Education and Long-Term Unemployment

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Education and Long-Term Unemployment

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Abstract[1] **:** This paper investigates the relationship between education and long-term unemployment when considering regional economic differences and other relevant variables at the individual and at the local level, using data from the 2004-2006 EU-SILC (11 countries). The analysis has been run using both a binary logit model and a binary scobit model. Our results suggest that the probability of an individual to be in long-term unemployment decreases with her educational level. There is a decrease in returns to education after the age of 40, which confirms the assumption of an obsolescence of skills defended in the human capital literature. With regard to the regional settings, younger workers (20-30) and older workers (50-65) tend to benefit more from the dynamics offered by highly competitive regions.

JEL classification: J64, J01, J24
Keywords: unemployment differentials, education and long-term unemployment, regional competitiveness.

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1. INTRODUCTION

Theoretical and empirical explanations to employment differentials have been studied widely by the economics literature since the 1980s. However, among these studies, only a few incorporate the population's educational attainment into the set of explanatory variables and even fewer adopt an international comparative perspective. As Brauns et al. (2001) point out, micro-level comparative research on unemployment is characterized as sparse and typically focuses on individual unemployment dynamics, duration dependence, and benefit disincentives. The present paper aims at contributing to this research gap by analyzing the role of the educational attainment of the population on unemployment differentials and the extent to which the importance of educational attainment depends on other factors, such as the age of the individual.

Table 1 shows unemployment rates by level of educational attainment at the EU-27 level as well as for the set of countries examined in this study (years 2004 to 2006). We can clearly observe that unemployment rates are negatively correlated with educational levels (except for Greece, where medium skilled workers experience the highest unemployment rates).

Based on this observation and supported by relevant literature (e.g., Burridge and Gordon, 1981; Siegers, 1983; Simon, 1988; Holzer, 1993; Malizia and Ke, 1993; Partridge and Rickman, 1995), our hypothesis is that low educational attainment has a significant negative impact on long-term unemployment which is examined as a proxy of (lack of) employability. The latter is broadly defined in this paper as a combination of individual characteristics, skills and external factors, such as labour market institutions and socio-economic status, influencing individual capacity to get into and to remain into employment (Arjona Perez, Garrouste and Kozovska, 2010; McQuaid and Lindsay, 2005).

We test for this assumption of a negative correlation between education level and the probability of long-term unemployment by investigating the following sub-hypotheses:

(i) the higher educated are better off than the lower educated;

(ii) the level of competitiveness of regions (at the NUTS 2 level) affects differently individuals depending on their age.

As well reviewed by Elhorst (2003), most studies are based upon single equation models (e.g., Beveridge curve modeling, cyclical sensitive modeling, amenity modeling), accounting identity models, implicit models (e.g., migration-based models, the NAIRU model and the Blanchard and Katz model) or simultaneous models. In this work we proxy the labour market dynamics with a composite indicator of regional competitiveness (RCI), which combines information on regional labor supply, labor demand and wage-setting parameters at the NUTS 2 level.

Our analysis investigates the determinants of long-term unemployment among active Europeans aged 20-65, who where employed in 2004 and may have entered into unemployment during 2005, using the European Union Income and Living Conditions survey (EU SILC) 2004-2006 data. We look at a sample of eleven countries, assuming different behaviors across age groups and education levels.

The remaining part of the paper is structured as follows: while section 2 presents relevant theoretical perspectives used to guide the analysis, section 3 describes the data and the empirical model, section 4 discusses the results and their implication and section 5 concludes.

2. LITERATURE REVIEW

A strong relationship between unemployment and education has been found in a number of studies, pointing out to different mechanism explaining the dynamics (e.g. Mincer, 1994; Spence, 1981; Kettunen, 1994; Winkelmann, 1996).The probability of (long-term) unemployment is unequally distributed among various groups in societies with considerable differences depending on educational qualifications (Wolbers, 2000). Increased education is likely to make the skills of an individual more valuable in production and consequently, for his/her employability prospects. In addition, it may also increase the efficiency of the matching process as more educated workers are more mobile and have a broader range of search possibilities, thus, decreasing their unemployment probability (Brunello et al, 2009).

This relationship between education and unemployment is explained partly by the signaling and screening theories. These studies suggest that employers hire workers on the basis of imperfect information about their real productivity levels (e.g. Stigler, 1962; Arrow, 1973) transmitted through their educational credentials, used as a filtering mechanism and a proxy for performance. Yet, Ho and Tan (2008) suggest that there is a non-monotonic relationship between human capital and unemployment, i.e. there is a threshold beyond which the impact of number of years of schooling on the probability of unemployment decreases.

In addition to education, other relevant factors for determining the probability of entering or exiting from unemployment are related to the individual's labour market biography. Prior working experience is considered as a way of accumulating human capital during one's professional career (Becker, 1964; Mincer, 1974). Individuals with more experience are more attractive to employers as they can potentially invest less in their training. In fact, in many European countries the rising incidence of youth unemployment has been a major social problem since the 1970s (Brauns et al., 2001). Many young people enter into unemployment spells after leaving education, increasing their risk to find themselves unemployed years later and to face extended periods of social marginalization during their early careers. We can expect the importance of work experience to be true for up to a certain amount and highly sensitive to the educational qualification. In fact, obsolescence of skills can also start to play a role for older workers whose attractiveness to the labour market could decrease with age, especially if they have lower educational qualifications.

Gender also has an important role. Women in general have less favorable prospects in the labour market as they often combine work with family duties and childcare (Wolbers, 2000; Blossfeld and Hakim, 1997). In fact, the unemployment rate for females in many European countries is higher than the one for men. Thus, we can expect that females would find it more difficult to exit from unemployment than males. Moreover, in many European countries a poor health, chronic diseases, and lifestyle factors are associated with being long-term unemployed or out of the labor market (Alavinia and Burdorf, 2008; Amilon and Wallette, 2009).

Furthermore, the type of contract is an important factor to consider when analysing the probability of falling into (long-term) unemployment. Its impact, however, depends greatly on the country taken into consideration. When examining the case of Germany, Giesecke and Groß (2003) found that fixed-term contracts increase the risk of finding another temporary job or of becoming unemployed after termination of the contract. Güell (2003) finds that for individuals in long-term unemployment spells, the probability of leaving unemployment decreased in the period after the introduction of fixed-term contracts in Spain. In any case, the influence of temporary/permanent contracts on entry and exit into/from (long-term) employment is highly dependent upon the country's specific labour market regulations. Another element to take into account is the occupational status, as the labour market demand and unemployment perspectives differ by field of work and complexity of the tasks (European Commission 2008).

General economic conditions at the regional level also affect substantially the transition rate from and to unemployment. Factors such as regional differences in industry composition, neighborhood effects affecting the equilibrium rate of unemployment, various shocks to aggregate demand and institutional settings have an important role in explaining regional unemployment patterns (Evans and McCormick, 1994).

As Machin and Manning (1999) point out, one of the distinctive features of many European labour markets is the high proportion of long-term unemployed. The definition of long-term unemployment varies across countries and across international statistical agencies, ranging between 6 months (e.g., U.S. Labour Department) and more than 12 months (e.g., Eurostat). The literature commonly makes use of the average minimum duration, namely 9 months, to characterize the entrance into a long-term unemployment spell. One reason for this choice is that job search efforts have proven to remain at a fairly high level for the first 9 months of unemployment but decline steadily thereafter, stabilizing at a much lower level after 18 months. Another reason for this 9-month threshold is that it also corresponds to the point after which the likelihood to leave unemployment declines due to the fact that employers tend to be more reluctant to hire someone unemployed for more than 9 months (Wong, Henson and Roy, 2005; Australian Council of Social Service, 2005).

Eurostat data for the EU shows that on average close to 45 % of the unemployed are in long-term unemployment (considered as being 12 months or more) with strong country differences (see Table 2.). A high proportion of long-term unemployment compared to total unemployment indicates that the burden of unemployment is concentrated on a relatively small number of people, often at risk of permanent detachment from the labour market (OECD, 2002). Heckman and Borjas (1980) find that past records of unemployment increase the probability of subsequent unemployment spells. Thus, future career prospects and income are strongly affected. OECD (2002) suggests that individuals in long-term unemployment are relatively more likely to become very-long-term unemployed in some countries and more likely to exit the labour force in others.

Longer periods in unemployment have serious impact on individuals as well as in broader macroeconomic terms. There is a large amount of literature focusing on the impact of unemployment on individual well-being with effects such as deterioration in self-esteem, health problems and higher suicide rates (e.g. Clark, 1996; Korpi, 1997; Winkelmann and Winkelmann, 1998). Another strand of the literature emphasises the adverse effects of a high level of long-term unemployment on the economy. Many of these studies focus on its influence on wage-setting behavior, as the upward pressure on wages from the supply side is likely to be higher in the presence of a high proportion of long-term unemployment within total unemployment (Machin and Manning, 1999). As described by Green (1984), long-term unemployment indicates that a substantial section of the labour force is in 'surplus to the requirements' of local employers. This 'surplus' may nevertheless coexist alongside relatively high rates of hiring and firing for other more employable parts of the labour force.

In the following section we propose a model for the analysis of long-term unemployment which takes into account the different factors presented above.

3. DATA AND EMPIRICAL MODEL

EU-SILC is a multidimensional micro data survey conducted at the household level. It collects information on individuals' labour market situation by month as well as

a number of relevant socio-economic variables such as health status, educational level, place of residence, type of occupation. In our study we use the EU-SILC 2004-2006 data for Austria (AT), Belgium (BE), Estonia (EE), Spain (ES), Finland (FI), France (FR), Greece (GR), Ireland (IE), Italy (IT), Luxembourg (LU) and Sweden (SE) to estimate the probability of being in unemployment for at least 9 months conditioned on the fact that the unemployment spell started in 2005 (after a period of employment). Thus, our sample is composed of individuals, aged 20-65 in 2006, who were active in 2004 and 2005 and may have entered a long-term unemployment spell (at least 9 consecutive months) in 2005. The total sample size is 100116 individuals (see Table 3 for summary statistics).

In order to explore the determinants of long-term unemployment on the European labour market, we estimate a binary response model in which we observe only the values of zero and one for the variable *Y* although there is a latent, unobserved continuous variable *Y** that determines the value of *Y*:

$$Y_i^* = \mathbf{X}_i\boldsymbol{\beta} + u_{i,} \qquad (1)$$

where

$$Y_i = 1 \text{ if } Y_i^* > 0$$
$$Y_i = 0 \text{ otherwise,}$$

and where **X** represents a vector of random variables, and *u* a random disturbance term. The response variable is *unempLT*, which takes value 1 if the respondent declares at least 9 consecutive months in unemployment in 2005 and value 0 otherwise (i.e. if employed and/or in unemployment for less than 9 months).

In the reduced model[2], among the microeconomic predictors composing **X** are the gender of the respondent, the number of years spent in paid work, the highest educational level completed (ISCED), the health status, the level of urbanisation of the place of residence, the type of most recent contract (permanent or temporary) and the main activity of business or employer (ISCO-88).

[2] The reduction of the model was guided by the significance of each predictor estimated through univariate logit regressions and tests of linearity of the remaining continous variables before and after transformation (Box-Tidwell test and Turkey-Pregibon test).

With regard to gender, our reference level is female. Highest educational level is reported according to the ISCED classification (levels 0 to 6 as proposed by UNESCO). The ISCED levels have been grouped in three categories taking respectively the value of 1 if low educated (ISCED 0-2), 2 if medium educated (ISCED 3-4) and 3 if high educated (ISCED 5-6), recomputed as dummies (edu1, edu2, edu3) where level 1 is the reference level. The health status is measured by the dummy variable *healthy* which takes value 1 if the respondent does not suffer from any chronic (long-standing) illness or condition and 0 otherwise. The level of urbanisation of the place of residence is a categorical variable that takes the value of 1 if thinly populated area, 2 if intermediate area and 3 if densely populated area. These categories have been recomputed as dummies urban1, urban2 and urban3 where level 3 is the reference level (and where level 2 was excluded from the reduced model due to non-significance). The type of contract is defined as permanent (=1) or temporary (=0) and the definition of the occupation follows the ISCO-88 at two digits with lower numbers corresponding to higher occupational level.[3]

The occurrence of a high proportion of long-term unemployed is an evidence of profound dysfunction in a local labour market area. Indeed, studies on unemployment differentials that take into account the regional perspective and use simultaneous modelling are based on the hypothesis that regional unemployment both affects and is affected by regional factors of labour supply, labour demand and wages (Elhorst, 2003).

In order to capture this regional market dynamics, we have added to the set of microdata extracted from the EU-SILC survey, a proxy index of regional competitiveness (RCI). The index is calculated at the NUTS 2 level and is composed of 11 pillars covering the characteristics of both the supply and the demand of the market (Figure 1). Each pillar is composed of a set of quantitative indicators which are aggregated based upon the literature and experts' assessment. The pillars are grouped into three sub-indexes, which are, in turn, summed up according to a specific weighting depending on the region's development stage (medium, intermediate or high) [4]. The RCI was added to

[3] ISCO 0, corresponding to armed force, has been excluded.
[4] For a detailed description of the computation of the index, see Annoni and Kozovska (2010).

the set of predictors of LT unemployment as a censored continuous variable, taking values from 0 to 100, linearized by subtracting its square.

The square of the experience predictor was also included in the regression to reflect the fact that the marginal effect of experience could decrease as the worker accumulates years spent in paid work.

The generic logit regression was re-ran disaggregating first by educational level and then by age group[5] to investigate potential differences in the probability to enter long-term unemployment spells between low educated, medium educated and high educated workers, but also between junior, experienced and senior workers. These disaggregations aim at exploring more specifically which groups of individuals are the most sensitive to unfavourable regional or geographical settings in terms of their probability to remain longer in unemployment.

Despite the apparent fit of our model (confirmed by the Box-Tidwell test and Turkey-Pregibon test on the linearity of the logit with the continuous, or censored continous, predictors), the sample distribution of the response variable, *unempLT*, reveals that less than 5% of the observations take a value of 1, suggesting that the distribution of the dependant variable is skewed (Hilbe, 2009). Therefore, it appeared relevant to remodel *unempLT* as skewed, rather than as symmetric distribution around a mean of 0.5, and to check the capacity of this new assumption to improve the fit of our logit model.

Skewed logistic regression (Scobit) was initially designed by Nagler (1994) to provide flexibility of where the logistic weight is distributed. The impact of the predictors can, therefore, be skewed away from 0.5, hence the name of the procedure. The scobit function is defined as

$$\Pr(y \mid x) = 1 - 1/(1 + \exp(xb))^{\alpha}$$

where the fitted y, or μ, is the probability that y takes the value of 1.

[5] Preliminary results where derived from an analysis on three age-groups (20-29 ; 30-49 and 50-65) . It revealed low significance of almost all parameters for the mid-aged group, which encouraged us to explore further potential behavioral differences within clusters. The results presented in this paper are therefore based upon a 7-level classification of age, namely 20-24 ; 25-29 ; 30-34 ; 35-39 ; 40-44 ; 45-49 ; and 50-65.

The scobit regression estimates μ, the probability of success, and an ancillary or location parameter that reflects the skew of the distribution. The point of the maximum impact of the scobit fitted values is constrained by the above formula to rest in the probability range of 0 to 0.632+, where 0.632+ is (1-1/*e.e*). The scobit model has itself been adjusted to allow for situations in which the maximum impact is outside the range specified above (Hilbe, 2009).

After refining our logit model as a scobit model, we found that the scobit model improves the fit of the logit model in the following cases: the generic regression, the low-educated and medium-educated workers regressions and the regressions by age-group for the 35 year-olds and above. The following section presents and discusses the robust results of the logit and scobit regressions on the reduced model[6].

4. RESULTS

We aim at evaluating the determinants of long-term unemployment as defined in Section 3, with a special emphasis on differentials between levels of educational attainment and age groups. The results of the model for the full sample (generic model) are presented in Table 4.

When considering the generic (non-disaggregated) equation, we find that all coefficients are statistically significant at the .001 level in both the logit and the scobit models. In particular, the higher the educational level, the lower the probability of being in long-term unemployment. In terms of individual characteristics, whereas gender seems to affect the job prospects, with females being more at risk of joblessness, a good health helps to avoid long-term unemployment spells. Experience has a positive role on individual job perspectives. The occupation and the type of contract the worker had before unemployment are two elements that play an important role on the probability of suffering long-term unemployment. Indeed, having a short-term contract or working in a low-skilled occupation (high ISCO) are associated with increased risk of staying in unemployment for more than 9 months.

Living in a competitive region (as proxied by the Regional Competitiveness Index) also reduces the probability of staying unemployed. On the contrary, the higher the degree of urbanization, the higher the chances of getting trapped in a long-term unemployment spell. This result is in line with the economic empirical literature which finds a positive correlation between long-term unemployment and living in urban areas (e.g., O'Connell, McGuinness and Kelly, 2010). However, it should be noted that this latter result is not confirmed for all countries. For instance, in France, the level of urbanism is negatively correlated with long-term unemployment at a .01 level of statistical significance[7].

Partial analysis by level of educational attainment (or skills): The sample has been split into three groups according to the educational level of the respondents - low (ISCED97 levels 0-2), medium (ISCED97 levels 3-4), high (ISCED97 levels 5-6) - to evaluate how the estimated quantitative effect of the control variables in our model vary for different workers according to their overall skills levels. The estimated coefficients for each group are shown in Table 5. What the results from both the logit and scobit regressions reveal is the predominant statistical significance of gender, experience and type of contract across educational groups. The main differences can be observed (i) for the health status which appears strongly significant only for the medium-skilled workers; (ii) for the level of urbanism which is significant for the low- and medium-skilled but not for the high-skilled; and (iii) for the RCI, which is non-significant for the low-skilled and significant only at the .05 level for the high-skilled (against a .001 level significance for the medium-skilled).

Partial results by age groups: The sample has been split into seven age groups (20-24, 25-29, 30-34, 35-39, 40-44, 45-49 and 50-65 years olds) to evaluate how the role of the independent variables such as educational attainment and regional factors vary for different workers according to their age. Beyond providing a clearer picture of the

[6] Our model only contains the subset of variables that we have found to be significant, after having run an univariate logit regression for each variable to test for their significance independently and having then applied two linearity tests on the continuous variables (experience, ISCO and RCI) before and after transformation.
[7] Although the results are not presented in this paper, the logit model was also run disaggregating by country. These results are available upon request to the authors.

potential disparities among mid-aged workers[8], this split allows for an in-depth analysis of the specific situation of groups considered at higher risk of unemployment, such as the youngster or mature workers and provides. These two later groups have indeed attracted much political (Cedefop, 2004; European Council, 2010) and research attention (e.g., Arulampalam, Gregg and Gregory, 2001; Boeri, Layard and Nickell, 2000). The estimation results are presented in Table 5.

Being a female increases the chances of remaining longer in unemployment, except for those workers close to retirement (50-65 year olds). Whereas the health status does not seem to affect the unemployment spell of the younger workers, its coefficient becomes statistically significant at mid-age (35-39 year-olds) and at the end of the career (50-65 year-olds). Moreover, although education attainment plays a significant role across ages, we observe a decrease in the effect education level after the age of 40, which confirms the assumption of an obsolescence of skills defended in the human capital literature (e.g., Ho and Tan, 2008). It is interesting to note that the marginal effect of higher-level skills (edu3) starts decreasing later (after the age of 50) than the marginal effect of medium-level skills (edu2) (after the age of 40). As expected, job experience has a similar effect on unemployment as educational attainment: among the youngest workers, a marginal increase in job experience reduces the probability of long-term unemployment relatively more than for the older workers. Despite the claim that temporary contracts may enlarge the employment opportunities of those at early stages of their career (Müller and Gangl, 2003), from our data, we observe that having a permanent contract is always significantly negatively correlated with long-term unemployment. Finally, with regard to the regional settings, younger workers (20-30) and older workers (50-65) tend to benefit more (as suggested by the negative and statistically significant correlation between RCI and long term unemployment observed in these sub-samples) from the dynamics offered by highly competitive regions than mid-aged workers (negative but non-significant coefficients). However, it is worth noticing the very weak value of the coefficients assigned to the RCI across age-groups, which reveals that in comparison to the other predictors plugged into our models, the RCI does not constitute

[8] Traditionally, mid-aged workers correspond to the 30 to 50 year-olds. As explained in Footnote 5, we decided to disaggregate further this age-group to identify better the nature of assumed underlying behavioral

the most important one. When differentiating the predictors' behavior across age groups, the degree of urbanization of the area in which the respondents live looses its statistical significance (except, to a certain extent, for the 50-65 year-olds, for whom it remains significant at the .05 level).

5. CONCLUSIONS AND FURTHER RESEARCH

This paper investigates the relationship between educational level and the probability of long-term unemployment when considering regional economic differences (as proxied by the index of regional competitiveness developed by Annoni and Kozovska (2010)) and other relevant variables at the individual level (gender, experience, occupation, type of contract and health status) as well as at the local level (degree of urbanization). We have used a binary response model (logit) having also searched a better fit of the model through a skewed logistic regression (scobit).

Considering the full sample from the EU-SILC 2005 of individuals aged 20-65, the results seem to confirm our initial hypothesis that the higher the educational level, the lower the probability of falling into long-term unemployment. The analysis of the results for the different age groups suggests that, although education attainment plays a significant role throughout the working life, there is a decrease in returns to education after the age of 40, which confirms the assumption of an obsolescence of skills defended in the human capital literature. With regard to the regional settings, younger workers (20-30) and older workers (50-65) tend to benefit more from the dynamics offered by highly competitive regions (as suggested by the negative and statistically significant correlation between RCI and long term unemployment observed in these sub-samples) than mid-aged workers (negative but non-significant coefficients).

Furthermore, we have explored the effect of the other variables as determinants of long-term unemployment after breaking down the sample by level of educational attainment. The health status appears to be significant only for the medium-skilled workers, the level of urbanism is significant for the low- and medium-skilled but not for the high-skilled, whereas the regional competitiveness is significant only at the .05 level

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heterogeneities.

for the high-skilled. These are some interesting findings which could be worth exploring further.

As an extension of the work presented in this paper, we are currently working on a disaggregation by country controlling for regional dummies, and we aim at exploring further controls on foreign background, household composition (using variables such as number of young children), the characteristics of national welfare systems and other aspects which may affect the motivation to exit unemployment (as for example, the existence of house mortgage or other debts).

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Figure 1. Composition of the Regional Competitiveness Index (RCI)

Source: Annoni and Kozovska (2010)

Table 1. Unemployment rates (%), by highest level of educational attainment (15-64 years old)

	Low (ISCED 0-2)			Medium (ISCED 3-4)			High (ISCED 5-6)		
	2004	2005	2006	2004	2005	2006	2004	2005	2006
EU-27	12.3	12.2	11.8	9.6	9.3	8.3	5.1	5.0	4.6
Belgium	12.1	14.1	14.0	7.4	8.5	8.2	3.7	4.4	4.5
Estonia	21.1	15.3	13.5	10.7	9.3	6.3	6.0	4.0	3.3
Ireland	7.8	7.4	7.1	3.9	3.9	4.1	2.3	2.5	2.5
Greece	9.6	9.0	8.3	12.4	11.9	10.7	7.9	7.9	7.3
Spain	12.9	11.1	10.5	11.0	8.8	8.1	8.3	6.8	6.1
France	13.0	13.0	13.2	8.4	8.0	8.1	6.5	6.2	5.8
Italy	9.7	9.3	8.2	7.2	7.0	6.2	5.2	6.1	5.3
Luxembourg	7.0	6.4	6.6	4.4	3.8	4.5	3.9	3.5	3.1
Austria	10.7	10.4	9.4	4.5	4.5	4.1	3.0	2.7	2.6
Finland	19.7	14.6	14.2	10.1	8.8	8.2	4.9	4.4	3.7
Sweden	10.3	14.4	13.9	6.7	7.2	6.3	4.0	4.8	4.4

Source: European Commission (2009)

Table 2. Long-term unemployment (12 months or more), % of total unemployment

	2004	2005	2006
EU-27	44.9	46.1	45.9
Belgium	49.6	51.7	51.2
Estonia	52.4	53.4	48.2
Ireland	34.3	33.4	32.2
Greece	54.8	52.1	54.3
Spain	32.6	24.5	21.7
France	39.0	41.1	42.1
Italy	49.6	49.9	49.6
Luxembourg	21.0	26.4	29.5
Austria	27.8	25.2	27.4
Finland	21.1	25.8	25.2
Sweden	17.8	:	:

Source: Eurostat

Table 3. Summary statistics of the variables

	Long Term Unemployment	Female	Experience	Low Educated	Medium Educated	High Educated	No chronic illness or condition	Thinly populated area	Intermediate area	Densely populated area	Permanent contract	Occupation	Regional Competitiveness index
Variable name	*unempLT*	*gender*	*exp*	*edu1*	*edu2*	*edu3*	*healthy*	*urban1*	*urban2*	*urban3*	*permcontract*	*isco*	*rci*
N	256731	256728	178032	250584	250584	250584	224426	256730	256730	256730	119630	167129	229752
min	0	0	0	0	0	0	0	0	0	0	0	1	8.9
max	1	1	65	1	1	1	1	1	1	1	1	93	92.6
mean	.0444707	.5088265	18.59067	.3425598	.4437634	.2136769	.79878	.3475753	.2585167	.393908	.8618156	49.02704	57.38684
sd	.2061388	.4999231	12.15657	.4745666	.4968284	.4099021	.400913	.4762012	.4378203	.4886158	.3450949	24.67474	17.77465

Table 4. Logit and scobit regressions on LT unemployment (full sample model and education-group models)

Model comparison of logit vs. Scobit (generic and education groups regressions)

	(1)		(2)		(3)		(4)	
	Generic		Low skilled		Medium skilled		High skilled	
	Logit	Scobit	Logit	Scobit	Logit	Scobit	Logit	Scobit
gender	0.2583***	0.3301***	0.2940***	0.4293**	0.2265**	0.3642**	0.2517*	0.2512
	(0.0513)	(0.0734)	(0.0815)	(0.1407)	(0.0782)	(0.1372)	(0.1247)	(0.1402)
exp	-0.1052***	-0.1450***	-0.1129***	-0.1853***	-0.0945***	-0.1733***	-0.1151***	-0.1265***
	(0.0074)	(0.0146)	(0.0111)	(0.0333)	(0.0120)	(0.0296)	(0.0189)	(0.0317)
exp_2	0.0016***	0.0023***	0.0017***	0.0029***	0.0014***	0.0028***	0.0022***	0.0024**
	(0.0002)	(0.0003)	(0.0003)	(0.0006)	(0.0003)	(0.0006)	(0.0005)	(0.0007)
edu2	-0.1950***	-0.2473**						
	(0.0592)	(0.0860)						
edu3	-0.5285***	-0.7094***						
	(0.0847)	(0.1293)						
healthy	-0.3226***	-0.4691***	-0.1697	-0.3140	-0.4482***	-0.6464***	-0.3175	-0.3649
	(0.0691)	(0.1008)	(0.1130)	(0.1759)	(0.1016)	(0.1664)	(0.1726)	(0.2376)
urban1	-0.2427***	-0.3842***	-0.2867**	-0.5122**	-0.2734**	-0.5388***	0.0009	-0.0313
	(0.0574)	(0.0912)	(0.0913)	(0.1796)	(0.0866)	(0.1593)	(0.1416)	(0.1895)
permcontract	-1.5231***	-2.1916***	-1.4541***	-2.3682***	-1.5587***	-3.2368***	-1.6241***	-1.7984***
	(0.0550)	(0.2552)	(0.0877)	(0.4808)	(0.0839)	(0.7155)	(0.1333)	(0.5136)
isco	0.0102***	0.0141***	0.0072***	0.0095**	0.0104***	0.0184***	0.0167***	0.0197*
	(0.0012)	(0.0020)	(0.0020)	(0.0031)	(0.0017)	(0.0038)	(0.0029)	(0.0081)
rci	-0.0263***	-0.0362***	-0.0131	-0.0221	-0.0352***	-0.0664***	-0.0350*	-0.0354*
	(0.0062)	(0.0090)	(0.0110)	(0.0180)	(0.0091)	(0.0186)	(0.0139)	(0.0150)
rci_2	0.0002***	0.0003***	0.0001	0.0002	0.0003**	0.0005**	0.0003*	0.0003*
	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0001)	(0.0002)	(0.0001)	(0.0001)
N	100116	100116	28155	28155	45440	45440	26521	26521
Log likelihood (Logit)	-7467.6171		-2749.5849		-3294.9883		-1410.7913	
Pseudo r2	0.1261		0.1214		0.1189		0.1245	
Prob>Chi2	0.0000		0.0000		0.0000		0.0000	
Log pseudolikelihood (Scobit)		-7454.9044		-2743.4021		-3281.7643		-1410.5540
Likelihood-ratio test of alpha=1								
Chi2(1)		25.43		12.37		26.45		0.47
Prob>Chi2		0.0000		0.0004		0.0000		0.4909

Standard errors in parentheses

* p<0.05, ** p<0.01, *** p<0.001

The likelihood ratio test evaluates if the scobit model is significantly different from a logistic model (alpha=1). With a Chi2 p-value under 0.05, the model is considered to differ from a similar logistic model.

The scobit regression is retained for interpretation in 3 cases out of 4, namely for the generic regression (model 1), the low skilled (model 2) and medium skilled (model 3) regressions. In the case of high skilled (model 4), the results from the logit regression are retained.

Table 5. Logit and scobit regressions on LT unemployment (full sample and age-group regressions)

Model comparison of logit vs. Scobit (generic and age groups regressions)

	(1)		(5)		(6)		(7)	
	Generic		20-24 year-olds		25-29 year-olds		30-34 year-olds	
	Logit	Scobit	Logit	Scobit	Logit	Scobit	Logit	Scobit
gender	0.2583***	0.3301***	0.4086**	0.4033**	0.2813*	0.2826*	0.0733	0.0996
	(0.0513)	(0.0734)	(0.1535)	(0.1465)	(0.1217)	(0.1415)	(0.1242)	(0.1398)
exp	-0.1052***	-0.1450***	-0.2569***	-0.2576**	-0.2609***	-0.2919***	-0.2376***	-0.2643***
	(0.0074)	(0.0146)	(0.0537)	(0.0812)	(0.0305)	(0.0616)	(0.0293)	(0.0434)
exp_2	0.0016***	0.0023***	0.0047***	0.0047***	0.0041***	0.0046***	0.0049***	0.0056***
	(0.0002)	(0.0003)	(0.0011)	(0.0013)	(0.0008)	(0.0010)	(0.0013)	(0.0016)
edu2	-0.1950***	-0.2473**	-0.4131**	-0.4101*	-0.3043*	-0.3666	-0.4389**	-0.5205*
	(0.0592)	(0.0860)	(0.1566)	(0.1609)	(0.1451)	(0.2030)	(0.1553)	(0.2049)
edu3	-0.5285***	-0.7094***	-0.9627**	-0.9506*	-1.0119***	-1.1808**	-0.7917***	-0.9063**
	(0.0847)	(0.1293)	(0.3706)	(0.3763)	(0.2033)	(0.3826)	(0.2013)	(0.2759)
healthy	-0.3226***	-0.4691***	-0.0883	-0.0782	0.0124	-0.0440	-0.1652	-0.2024
	(0.0691)	(0.1008)	(0.2575)	(0.2485)	(0.2216)	(0.2957)	(0.1978)	(0.2296)
urban1	-0.2427***	-0.3842***	-0.2305	-0.2221	-0.1595	-0.2041	-0.2278	-0.2564
	(0.0574)	(0.0912)	(0.1603)	(0.1575)	(0.1329)	(0.1815)	(0.1456)	(0.1672)
permcontract	-1.5231***	-2.1916***	-0.7799***	-0.7608***	-1.2050***	-1.3611***	-1.3941***	-1.5318***
	(0.0550)	(0.2552)	(0.1547)	(0.1519)	(0.1222)	(0.3155)	(0.1284)	(0.2305)
isco	0.0102***	0.0141***	0.0080*	0.0080*	0.0085**	0.0094**	0.0105***	0.0121***
	(0.0012)	(0.0020)	(0.0038)	(0.0037)	(0.0029)	(0.0035)	(0.0030)	(0.0036)
rci	-0.0263***	-0.0362***	-0.0531**	-0.0495**	-0.0453***	-0.0555*	-0.0153	-0.0211
	(0.0062)	(0.0090)	0188)	(0.0168)	(0.0130)	(0.0237)	(0.0144)	(0.0180)
rci_2	0.0002***	0.0003***	0.0003	0.0003	0.0003**	0.0004*	0.0001	0.0001
	(0.0001)	(0.0001)	0002)	(0.0002)	(0.0001)	(0.0002)	(0.0001)	(0.0002)
N	100116	100116	5070	5070	10508	10508	13344	13344
Log likelihood (Lo	-7467.6171		-788.8871		-1273.8130		-1230.9212	
Pseudo r2	0.1261		0.0707		0.1064		0.1214	
Prob>Chi2	0.0000		0.0000		0.0000		0.0000	
Log pseudolikelihood (Scobit)		-7454.9044		-788.4724		-1273.4634		-1230.4060
Likelihood-ratio test of alpha=1								
Chi2(1)		25.43		0.83		0.70		1.03
Prob>Chi2		0.0000		0.3625		0.4031		0.3101

Table 5. (Cont.)

(8)		(9)		(10)		(11)	
35-39 year-olds		40-44 year-olds		45-49 year-olds		50-65 year-olds	
Logit	Scobit	Logit	Scobit	Logit	Scobit	Logit	Scobit
0.1462	0.2746	0.1997	0.3036	-0.0320	0.1863	-0.3548**	-0.3216
(0.1435)	(0.2054)	(0.1644)	(0.2127)	(0.1775)	(0.2926)	(0.1364)	(0.2071)
-0.2208***	-0.3122***	-0.0495	-0.1295	-0.0475	-0.1731*	-0.0157	-0.0442
(0.0213)	(0.0567)	(0.0443)	(0.0831)	(0.0397)	(0.0876)	(0.0249)	(0.0450)
0.0034***	0.0052**	-0.0017	-0.0006	-0.0013	0.0003	-0.0006	-0.0005
(0.0005)	(0.0016)	(0.0016)	(0.0024)	(0.0012)	(0.0022)	(0.0005)	(0.0009)
-0.5757***	-0.7768***	-0.0299	-0.0332	0.0711	0.0880	-0.0470	-0.1487
(0.1658)	(0.2336)	(0.1743)	(0.2444)	(0.1815)	(0.3035)	(0.1467)	(0.2262)
-1.0470***	-1.5054***	-0.7753**	-0.9307*	-0.8067**	-1.4303**	-0.0007	0.0323
(0.2324)	(0.3767)	(0.2723)	(0.3771)	(0.3038)	(0.5064)	(0.2071)	(0.2993)
-0.6396***	-0.7220**	-0.3476	-0.5110	-0.0217	-0.1046	-0.3513**	-0.4867*
(0.1800)	(0.2252)	(0.1904)	(0.2651)	(0.2031)	(0.3214)	(0.1326)	(0.1902)
-0.1444	-0.1679	-0.1530	-0.4295	-0.4388*	-0.5976	-0.2947*	-0.5495*
(0.1591)	(0.2034)	(0.1668)	(0.2739)	(0.1858)	(0.3063)	(0.1435)	(0.2456)
-1.5965***	-2.0278***	-1.8960***	-2.6503***	-2.0576***	-3.5398***	-1.9485***	-3.1958***
(0.1467)	(0.3269)	(0.1629)	(0.4644)	(0.1732)	(0.5969)	(0.1383)	(0.8411)
0.0066	0.0080	0.0104**	0.0164**	0.0110**	0.0185**	0.0166***	0.0261***
(0.0034)	(0.0045)	(0.0035)	(0.0057)	(0.0037)	(0.0060)	(0.0029)	(0.0068)
0.0085	0.0077	0.0002	-0.0025	0.0078	0.0141	0.0665**	0.1060**
(0.0179)	(0.0229)	(0.0209)	(0.0320)	(0.0214)	(0.0358)	(0.0225)	(0.0372)
-0.0001	-0.0001	0.0001	0.0002	0.0000	0.0000	-0.0004*	-0.0007*
(0.0002)	(0.0002)	(0.0002)	(0.0003)	(0.0002)	(0.0003)	(0.0002)	(0.0003)
14341	14341	15041	15041	14482	14482	27330	27330
-979.3415		-872.3180		-767.2359		-1368.8470	
0.1691		0.1551		0.1858		0.1102	
0.0000		0.0000		0.0000		0.0000	
	-976.0921		-868.3392		-757.7762		-1363.2546
	6.50		7.96		18.92		11.18
	0.0108		0.0048		0.0000		0.0008

Standard errors in parentheses

* p<0.05, ** p<0.01, *** p<0.001

The likelihood ratio test evaluates if the scobit model is significantly different from a logistic model (alpha=1). With a Chi2 p-value under 0.05, the model is considered to differ from a similar logistic model.

The scobit regression is retained for interpretation in 5 cases out of 8, namely for the generic regression (model 1) and the regressions on the 35 year-olds and above (models 8 -11). In the case of the 20-24, 25-29 and 30-34 year-olds (models 5-7), the results from the logit regression are retained.

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Abstract
This paper investigates the relationship between education and long-term unemployment when considering regional economic differences and other relevant variables at the individual and at the local level, using data from the 2004-2006 EU-SILC (11 countries). The analysis has been run using both a binary logit model and a binary scobit model. Our results suggest that the probability of an individual to be in long-term unemployment decreases with her educational level. There is a decrease in returns to education after the age of 40, which confirms the assumption of an obsolescence of skills defended in the human capital literature. With regard to the regional settings, younger workers (20-30) and older workers (50-65) tend to benefit more from the dynamics offered by highly competitive regions.

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