited from computerization by utilizing their manpower more effectively (Autor et al., 1998; Mortensen and Pissarides, 1999).

Skill-biased technological change has also led to changes in the organizational structure of companies. For instance, the use of computer technology has increased firms' ability to monitor work (Acemoglu, 1999, 2002; Autor et al., 1998). Moreover, it was stated that:

> 'high wage firms are more selective in hiring than they were two decades ago, the distribution of physical capital to labor ratios across industries has become more unequal, workers appear to be better matched to their jobs, the distribution of on-the-job training across education groups has become more unequal, and some of the jobs in industries and occupations that typically pay close to the median of the wage distribution have been replaced by jobs from the more extreme parts of the quality distribution of jobs' (Acemoglu, 1999: 1260–1261).

However, later Autor et al. (2003) claim that the low skilled are only little affected by technological progress, since routine labour is often done by medium skilled workers. In a more current article, Autor (2010) confirms a decrease in middle-wage, middle-skill white collar and blue collar jobs within the US and Europe. Manning (2004) argues however, that 'employment of the less-skilled is increasingly dependent on physical proximity to the more-skilled and may also be vulnerable in the long-run to further technological developments (Manning, 2004: 581)'.

Acemoglu (2002) found some evidence that labour market institutions and skill-biased technological change interact with each other. Employment protection rules have turned out to play a prominent role in this context. He argues that:

> 'Job security measures reduce job destruction by increasing actual or implicit firing cost, but also reduce the incentive to create new jobs in response to changing technology patterns of demand, as firms hesitate before getting stuck with unwanted employees' (Acemoglu, 2002: 243).

The question that arises in this context is, whether technological progress and the related polarization of labour markets has changed flexibility demands for different skill groups and how these changes might alter the relation between EPL and individual unemployment risks. If technological progress would increase the need for functional flexibility for the highly skilled and the need for numerical flexibility for less skilled workers, technological progress strengthens the positive and negative effects of EPL described above on individual unemployment risks related to the skill levels acquired.

Thus, in countries with a high level of skill-biased technological change one may assume that the highly skilled are less harmed by strict EPL in contrast to less educated workers. The negative effects of strict EPL might predominate the positive effects in the case of the less skilled, and turn into stricter employment barriers increasing individual unemployment risks – particularly the risk of being long-term unemployed – by reducing hiring chances.

However, in economies with less technological progress, the relationship between EPL and individual unemployment risks should be more similar for the different skill groups. Highly, medium and low skilled workers partly compete for the same jobs. The need for numerical flexibility in the case of unqualified work is less strong. The positive employment effects due to strict EPL are therefore more likely to dominate in countries with less technological progress. However, whether the adverse or beneficial effects actually predominate remains an empirical question.

3. Data and methods

3.1. Data

Micro-level data is based on the European Labour Force Survey (LFS) from 2008. The LFS collects information on demographic, social and economic characteristics of numerous European countries (German Federal Statistical Office, 2012). Due to restrictions in the availability of macro-level data, the study includes 21 countries: Austria, Belgium, Czech Republic, Germany, Denmark, Estonia, Spain, Finland, France, Greece, Hungary, Ireland, Italy, Luxembourg, the Netherlands, Norway, Poland, Portugal, Sweden, Slovenia and the UK.[1] Only the working population is included, i.e. employed and unemployed people aged between 15 and 64 years old. In total, these constitute 1.6 million respondents.

Individual level variables

The employment status is at the focus of the analysis. At first, the analysis differentiates between being unemployed and being employed; all other groups are excluded. The variable is coded 1 if the individual is unemployed and 0 if the individual is employed. The second part of the analysis also accounts for long-term unemployment. In order to test whether unemployment remains more permanent in countries with strict EPL or not, the unemployed are distinguished according to the length of unemployment. The variable is coded 1 if

[1] Slovakia has been identified as an outlier, with a low skilled unemployment rate of 40%. The Czech Republic, in comparison, which is the second worst performing country in this context, has a low skilled unemployment rate of 19%

unemployment lasts more than 12 months and 0 otherwise.[2] Several socio-demographic attributes are included as control variables in the models. These are gender, age, marital status and nationality. Age is divided into three groups: 15–24; 25–54; and 55–64 years old. The binary variable ‘nationality’ is coded 1 for respondents not having the citizenship of their residence and 0 for the opposite situation. Marital status is 1 for individuals being married and 0 otherwise. On the individual level, it is also controlled for the reference week respondents refer to. In most countries, surveys were equally spread over the whole year, while some were concentrated only on specific time periods. Individual unemployment risks, however, vary over time. Due to the in 2008 beginning economic crises, they increase the more the year has progressed.

Individuals are grouped according to their acquired skill level. Education is classified on the basis of the ISCED-97 scheme (UNESCO, 2010). Respondents who have completed lower secondary education at most are categorized as low skilled (ISCED 0-2); those with upper secondary and post-secondary education are classified as medium-skilled (ISCED 3-4); and individuals with the first or second stage of tertiary education are defined as highly skilled (ISCED 5-6).

Country level variables

The level of employment protection legislation is measured by an EPL index provided by the OECD for the year 2008 (OECD, 2012). The index includes dismissal rules for regular employment and restrictions on the use of temporary employment. It consists, i.a. of information on procedural processes, compensation payments, notice periods and the difficulty to enforce a dismissal. It also captures information on the requirements and restrictions of using temporary employment, i.e. fixed-term or temporary work agency employment (for detailed information, see Venn, 2009). Data refers to the year 2008. The strictness of EPL is valued on a scale from 0 to 6, with larger numbers meaning stricter regulation. Since the regulation of the different dimensions might be influenced by each other, the use of the overall index seems to be more reasonable than looking at one specific dimension only. Due to methodological restrictions resulting from the low degree of freedom

[2] In order to analyse whether unemployment is more likely to be permanent or not according to different levels of EPL, this approach has the advantage – in contrast to looking at the long-term unemployment rate – that it is not biased by the general risk of being unemployed. For example: in country A, the relative risk that unemployment remains permanent is 20%; in country B, it is 40%. The unemployment rate in country A is 10%; in country B, it is 5%. The corresponding long-term unemployment rates in both countries are 2%, although it is much more difficult to overwhelm unemployment in country B.

at the country level, it should be avoided so as to include each of the three sub-indicators separately.

Figure 1 provides an overview on the EPL indicator. With a value of 0.75, the UK had the most flexible EPL in 2008. Ireland (1.1), Denmark (1.5) and Hungary (1.7) also have relatively liberal dismissal rules. In contrast, Spain (3.0), France (3.1), Portugal (3.2) and Luxembourg (3.3) show comparatively strict employment protection regulations. The average value of the EPL index over all countries is 2.2.

[Figure 1 about here]

In order to represent the level of skill-biased technological progress that has taken place within countries, and which is reflected in the labour market, the share of employment in (medium-) high-tech manufacturing are taken into account, as well as employment in knowledge-intensive services. Information is taken from the European Innovation Scoreboard and refers to the year 2008 (PRO INNO EUROPE, 2009).

Figure 2 gives an overview on the distribution of these indicators. By looking at the technological progress expressed in shares of employment relative to the total employment rate, Portugal (13.1%), Greece (13.4%) and Poland (14.9%) bring up the rear with less than 15% employment in (medium-) high-tech manufacturing and knowledge-intensive services in sum. Germany has a total share of 26.3% at the top of the league, closely followed by Luxembourg (25.0%) and Sweden (24.7%). The average lies at 20.6%. Between the different sectors, there are large differences depending on the economic structure of the country. With a share of 1.2%, the lowest proportion of employment in (medium-) high-tech manufacturing can be observed in Luxembourg; conversely, it has by far the highest employment rate in knowledge-intensive services (24.0%). The Netherlands also has a very low share in (medium-) high-tech manufacturing (3.2%), but a big knowledge-intensive sector (18.0%). Greece shows very little technological progress according to the distribution of employment for manufacturing (2.4%) and services (11.1%), and takes the second-to-last place for both. The Czech Republic (10.9%), Hungary (8.8%) and Slovenia (9.1%) all show a relatively strong progress in the manufacturing sector. The average share of employment in (medium-) high-tech manufacturing over all countries is 5.9%; the share is 14.7% in knowledge-intensive services.

[Figure 2 about here]

At the country level it is also controlled for the growth in the gross domestic product. In order to measure the general economic activity and power of the country, the average growth rates of the last three years are used. [3]

3.2. Methods

The analysis starts with some descriptive and bivariate findings, providing insights into the relationship between individual unemployment risks and country level determinants.

Since the data structure is hierarchical – individuals are nested in countries – multi-level modelling has been applied. Multi-level regressions allow simultaneous estimations of variations at various levels (Raudenbush and Bryk, 2002). Moreover, they account for compositional effects due to the specific structure of the labour force, such as differences in the age structure or the degree of female employment. The dichotomous nature of the two dependent variables suggests using logistic regression techniques. The analysis concentrates on random intercept models with varying macro-level determinants, which are expressed in the following logit link function:

(Level 1) $$\eta_{ij} = \log(\varphi_{ij} /1 - \varphi_{ij}) = \beta_{0j} + \beta_{1j}\, \chi_{1j}$$

where η_{ij} is the log of the odds of success; and φ_{ij} is the probability that the observed event (i.e. being long-term unemployed) occurs. The term on the right of the equation includes the structural model. β_{0j} represents the context dependent regression intercept; β_{1j} is the regression slope; and χ_{1j} is the micro-level predictor. Within the analysis represented in the following section, the micro-level predictor contains the control variables for age, gender, marital status, nationality and the reference week of the interview.

The structural equation of the macro-level models corresponds to the equation of a linear multi-level model. Within the analysis, the intercept β_{0j} is assumed to vary by context:

(Level 2) $$\beta_{0j} = \gamma_{00} + \gamma_{01} W_1 + \gamma_{02} W_2 + \gamma_{03} W_1 W_2 + \gamma_{04} W_3 + u_{0j}$$

The regression intercept β_{0j} encompasses every country j at a context independent intercept γ_{00} , plus slope γ_{01} and a macro-level predictor W_1 for the level of employment protection

[3] Models have also been calculated with the average growth in GDP over the last five years. The results show no differences concerning the significance or direction of the effect.

legislation; slope γ_{02} and W_2 represent one of the technological progress indicators; and slope γ_{03} represents the interaction between both macro-level predictors W_1 und W_2 in the model. It is expected that γ_{03} is negative for the highly skilled workforce and positive for the low skilled. W_3 represents the control variable at the country level by measuring the average GDP growth between the years 2006 and 2008. Moreover, the equation contains the residual term u_{oj}. Since there are only a limited number of countries, the model has only sparse degrees of freedom. Therefore, it is not possible to control for numerous country variables simultaneously (Maas and Hox, 2004).

In order to avoid three-way interaction effects, models are estimated separately for the different skill groups. Multi-level models have been calculated with the software program HLM 6.06. The data is weighted at the individual level by the design weight provided with the LFS in order to account for potential selection biases.

4. Results

4.1. Descriptive results

Figure 3 displays individual unemployment rates for the low, medium- and highly skilled in each country based on the data from the LFS. There is much more variation between countries in the unemployment rates of the low skilled than in the other two groups. The low skilled unemployment rates range from 5.1% in the Netherlands to 19.4% in the Czech Republic. The unemployment rates for medium-skilled individuals vary from 2.0% in Norway to 11.1% in Spain; meanwhile, the highly skilled rates range from 1.2% in Norway to 7.0% in Portugal. For the latter two groups, unemployment is particularly high in Southern European countries. Furthermore, Greece is the only country where unemployment risks for the medium-skilled are higher compared to the low skilled.

[Figure 3 about here]

Figure 4 represents the proportion of the unemployed for whom unemployment lasts longer than 12 months. As such, the deviations between skill groups are now lower compared to the distribution of unemployment risks. While again the low skilled face the highest risk on average, in some countries it is more likely that unemployment lasts more than 12 months for the highly skilled than for less skilled non-workers. This is true for Sweden, Denmark, Finland and Germany. In Norway and the Netherlands, the proportion of long-term unemployed is highest for the medium-skilled, but only with little differences to the other two groups.

The comparison of Figures 3 and 4 illustrates that the likelihood to be long-term unemployed is only partly related to the general unemployment risk. Spain, for instance, has relatively high unemployment rates, but unemployment seldom lasts longer than a year. In the Netherlands or Luxembourg, in contrast, unemployment rates are rather low, but job losses result relatively often in long-term unemployment.

[Figure 4 about here]

4.2. Bivariate relations

The bivariate results presented in Tables 1 and 2 demonstrate the relationship between the skill-specific unemployment rates and the proportion of long-term unemployment with the level of EPL and the technological progress observable in the labour markets, respectively. A significant relationship between EPL and unemployment exists only for the highly skilled labour force. The direction of the correlation is positive. Stricter dismissal rules are related to higher unemployment rates for the highly skilled. The share of employment in (medium-) high-tech manufacturing and knowledge-intensive services only correlates significantly with the highly skilled unemployment rate. Here, the relationship is negative, meaning that the higher the share of employment in both sectors, the lower the unemployment risks for highly qualified workers. By distinguishing both sectors, the coefficients are still negative, but lose significance. This indicates that the described correlation applies only in countries where technological advancements have been established in both sectors to a large degree. However, the share of employment in (medium-) and high-tech manufacturing is positively correlated to the low skilled unemployment rate. Thus, technological progress in manufacturing seems to lower the employment chances of the less educated workforce. There is no significant relationship between employment in knowledge-intensive services and unemployment. Table 1 shows that EPL is not correlated to the level of technological progress.

[Table 1 about here]

The proportion of long-term unemployed among all unemployed respondents within a country is not related to the level of EPL (Table 2). The level of technological progress that is represented in the distribution of employment only correlates significantly between the share of employment in knowledge-intensive services and long-term unemployment risks for the low and medium-skilled workforce. For both groups, the relation is negative. Technological progress established in the service sector therefore seems to diminish long-term unemployment risks for these two groups.

[Table 2 about here]

4.3. Multi-level analyses

The bivariate estimations do not allow either for differences in the composition of the labour force, nor for relations between macro-level determinants. The multi-level models presented in this chapter show that the bivariate results are biased by both restrictions. Table 3 presents the results of the multi-level logistic regression analysis for the three skill groups separately (under the control of the individual level variables and GDP growth). Because relations are not linear, coefficients within and between models of different skill groups are not directly comparable. Firstly, the effect of EPL on the likelihood to be unemployed has been estimated exclusively for each skill group. Secondly, the indicators measuring the level of technological progress established at the labour markets have been added, as well as its interaction with EPL.

As Table 3 shows, EPL is positively and significantly related to risk of unemployment for all three skill groups. Converted into percentage points, changes are very similar. An increase in EPL by unit above the average is related to an increase in the probability to be unemployed by 1.46 percentage points for the low skilled, 1.62 for the medium skilled and 1.19 for the highly skilled. In relative terms, however, unemployment risks increase much stronger the higher the individual skill level is. An increase in EPL of unit is, for example, related to an increase in the probability of unemployment by around 12%, for the highly skilled unemployment risks raise, in contrast, by 31%.[4]

However, in the case of the low skilled, EPL loses significance when the macro-determinants for employment in (medium-) high-tech manufacturing and employment in knowledge-intensive services are included separately. For the medium- and highly skilled, the

[4] Unemployment probabilities can be calculated by $1/[1+\exp(-\eta_{ij})]$. The probabilities are estimated under the control of GDP growth and refer to an average increase by 3 % within the last three years.

coefficients remain positive and significant in all models. There are negative interactions between the level of technological progress and the unemployment risks of the highly qualified workforce. The positive effect of EPL is somewhat lower when the total share of employment in both the (medium-) and high-tech manufacturing and the knowledge-intensive service sector is higher.

[Table 3 about here]

By distinguishing the two sectors, the effect is only significant for employment in knowledge-intensive services. For the medium-skilled, the interaction effect is only significant if employment in both sectors is taken into account as a whole. The effect goes into the same direction as for the highly skilled. In the case of the low skilled, no significant interaction effect between EPL and the macro-level determinants measuring the level of technological progress can be detected.

In order to illustrate the results of the logistic multi-level regression analysis, the corresponding probabilities have been estimated as exemplary for the highly skilled by taking the total share of employment in (medium-) high-tech manufacturing and knowledge-intensive services into account. The graph presents the individual unemployment probabilities due to differences in EPL and for varying proportions of technological progress. Probabilities are estimated for three different levels of EPL (average = 2.06; average plus 1 unit; average minus 1 unit) and three different employment shares in (medium-) high-tech manufacturing and knowledge-intensive services (average = 20.6 %; average plus 10 percentage points; average minus 10 percentage points).

[Figure 5 about here]

Figure 5 demonstrates the moderating effect technological progress has on the impact of EPL.In countries with a very low share of employment in (medium-) high-tech manufacturing and knowledge-intensive services, EPL is strongly positively related to the unemployment risks of the highly skilled. The differences in unemployment probabilities become smaller when the share of employment in both sectors is higher. In countries with a large technological advancements – i.e. when the share of employment in (medium-) high-tech manufacturing and knowledge-intensive services is very pronounced – the effect of EPL changes its direction; EPL is then negatively related to the unemployment risks of the highly skilled, i.e. the highly skilled face lower unemployment risks when EPL is stricter.

However, individual unemployment risks comprise both the frequency of job losses and the duration of unemployment. Both aspects raise the probability to be unemployed at the reference week.

[Table 4 about here]

Therefore, in a second step, the article concentrates on the likelihood of being long-term unemployed for those having already lost their jobs. The results in Table 4 show that the main effect of EPL on the likelihood of being long-term unemployed is not significant. This means that it does not depend on the strictness of the implemented dismissal rules, regardless of whether unemployment is mostly short- or long-term. However, there are a few exceptions. For the highly skilled, the main effect of EPL is significant and positive when employment in (medium-) high-tech manufacturing is included. If employment in knowledge-intensive services is taken into account, the interaction effect between EPL and the share of employment becomes significant, while the main effect is negative and insignificant. In contrast to the previous analysis, the interaction effect is now positive. The higher the share of employment in knowledge-intensive services, the more likely it is that strict EPL increases the probability for the highly skilled to be long-term unemployed; whereas, as Table 4 shows, the general likelihood to be unemployed at all, in relation to strict EPL, shrinks with an increase in the share of employment in the service sector. The same can be observed for individuals who are medium-skilled. However, the models generally show that the relationship between EPL and long-term unemployment is not robust.

5. Discussion

The multi-level analyses have shown that the relationship between EPL and unemployment is positive for all skill groups. The negative impact due to high labour costs and restricted flexibility thus seem to dominate the positive benefits that are connected with higher levels of job security. However, this relationship becomes smaller – at least for the medium- and highly skilled – with higher levels of technological progress, as reflected in the employment rates in (medium-) high-tech manufacturing and knowledge-intensive services. In countries with very large technological advancements, the relation can even be negative. The study, therefore, demonstrates that strict EPL is not associated with higher unemployment risks per se. It also illustrates that flexibility demands for medium- and highly skilled workers vary due to the level of technological progress. The results underline the hypothesis that the need for functional flexibility increases with the implementation of technological improvements for the medium and highly skilled, and that employers are more interested in long-lasting and stable job relationships, so that the positive consequences of strict EPL can finally prevail.

For the low skilled, in contrast, the relationship between EPL and unemployment is not moderated by the level of technological progress. For this group, stricter dismissal rules are always related to higher unemployment risks. The need for numerical flexibility does not change with the implementation of technological advancements. The demand for simple tasks and workers that are easily substitutable seem to be independent from economic developments in contrast to the demand for better skilled workers.

The fact that the relationship between EPL and unemployment works in the opposite direction for the low and the better-skilled individuals in countries with very high levels of technological progress indicates that job markets are probably not independent from each other. In fact, low and better-skilled workers might be substituted by each other. This is also related to higher levels of inequality concerning individual unemployment risks to the detriment of the low skilled.

The results also show that there are differences due to the sectors in which technological progress is reflected. One has to distinguish between the general technological progress that is represented by high employment rates in both (medium-) high-tech manufacturing and knowledge-intensive sectors, and the consideration of the two sectors separately. Seen in isolation, the interaction between EPL and technological progress is only meaningful for the share of employment in knowledge-intensive services, and then only for the highly skilled. One reason for this might be that the proportions of employment in the specific sectors (particularly in manufacturing) are too small to significantly affect outcomes of the whole labour market.

One striking result of the study is the missing robust relationship between EPL and the likelihood to be long-term unemployed. In contrast to the theoretical literature and past empirical findings, strict EPL does not necessarily turn into an employment barrier for those being out of work. It can also lead to more frequent unemployment periods. If very strict dismissal rules are implemented in a country, employers might prefer to try to use legitimated exit options, e.g. employees might be terminated more often after a trial period ends, or fixed-term contracts are prolonged less often. A high share of employment in knowledge-intensive services alone can strengthen the long-term unemployment risks for the medium- and highly skilled. However, in this context it is important to note that prior studies concentrating on EPL reforms have examined short-term effects only resulting from one year to another.

Since this analysis is cross-sectional, no reliable predictions can be made concerning future effects resulting from changes in employment protection legislation. The results indicate, however, that more flexible dismissal rules generally improve the employment chances of workers. They also show that the relationship between EPL and unemployment is not one-dimensional. If the technological progress continues, we should expect further relaxation of dismissal rules, thus leading to strong negative labour market results – at least for the medium- and highly skilled. By looking at the distribution of employment in (medium-) high-tech manufacturing and knowledge-intensive services, an increase in unemployment risks by relaxing EPL could be anticipated particularly for Sweden, Luxembourg and Germany, while in countries like Portugal, Greece and Estonia, which only show rather low technological progress, the deregulation of EPL will probably result in lower unemployment risks for the medium and highly skilled.

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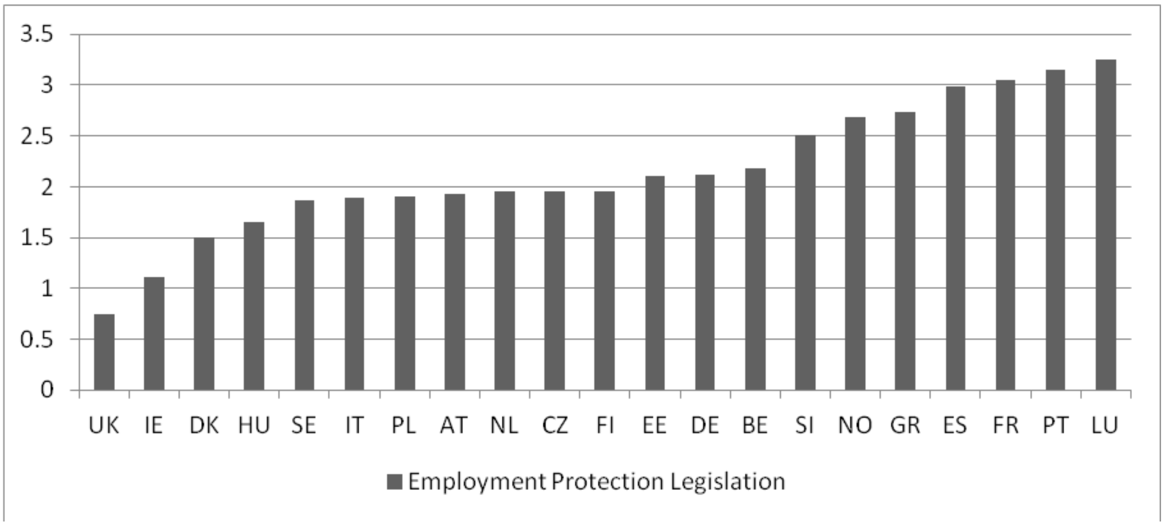
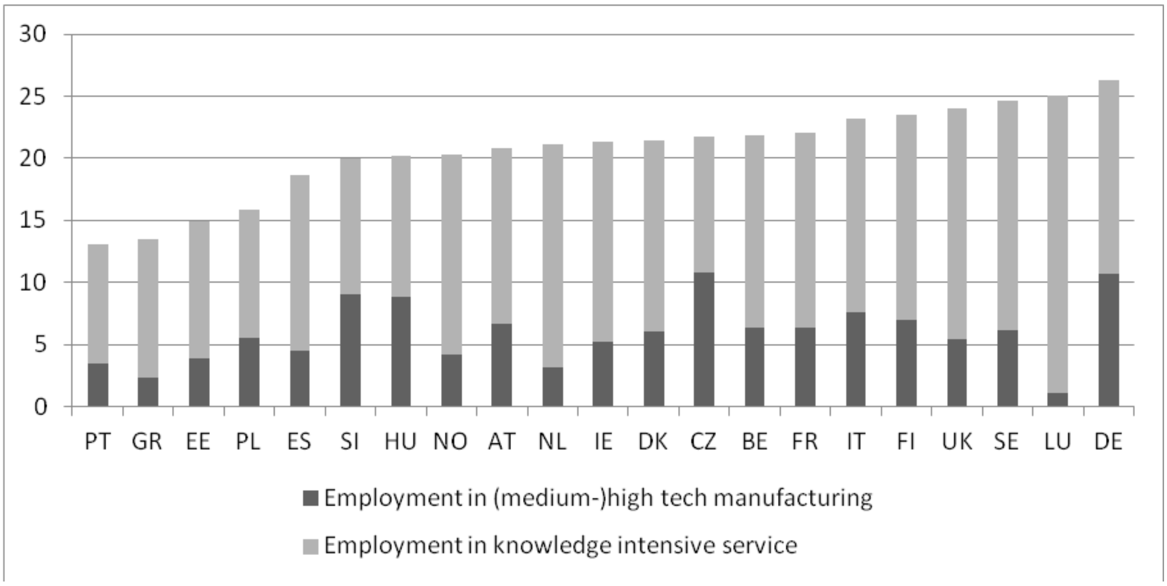
Figures

Figure 1: Employment Protection Legislation



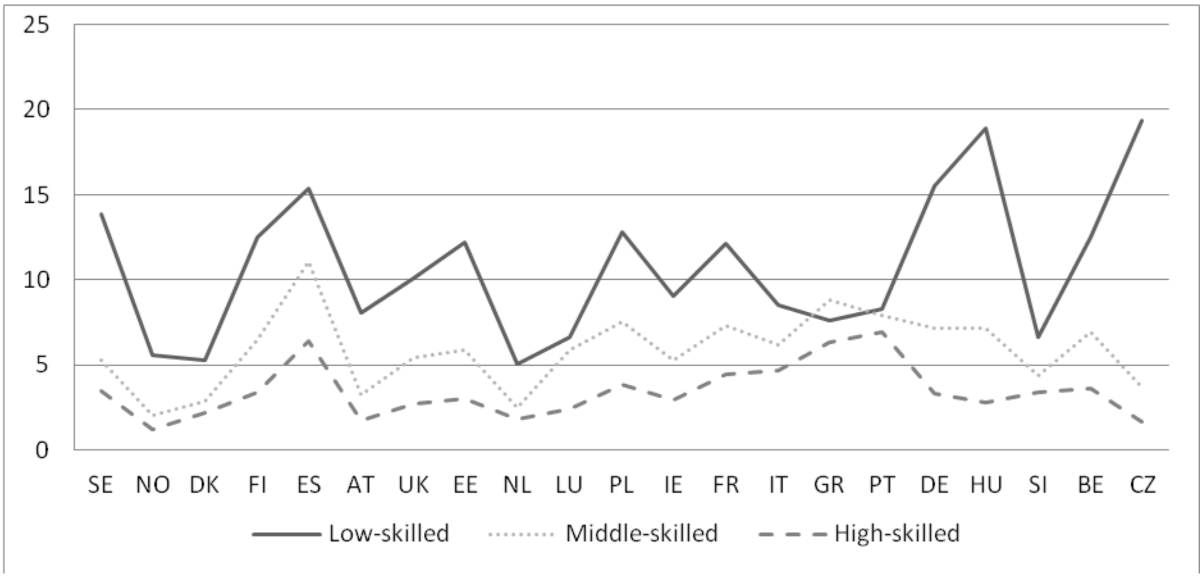
Source: OECD (2012).

Figure 2: Technological progress within national labour markets



Source: PRO INNO EUROPE (2009).

Figure 3: Skill-specific unemployment rates

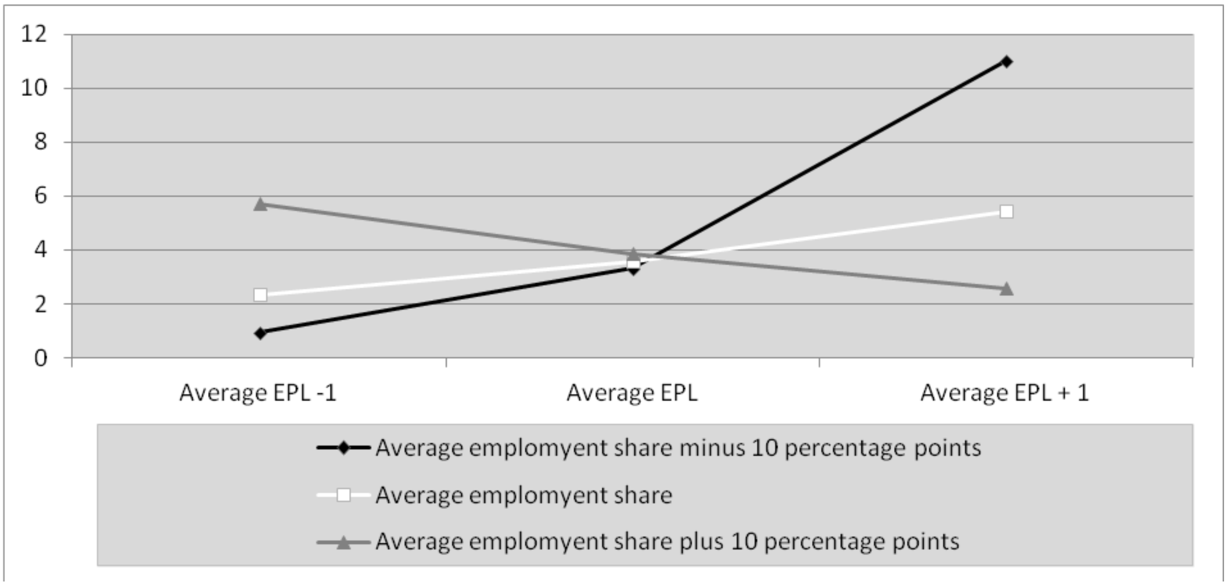


Source: Own calculations on the basis of the LFS (2008)

Figure 4: Long-term unemployment risks (in percentage)

Source: Own calculations on the basis of the LFS (2008); only respondents are included who were unemployed at the reference week.

Figure 5: Unemployment probabilities for the highly skilled due to changes in EPL and different employment shares in (medium-) high-tech manufacturing and knowledge intensive service (in percentages)



Source: Own calculations. Data represent probabilities for men, aged between 25 and 54 years old, not married, having the nationality of the country of residence which had an average growth in GDP of 3% between 2006 and 2008.

Tables

Table 1: Unemployment rates and macro-level determinants

	Low skilled: unemployment rate	Medium-skilled: unemployment rate	Highly skilled: unemployment rate	EPL
EPL	-0.1261	0.3596	0.4646*	
Employment in (medium-) high-tech manufacturing and knowledge-intensive services	0.1246	-0.3106	-0.5085*	-0.3059
Employment in (medium-) high-tech manufacturing	0.5802*	-0.1163	-0.2364	-0.3516
Employment in knowledge-intensive services	-0.291	-0.2389	-0.3578	-0.0634

Sources: LFS (2008); PRO INNO EUROPE (2009); own Calculations.
* significant at the 10% level.

Table 2: Long-term unemployment risks and macro-level determinants

	Low skilled: long-term unemployment risk	Medium-skilled: long-term unemployment risk	Highly skilled: long-term unemployment risk	EPL
EPL	0.0897	0.1644	0.2755	
Employment in (medium-) high tech manufacturing and knowledge-intensive services	-0.1536	-0.2132	-0.0093	-0.3059
Employment in (medium-) high tech manufacturing	0.3386	0.3198	0.1662	-0.3516
Employment in knowledge-intensive services	-0.4053*	-0.4538*	-0.1303	-0.0634

Sources: LFS (2008); PRO INNO EUROPE (2009); own calculations.
* significant at the 10% level.

Table 3: Multi-level logistic regression analysis – Skill-specific unemployment risks

	Low skilled				Medium-skilled				Highly skilled			
Intercept	-2.192		-2.426		-2.816		-3.115		-3.343		-3.556	
	(0.126)	***	(0.244)	***	(0.148)	***	(0.194)	***	(0.141)	***	(0.199)	***
EPL	0.128		0.270		0.225		0.401		0.285		0.436	
	(0.050)	**	(0.119)	**	(0.048)	***	(0.095)	***	(0.058)	***	(0.080)	***
Employment in (medium-) high-tech manufacturing + knowledge-intensive services			0.030				0.032				0.008	
			(0.019)				(0.018)	*			(0.014)	
EPL * Employment in […] manufacturing and […]service			-0.052				-0.071				-0.085	
			(0.041)				(0.033)	**			(0.027)	***
Variance Component	0.114	***	0.113	***	0.123	***	0.117	***	0.097	***	0.086	***
Chi-Square	2908.07		3054.477		2897.304		4130.644		1085.525		846.707	
Intercept	-2.192		-2.237		-2.816		-2.850		-3.343		-3.332	
	(0.126)	***	(0.152)	***	(0.148)	***	(0.172)	***	(0.141)	***	(0.153)	***
EPL	0.128		0.140		0.225		0.248		0.285		0.299	
	(0.050)	**	(0.081)		(0.048)	***	(0.075)	***	(0.058)	***	(0.059)	***
Employment in (medium-) high-tech manufacturing			0.035				0.032				0.004	
			(0.022)				(0.019)				(0.017)	
EPL * Employment in (medium-) high-tech manufacturing			-0.001				-0.056				-0.073	
			(0.044)				(0.070)				(0.093)	
Variance Component	0.114	***	0.111	***	0.123	***	0.122	***	0.097	***	0.108	***
Chi-Square	2908.07		3224.215		2897.304		3138.547		1085.525		1100.235	
Intercept	-2.192		-2.066		-2.816		-2.748		-3.343		-3.307	
	(0.126)	***	(0.292)	***	(0.148)	***	(0.247)	***	(0.141)	***	(0.234)	***
EPL	0.128		0.116		0.225		0.243		0.285		0.359	
	(0.050)	**	(0.155)		(0.048)	***	(0.120)	*	(0.058)	***	(0.125)	**
Employment in knowledge-intensive services			-0.045				-0.036				-0.054	
			(0.038)				(0.029)				(0.027)	*
EPL * Employment in knowledge-intensive services			-0.020				-0.029				-0.069	
			(0.043)				(0.033)				(0.034)	*
Variance Component	0.114	***	0.121	***	0.123	***	0.129	***	0.097	***	0.079	***
Chi-Square	2908.07		3146.156		2897.304		2639.358		1085.525		744.522	
N	389,468		389,468		727,360		727,360		332,398		332,398	
N	21		21		21		21		21		21	

Source: Own calculations.

Models control for individual level variables and GDP growth. Macro variables in the table are mean centred. Robust standard errors in parentheses.

*** significant at the 1% level; ** significant at the 5% level; * significant at the 10% level.

Table 4: Multi-level analysis – Skill-specific long-term unemployment risks

	Low skilled				Medium-skilled				Highly skilled			
	-0.269		-0.713		-0.724		-1.271		-0.859		-1.614	
Intercept	(0.204)		(0.341)	*	(0.252)	**	(0.373)	***	(0.306)	**	(0.430)	***
	-0.046		0.142		0.029		0.318		0.137		0.541	
EPL	(0.184)		(0.328)		(0.226)		(0.377)		(0.239)		(0.397)	
Employment in (medium-) high-tech			0.103				0.109				0.138	
manufacturing and knowledge-intensive services			(0.032)	***			(0.046)	**			(0.047)	**
EPL * Employment in […] manufacturing and			0.118				-0.043				-0.079	
[…] service			(0.114)				(0.137)				(0.142)	
Variance Component	0.461	***	0.348	***	0.474	***	0.356	***	0.529	***	0.339	***
Chi-Square	2685.564		3128.379		3063.319		3234.637		950.440		1113.984	
	-0.269		-0.471		-0.724		-0.955		-0.859		-1.130	
Intercept	(0.204)		(0.224)	*	(0.252)	**	(0.165)	***	(0.306)	**	(0.157)	***
	-0.046		0.005		0.029		0.118		0.137		0.232	
EPL	(0.184)		(0.119)		(0.226)		(0.111)		(0.239)		(0.123)	*
Employment in (medium-) high-tech			0.150				0.170				0.192	
manufacturing			(0.030)	***			(0.031)	***			(0.039)	***
EPL * Employment in (medium-) high-tech			0.006				0.042				-0.105	
manufacturing			(0.181)				(0.075)				(0.147)	
Variance Component	0.461	***	0.256	***	0.474	***	0.232	***	0.529	***	0.207	***
Chi-Square	2685.564		1800.711		3063.319		1862.762		950.440		610.635	
	-0.269		0.601		-0.724		0.333		-0.859		0.087	
Intercept	(0.204)		(0.550)		(0.252)	**	(0.565)		(0.306)	**	(0.566)	
	-0.046		-0.612		0.029		-0.628		0.137		-0.485	
EPL	(0.184)		(0.393)		(0.226)		(0.375)		(0.239)		(0.373)	
			-0.114				-0.153				-0.122	
Employment in knowledge-intensive services			(0.062)	*			(0.066)	**			(0.063)	*
EPL * Employment in knowledge-intensive			0.182				0.208				0.210	
services			(0.106)				(0.159)	*			(0.113)	*
Variance Component	0.461	***	0.438	***	0.474	***	0.414	***	0.529	***	0.482	***
Chi-Square	2685.564		2087.684		3063.319		2376,956		950.440		701.739	
N	37,038		37,038		41,129		41,129		12,296		12,296	

Source: Own calculations.
Models control for individual level variables and GDP growth. Macro variables in the table are mean centred. Robust standard errors in parentheses.
*** significant at the 1% level; ** significant at the 5% level, * significant at the 10% level.

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