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Returns to skills and work experience in Europe. Same or different?

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Abstract

We estimate the Mincer equations for a set of European countries. Cross country heterogeneity of parameters, describing the impact of years of schooling and experience on wages, was obtained by the application of the system of Seemingly Unrelated Regression Equations (SURE). The differences between parameters were formally tested given two alternative stochastic assumptions. In the first model, no contemporaneous correlations between error terms in the system is imposed. This may be related to the standard country regression approach. In the second approach an unrestricted covariance matrix is considered, making error terms stochastically dependent. The contemporaneous correlations of error terms in the SURE system were empirically supported. Also, rich parameterisation of the covariance matrix of contemporaneous relations reduced the statistical uncertainty about differences in parameters describing the return on education effect. Consequently, substantial country heterogeneity of return on education, which seems intuitively correct, was obtained in the system of regressions with a complex stochastic structure.

Keywords: Mincer equation, returns to skills, SURE, Zellner estimator

JEL: J31, C31

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1 Introduction

The analyses of the impact of skills on earnings receive unabated attention since Adam Smith's *Wealth of Nations*, published in 1776. In his critical work the author explains that skilled workers are required to go through an apprenticeship program, in contrast to common labour, which is "free and open to everybody" (see Chiswick 2003, p. 3–4). The relationship between earnings and investment in education or training is obvious for Smith. Some of the time spent at the craft by the master or the apprentice are devoted to this training activity. Thus, Smith highlights the importance of the investment in on-the-job training.

The earliest analyses of human capital were focused on the strength of its impact on earnings. The point of departure was the widespread skewness of the empirical distribution of wages, reported initially by Francis Galton. Also Robert Gibrat explained the existence of the positive skewness of the distribution of wages by the determination of wages not only by labour productivity, but by many other, non-measurable factors (see Cichy 2005, p. 2).

The issues of human capital were analysed by many economists despite serious problems with the formal concept and methods of measurement. The pioneer attempts of human capital measurement and estimation of its impact on the distribution of wages were undertaken by Mincer (1958). In his seminal paper the author underlined that human capital itself (as measured by the level of skills and abilities of an individual) is a non-measurable variable. However, he introduced the concept of investment in human capital interpreted as the process of learning and gaining the abilities. Mincer identifies two kinds of investments in human capital, namely the investment in formal education (measured by years of schooling completed) and investment during the working life (measured by years of work experience). The contribution of Mincer to the research on human capital is enormous. He analysed both the impact of individual schooling, as well as work experience on the properties of the distribution of earnings. He found that inequality in wages increases with the schooling level, age and with occupational hierarchy (see Chiswick 2003, p. 5–8).

The theoretical background that enables to describe formally the economic impact of human abilities on wages is the Mincerian model. It assumes quadratic dependence between the logarithm of the expected earnings and the given number of years of schooling. According to the Mincer model the earnings of an individual form an increasing function of the level of education, as measured by the years of formal schooling. Also, it is an increasing and concave function of experience, measured simply by the age of an individual. The original version of the Mincerian model was subject to many generalisations. According to Lemieux (2006) the most important generalisation involves a much more complicated nonlinear relationship between the rates of returns from human capital investment and earnings. In spite of many generalisations, it seems that the Mincerian model is still a base for empirical analyses of wage distribution as well as the relation between wages and the existing human capital.[1]

One can also point out some disadvantages of the Mincerian model. First, the model does not take into account other determinants of wages beyond the level of education and work experience. Furthermore, it is possible to study and work simultaneously. It is worth mentioning that reflecting such a case in economic data is nearly impossible.

[1] The human capital earnings function has become a technique accepted for example by the courts in analyses of earnings. It is used to estimate the value of lost earnings due to injury or death or resulting from discrimination (see Chiswick 2003, p. 25).

Initially Mincer estimated the rates of returns from on-the-job training and their impact on wage distribution for several different occupations. He showed that earning profiles imply a decline in on-the-job training investment with age. Mincer also showed that on-the-job training investments increase with the level of schooling. Mincer concept prompted new studies, however, the necessity of some modification of the model was crucial, the non-linear relationship between wages and schooling receiving particular attention; see Lemieux (2006, p. 4) and many others.

Starting from Mincer (1974) the issues of wage and human capital distribution have been studied by many authors. Empirical analyses indicate that the return rate on education is no greater than 10% of initial income per additional year of education or 30–35% in the case of moving to a higher educational tier. Several reviews of empirical results can be found in the literature (see Psacharopoulos 1994; Psacharopoulos, Patrinos 2004; Hanushek, Woessmann 2010; Strauss, de La Maisonneuve 2007). Initially, in the problem of estimation of the return on education, the simple linear regression with an OLS estimator have been commonly used (see Becker, Chiswick 1966; Mincer 1974). In the last decade also a quantile regression estimator was used by, among others, Ning (2010) or Newell and Reilly (2001). There are, however, numerous contesting opinions in the literature expressing reservations towards empirical results based on simple econometric frameworks. The issue of selection problems and heterogeneity in returns was addressed by Carneiro and Heckman (2002) and Blundell, Dearden and Sianesi (2005). Also the decision made by an individual to obtain more education involves many factors, like individual ability, family background and preferences, which may be measured only imprecisely. The endogeneity and causality problems in labour market studies was addressed by Heckman (1974), Heckman, Lochner and Todd (2006, 2008) and Li and Tobias (2011). The impact of this effects on the return on education was discussed by Card (2001). Also, the importance of the observed and unobserved heterogeneity in the estimation of the return on education parameters was analysed by Willis and Rosen (1979). As heterogeneity seems to be a serious and interesting problem the analyses of heterogeneity were undertaken with respect to particular education levels (see Aakvik, Salvanes, Vaage 2010) as well as different groups (Henderson, Polachek, Wang 2011) and parameter estimates (Koop, Tobias 2004).

Parameters of the Mincer regression are estimated with the use of both individual and aggregated data observed for a particular country by labour force or employers' surveys. On the macro level, the Mincerian equation was estimated on the basis of regressions for both the cross-section data and the time series (see Hausman, Taylor 1981; Moretti 2004; Krueger, Lindahl 2001). The main assumption for cross sectional analysis is the homogeneity of regression parameters. Consequently, the impact of education and experience on the observed wages does not vary across countries or across any groups of individuals.

Cross-country regressions were also performed by Hanushek and Zhang (2006) and recently Hanushek et al. (2015), Montenegro and Patrinos (2014). They reported country heterogeneity of returns to human capital resulting in the variability of estimated values of parameters across countries. The authors applied a multilevel modelling strategy, building the regression of the variability of the obtained returns to skills on alternative skill measures (like numeracy, literacy, problem solving and others). However, a detailed insight into the significance of the observed differences in returns to skill is missing. Since the stochastic assumptions imposed in the underlying regression models may be diverse, the issue of formal statistical testing if observed returns to skill are different, is important.

The main goal of the paper is to analyse the empirical importance of heterogeneity of the return on education effect across European countries. We check if the standard econometric strategy utilising panel regression is correct in the view of aggregated data. Since the panel data approach relies on the imposed constancy of the return on education effect across the analysed set of countries, we relax this assumption in our research. The variability of parameters, describing the impact of years of schooling and experience on wages is due to the application of the system of Seemingly Unrelated Regression Equations (SURE). Each equation in the system is the Mincer regression corresponding to a particular country. The differences between parameters were tested given two alternative stochastic assumptions. In the first model, no contemporaneous correlations among error terms in the system are imposed. It is equivalent to the estimation of return on education effects in each country separately. In the second approach the unrestricted covariance matrix of the error term is considered. Hence possible non-zero correlations may change the statistical inference of parameters of interest. We discuss the results of testing and provide the classification of European countries with respect to the strength of the return on education effect.

2 Parameter heterogeneity in Mincer equation

The standard regression form of the Mincer equation, with observables limited to a particular country can be written in the following form:

$$\ln wage_t = \alpha_0 + \alpha_1 edu_t + \alpha_2 age_t + \alpha_3 age_t^2 + \varepsilon_t, \quad t = 1,\ldots,T \tag{1}$$

where $\ln wage_t$ is the logarithm of the hourly wage observed in the t-th major occupation group, while age_t and edu_t describe the age and the average level of education in the group.

According to Mincer (1974) and Heckman, Lochner and Todd (2006) when specific measures of post-school investment are unavailable, potential work experience can be approximated simply by age. In Zoghi (2010), Lacuesta, Puente and Cuadrado (2011), Bolli and Zurlinden (2012), Nilsen et al. (2011) the *age* or *work experience* variables are used only up to the particular age group, because observations of the exact number of years corresponding to those variables are not available. Also, using age intervals makes it possible to weaken the internationally unstable relationship between age and work experience.

The parameters of interest are α_2 and α_3, describing the impact of age to salary. Parameter α_1 informs about the strength of the return on education effect. Suppose we observe the aforementioned variables for the j-th country ($j = 1,\ldots, n$) and we want to formulate the Mincer equation with structural parameters that vary across countries. Let us consider the following system of regressions:

$$\ln wage_{tj} = \alpha_{0j} + \alpha_{1j} edu_{tj} + \alpha_{2j} age_{tj} + \alpha_{3j} age_{tj}^2 + \varepsilon_{tj}, \quad j = 1,\ldots,n \tag{2}$$

where j denotes the number of country.

The error term ε_{tj} in (2) captures the impact of effects unrelated to age and the average level of education in the group on the variability of wage. Those effects may concern country-specific structural or institutional conditions, cultural differences, the distribution of talents and others. Hence the proper stochastic assumptions in (1) and (2) are crucial when modelling the relationship between wage and the level of education. In regression (2), which has its roots in the Mincer theory, the endogeneity problem can be met, particularly with reference to the education variable. In order to resolve that problem estimation techniques using instrumental variables (the IV approach) can be applied. However, as Dickson and Harmon (2011) or Heckman and Urzua (2010) suggest IV estimates rest on strong a priori data assumptions and the results may vary with respect to different sets of instruments applied in the estimation.

The standard assumption that, for each t, Gaussian error terms ε_{tj} in (2) are uncorrelated, makes the system of equations independent. This case, denoted by M_0, formally refers to the standard empirical strategy when country Mincer regressions are estimated separately. However, in general, error terms ε_{tj} may exhibit cross correlation and the system (2) can be treated as a Seemingly Unrelated Regression Equations (SURE) model. We define such a case as M_1. Non-zero contemporaneous correlations of error terms in (2) define a more ample stochastic structure and makes it possible to test formally M_0 as a special case. Also the standard interpretation of non-zero contemporaneous correlations is used as indicators describing linkages in the variability of the related variable across countries.

Denote by $\varepsilon_t = (\varepsilon_{t1},...,\varepsilon_{tn})$ the row vector of error terms in group t with the covariance matrix Σ. In the case of model M_1 the matrix Σ is symmetric and positive definite with $n(n+1)/2$ free elements σ_{ii}^2, $i = 1,\ldots, n$ and $j = 1,\ldots, n$. The standard notation denotes the variance of the error terms in the i-th country as $\sigma_{ii}^2 > 0$ and the covariance between error terms in the j-th and the i-th country is denoted by σ_{ij}^2. The system of equations (2) can be formulated in the following standard regression form:

$$y^{(j)} = x^{(j)}\alpha^{(j)} + \varepsilon^{(j)},\ j = 1,...,n$$

where:

$$y^{(j)} = (y_{1j},...,y_{Tj})',\ x^{(j)} = (x_{1j}',...,x_{Tj}')',\ \text{with}\ x_{tj} = (1,\ edu_{tj},\ age_{tj},\ age_{tj}^2),\ \ \varepsilon^{(j)} = (\varepsilon_{1j},...,\varepsilon_{Tj})'$$

and $\alpha^{(j)} = (\alpha_{0j}, \alpha_{1j}, \alpha_{2j}, \alpha_{3j})'$

In the next step we stack the observations expressing the system of regression equations in the closed form:

$$Y = X\alpha + \varepsilon \tag{3}$$

where:

$$Y_{[nTx1]} = (y^{(1)}{}',...,y^{(n)}{}')',\ \varepsilon_{[nTx1]} = (\varepsilon^{(1)}{}',...,\varepsilon^{(n)}{}')',\ \alpha_{[n4x1]} = (\alpha^{(1)}{}',...,\alpha^{(n)}{}')'\ \text{ and:}$$

$$X_{[nTxn4]} = \begin{pmatrix} x^{(1)} & 0_{[Tx4]} & \cdots & 0_{[Tx4]} \\ 0_{[Tx4]} & x^{(2)} & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0_{[Tx4]} \\ 0_{[Tx4]} & \cdots & 0_{[Tx4]} & x^{(n)} \end{pmatrix}$$

Simple calculations yield the form of the covariance matrix for the error term ε in (3):

$$V(\varepsilon)=\Sigma\otimes I_n$$

where $\otimes$ denotes the Kronecker product.

The form of the covariance matrix of ε makes the system (3) a generalised linear regression. Given Σ, the Aitken Generalised Least Squares estimator of all parameters in the system can be expressed in the following form:

$$\hat{\alpha}_{GLS}=\left(X'(\Sigma\otimes I_n)^{-1}X\right)^{-1}X'(\Sigma\otimes I_n)^{-1}y$$

with the covariance matrix of estimator given as follows:

$$V(\hat{\alpha})=\left(X'(\Sigma\otimes I_n)^{-1}X\right)^{-1}$$

In the M_0 case, where $\Sigma=diag(\sigma_{11}^2,\ldots,\sigma_{nn}^2)$ we have:

$$\hat{\alpha}=\hat{\alpha}_{OLS}=(X'X)^{-1}X'y$$

which is equivalent to the application of the *OLS* estimator for each equation separately.

In the general case, M_1, we have to estimate the covariance matrix Σ. In the empirical part of the paper we apply the Zellner (1962) method, and estimate elements of matrix Σ on the basis of OLS residuals, denoted by $\hat{\varepsilon}_{[nTx1]}=(\hat{\varepsilon}^{(1)}{}',\ldots,\hat{\varepsilon}^{(n)}{}')'$. The estimated *GLS*, proposed by Zellner (1962) takes the form:

$$\hat{\alpha}_{EGLS}=\left(X'(S\otimes I_n)^{-1}X\right)^{-1}X'(S\otimes I_n)^{-1}y$$

with an approximated small sample covariance matrix of the estimator:

$$\hat{V}(\hat{\alpha}_{EGLS})=\left(X'(S\otimes I_n)^{-1}X\right)^{-1}$$

where

$$S=\frac{1}{T}(\hat{\varepsilon}^{(1)},\ldots,\hat{\varepsilon}^{(n)})'(\hat{\varepsilon}^{(1)},\ldots,\hat{\varepsilon}^{(n)})$$

The empirical importance of the system of regressions is supported when matrix S indicates that Σ is not diagonal. It is clearly implied by possible cross correlations of error terms. Non-zero contemporaneous correlations can be interpreted in several ways. Firstly, there might exist important explanatory variables in the system that were omitted in the analyses. Since we are working on the basic theoretical Mincer formula, those correlations are proxies for all factors that would determine the excess of observed wages from theoretically driven levels. Secondly, the SURE model applied in estimating the parameters of the Mincer equation postulates cross-country heterogeneity, but still makes it possible to include some cross-country linkages. Contemporaneuos correlations can be interpreted as a measure of the impact of those linkages on the returns to education. Another important issue making the system analysis possible and nontrivial is the form of the matrix X of explanatory variables. In the case of the system of regressions (3) the same matrix of explanatory variables is applied in each equation, namely for each $j=1,\dots,n$ we have $x^{(j)}=x$. Consequently, matrix X takes the form:

$$X_{[nTxn4]}=\begin{pmatrix} x & 0_{[Tx4]} & \cdots & 0_{[Tx4]} \\ 0_{[Tx4]} & x & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0_{[Tx4]} \\ 0_{[Tx4]} & \cdots & 0_{[Tx4]} & x \end{pmatrix}=x\otimes I_n \tag{3}$$

This extremely simplifies the method of estimation since some basic properties of the Kronecker product yield:

$$\hat{\alpha}_{GLS}=\left((x\otimes I_n)'(\Sigma\otimes I_n)^{-1}(x\otimes I_n)\right)^{-1}(x\otimes I_n)'(\Sigma\otimes I_n)^{-1}y=(X'X)^{-1}X'y=\hat{\alpha}_{OLS}$$

This result stays correct no matter if the covariance matrix is diagonal or unrestricted. However, in the case of matrix (3) the difference between estimation with the use of $\hat{\alpha}_{GLS}$ and $\hat{\alpha}_{OLS}$ is more subtle and concerns the form of the covariance matrices. Since $\hat{\alpha}_{OLS}$ results from the assumption that matrix Σ is diagonal, the small sample approximation of the covariance matrix of the estimator $\hat{\alpha}_{OLS}$ is of a similar form as in the case of $\hat{\alpha}_{OLS}$, but the diagonal matrix $S_{diag}=diag\{s_{11}^2,\dots,s_{nn}^2\}$ is applied as an estimator of $\Sigma=diag(\sigma_{11}^2,\dots,\sigma_{nn}^2)$:

$$\hat{V}(\hat{\alpha}_{OLS})=\left(X'(S_{diag}\otimes I_n)^{-1}X\right)^{-1}$$

with $s_{jj}^2=\frac{1}{T}\hat{\varepsilon}^{(j)}{}'\hat{\varepsilon}^{(j)}\quad j=1,\dots,n.$

The diagonal elements of $\hat{V}(\hat{\alpha}_{OLS})$ and $\hat{V}(\hat{\alpha}_{EGLS})$ are the same and hence the inference about standard errors of structural parameters is the same. However, the matrix $\hat{V}(\hat{\alpha}_{EGLS})$ is not block diagonal, and in the case of the estimation of functions involving regression parameters from different equations, the inference for *EGLS* may not be equivalent to the *OLS*.

In the empirical part of the paper we test the statistical significance of differences between parameters describing the return on education, namely α_{1j} for $j=1,\dots,n$ across countries; see equation (2). We will perform it according to the standard testing procedure that involves the estimation of a linear combination of structural parameters. Suppose we are interested in a linear combination of structural parameters in (3) of the form $\gamma=c_{[n4x1]}\cdot\alpha_{[n4x1]}=(c^{(1)}{}',\dots,c^{(n)}{}')\cdot(\alpha^{(1)}{}',\dots,\alpha^{(n)}{}')'$. The vector $c_{[n4x1]}$ contains coefficients of a particular linear combination and is known. We define the *EGLS* and *OLS* estimator of the function of interest γ as follows:

$$\hat{\gamma}_{OLS}=c\cdot\hat{\alpha}_{OLS}$$

and

$$\hat{\gamma}_{EGLS}=c\cdot\hat{\alpha}_{EGLS}$$

The small sample approximation of the variance of estimators is given as follows:

$$\hat{V}(\hat{\gamma}_{OLS}) = c \cdot \hat{V}(\hat{\alpha}_{OLS}) \cdot c'$$

and

$$\hat{V}(\hat{\gamma}_{EGLS}) = c \cdot \hat{V}(\hat{\alpha}_{EGLS}) \cdot c'$$

If the linear combination γ involves parameters from different equations, the variance obtained on the basis of the *OLS* estimator is different from the one obtained according to the EGLS procedure. This may cause different results of inference about γ, particularly in the case of testing the significance of certain restrictions.

The aforementioned procedure can be applied for system (2) in testing the country heterogeneity of parameters. Suppose we are interested in testing whether the difference between return on education in the *i*-th country is significantly different from the return on education in the *j*-th country. More formally we are interested in testing the following hypothesis framework:

$$\begin{aligned} H_0 &: \alpha_{1i} - \alpha_{1j} = 0 \\ H_1 &: \alpha_{1i} - \alpha_{1j} \neq 0 \end{aligned} \qquad (4)$$

This can be conducted on the basis of the function $\gamma^{ij} = c_{[n4x1]} \cdot \alpha_{[n4x1]}$, with $c_{[n4x1]} \cdot (c^{(1)}{'}, \ldots, c^{(n)}{'})$ such that $c^{(i)} = (0,1,0,0)$, $c^{(j)} = (0,-1,0,0)$ and $c^{(m)} = (0,0,0,0)$ for all remaining m, namely for $m \in \{1,\ldots,n\} \setminus \{i,j\}$. In this case, the γ^{ij} simply means the difference between $\alpha_{1,i}$ and $\alpha_{1,j}$ and testing country heterogeneity can be equivalently performed on the basis of the following testing hypothesis:

$$\begin{aligned} H_0 &: \gamma^{ij} = 0 \\ H_1 &: \gamma^{ij} \neq 0. \end{aligned}$$

The standard procedure of the Student-*t* test can be applied, with the test statistics utilising the standard errors defined as square roots of $\hat{V}(\hat{\gamma}_{EGLS})$ in the case of *EGLS* estimation procedure or square roots of $\hat{V}(\hat{\gamma}_{OLS})$ in the case of the simpler method, based on the *OLS* estimator. It is interesting how the form of matrix Σ influences the results of testing the heterogeneity of parameters. In the empirical part of the paper we perform those tests, making comparison of results between both the forms of matrix Σ.

We can also perform the testing procedure when comparing returns to age on the basis of the pseudo elasticity of wages with respect to the age variable. In this case the following linear functions of parameters and age are subject to estimation:

$$\delta_j = \alpha_{2,j} + 2\alpha_{3,j} edu$$

Also statistical testing of the significance of cross-country differences can be performed similarly as in (4).

3 Empirical analysis

The empirical analysis presented in the paper is based on the cross-section series taken from the European Union Structure of Earnings Survey (SES), a large representative enterprise sample survey. The SES provides comparable information on the level of remuneration and characteristics of employees such as sex, age, occupation. The SES data are representative and contain information taken from enterprises with at least 10 employees operating in all areas of the economy except public administration. Consequently, our dataset does not include information about individuals working in small firms and the self-employed.

However, as Eurostat data shows that the majority (ca. 70–80%) of workers are employed in enterprises with at least 10 employees and the structures of employment across analysed countries do not differ substantially, we do not expect a serious impact of this drawback.

Business activities, which are included in the survey, are those from enterprises operating in sections B to S excluding O according to NACE Rev.2 (http://ec.europa.eu/eurostat/ramon/nomenclatures/index.cfm?TargetUrl=ACT_OTH_DFLT_LAYOUT&StrNom=NACE_REV2&StrLanguageCode=EN). The selection of the sample and the survey itself are carried out by national statistics offices. The invaluable advantage of the survey is the credibility of data concerning wages. In contrast to data from the Labour Force Survey (LFS), data on remuneration is the real data coming from employers and not those declared by respondents. We do not have access to the observed individual wages from the SES, hence in the empirical analysis we consider partially aggregated information with respect to the average wage corresponding to a particular occupational group and an appropriate age group.

The structure and distribution of remunerations can be described by the human capital level. The available dataset contains information about occupation. It can be easily used to obtain approximated values of the education level. The occupation (profession) is defined as a set of tasks and duties characterized by high degree of similarity. A given occupation needs suitable skills and knowledge. A skill is defined as the ability to carry out the tasks and duties of a given job.[2] According to ISCO-08 we separate four major levels of skills. Skill levels are defined by considering the level of education and qualifications gained by on-the-job training or practice. The key factor for the classification of professions is the level of required qualifications rather than the way of achieving them. According to ISC-08 methodology there are four levels of skills (see Table 1). The first level requires elementary qualifications and primary education or the first stage of basic vocational education. The second level involves individuals with some degree of secondary education (basic vocational, general and vocational comprehensive) and post-secondary or non-tertiary levels. The third level is related to education accomplished in the first stage of tertiary education. The forth level includes individuals with tertiary level of education accomplished.

Table 2 presents the basic descriptive statistics of wages in selected EU countries in 2010 and 2014. In 2010 the lowest hourly wage (4.2 Purchasing Power Standard – PPS) was posted in Latvia. The highest remunerations (almost 5 times higher) were reported in Sweden and Denmark. Generally, in the group of CEE countries, wages in 2010 were below 10 PPS. In 2014, the wage distribution stayed unchanged – wages were still the lowest in the CEE countries, in particular in Bulgaria, Romania and Macedonia (ca. 5–6 PPS). But the pay gap between the economies with the highest and the lowest wages narrowed. We can add that relatively low hourly wages at the level of approx. 6 PPS in 2010 and

[2] International Standard Classifications: ISCO-08, International Labour Office, Geneva: ILO, 2012, vol. 1.

2014 are noted in Bulgaria, Romania and Lithuania. In other CEE countries (except for Slovenia) they are at the level of 6–10 PPS in both the considered periods.

One can find a similar pattern when studying the diversity of wages. The study of wage diversification broken down by occupational groups indicates that the Portuguese economy is definitely the leader in this category (the coefficient of variation, cv, equals 0.7 in both 2010 and 2014). Similarly, in Italy and Romania, wages are pretty diversified by professional groups. The lowest variation coefficients near 0.3 in both the analysed periods was observed in the Scandinavian countries (Denmark, Sweden and Norway). A slightly higher coefficient (cv around 0.3–0.4) was noted in Switzerland, the Netherlands, and the Baltic States as well as Finland and Ireland. In other examined economies the hourly wages are moderately diversified (coefficients of variation amounting to approx. 0.4–0.6).

The preliminary qualitative analyses (see Table 2) indicate that the existing diversification of wages in Europe with respect to the level of skills and labour market experience is strong. We expect observed higher wages to accompany higher level of human capital accumulated by individuals. Our research strategy takes into account those empirical effects. Consequently, we estimate the total impact of changes in human capital on the wage level in European countries.

The parameters of regression equation (2) were subject to estimation. We assume that:

edu_{tj} – mean skill level measured according to ISCO-08 of the employee in the *t*-th major occupation group in country *j*;

age_{tj} – work experience measured by the age interval that the employee falls into in the *t*-th major occupation group in country *j* (there are 5 intervals for age: 2 – less than 30 years old, 3 – from 30 to 39 years old, 4 – from 40 to 49 years old, 5 – from 50 to 59 years old, 6 – 60 years old or over);

α_{0j} – intercept for country *j*; α_{1j} shows the relative change of a worker's salary due to the increase in the level of skills; α_{2j} , α_{3j} show the impact of work experience on wages.

The parameters of the above equation were OLS-estimated using cross-section data (70 observations for every country) concerning men and women in 2010 and 2014 in 28 European countries.[3]

The estimated[4] returns on education are presented in Figure 1. Depending on the country of the region, the improvement of skill level resulted in a 17–46% change of salaries. The estimated value of parameter α_{1j} can be treated as a measure of returns to education in the *j*-th country. As it was mentioned above, the level of skills can be mapped easily onto education level.

The estimated α_{1i} parameters for the 28 European countries point to increasing returns on education in selected emerging economies (see Münich, Svejnar, Terrell 2005; Vujčić, Šošić 2009; Li et al. 2013; Bargain et al. 2009). The analysis of results presented in Table 3 indicates that the lowest returns on education were noted in Scandinavian economies, particularly in Denmark (16% in 2010 and 17.7% in 2014), Norway (18.9% in 2010 and 19.2% in 2014) and Sweden (19.4% in 2010 and 19.8% in 2014). The highest studied rates in 2010 can be found in Portugal (49%), Romania (47%) and Bulgaria (43.5%). In these economies, in 2014, rates were slightly lower and amounted to 43–44%. Slightly lower returns on education (around 35–40%) in both the analyzed periods were noted in Italy, the Czech Republic, Croatia, Hungary, Poland and Slovenia. In Switzerland, Iceland and in the selected economies of the old EU15 (the Netherlands, Ireland, Finland, Belgium and France) the returns on education are at the level of 23–30% in both years. Furthermore, the ranking of countries in terms of returns to education did not change significantly between 2010 and 2014 (see Figure 1).

[3] The whole sample of European countries cannot be considered due to serious lacks of data.
[4] The detailed estimation results are available on request.

As we mentioned before, the Mincerian wage equation makes it possible to estimate returns to work seniority. In most of the analysed countries work experience plays a significant role in wage formation (see Table 3 and Table 8). We take into account nonlinear dependency between wages and work experience (resulting from the extended Mincer equation). In general, the level of wages can be described by a quadratic function of individuals' work seniority. Each additional year of work experience is connected with an increase in the wage, however this effect stays true until the maximum level of compensation is reached. Then the average wage does not rise. Table 3 presents the average values of estimated returns to work experience assuming that age is the average value of the work experience variable in the sample. In a few cases the estimated average returns to work seniority are statistically indistinguishable from zero at any reasonable level of significance. In 2010, this pattern applies to Latvia, Bulgaria, Lithuania, Slovakia, Iceland, Romania and the Czech Republic and in 2014 to Estonia, Bulgaria, Lithuania, Slovakia and Romania. Furthermore, in two cases (Estonia in 2010 and Latvia in 2014) estimated average returns to work experience are significant and negative which we find a bit puzzling in terms of the Mincerian framework interpretation.

At the same time, the estimated parameters of the Mincer equation make it possible to determine the value of the age variable for which the wage does not increase and reaches the maximum. It turns out that in the case of the economies with average negative returns to experience the maximum wage is obtained in a relatively young group (30–39 years old). Moreover, these statistically insignificant or negative values of returns to age are found in the emerging economies with transformation experience. In these cases the age is not always related to professional experience gained in the market economy. With that in mind the results concerning work experience should be interpreted with caution. Furthermore, the comparison of the estimated parameters describing the impact of professional experience on wages indicates that there are no changes between the analyzed periods so the returns to work experience stay constant (see Figure 2).

The differences in returns to work experience are also diversified among countries. The highest returns are obtained in the case of the Portuguese and Italian economies, around 13–14%. These countries are characterized by quite high rates of returns to education (in particular Portugal) and strongly diversified wages. Relatively high (around 10–12% for each additional 10 years of professional experience) returns to work experience in both analyzed periods were found in Belgium, the Netherlands, Germany, Spain and Austria. In other economies these rates are at the level of 9% or less.

The system of regressions (2) enables us to formally test differences in parameters across countries. In particular, we are interested in testing whether the parameters describing the return on education (α_{1j}) and the return to work experience (α_{2j} and α_{3j}), are heterogeneous across countries in both periods. Those parameters are individually statistically significant in most cases, however, a detailed insight into its heterogeneity across countries is subject to analysis. We perform a series of tests of the form presented in (4) and we conduct them in pairs given two alternative assumptions imposed on the distribution of the error terms. The results of tests are compared when diagonal matrix with different variances attached to error terms for a particular country is considered and, alternatively, when the covariance matrix Σ is unrestricted. The point estimates of parameters, as well as individual standard errors are the same in the case of the OLS and Zellner estimators. However, the inference about functions of interests involving parameters from different equations may be different in both cases.

The main results of the testing procedures are presented in Tables 4–7. The provided division into groups is qualitative. In the case of countries in the same group there is no data evidence against the zero hypothesis in (4) at a 10% significance level. However, it does not mean that a given country being qualified to a specific group is not similar to countries from other groups. In other words, all countries in a given group have statistically indistinguishable returns to education (or work experience) and at least one of these countries has a statistically different return than countries in other groups. We depict the groups of countries with a similar, statistically indistinguishable return on education effect. The results presented in Table 4 are obtained for returns to education in the case of a diagonal covariance matrix Σ and an unrestricted matrix in 2010. Table 5 presents equivalent results for 2014. In the case of the diagonal covariance matrix the results for country heterogeneity of return on education are vague and can be attributed only with great uncertainty. We identify only six groups of countries (with diverse composition) with the same effect in both years. The first group consist of Denmark, Norway and Sweden and stays unchanged between these years. The second group that stays unchanged over time covers Bulgaria, Romania and Portugal. The selected CEE countries (namely Poland, Croatia, Slovenia, the Czech Republic and Hungary) as well as Italy form another group which is supplemented by Slovenia and Estonia in 2010 and by Germany in 2014. In 2014 Estonia and Slovenia are categorized in a different group consisting of Macedonia, Latvia, Spain, Austria, Lithuania and the United Kingdom. Germany joins that group in 2010. The Netherlands, Iceland, Ireland, Finland, Switzerland, Belgium and France are countries divided into two groups with a different combination in 2010 and 2014.

The statistical uncertainty about the differences between parameters describing the return on education in a particular country is substantial. Hence, given the simple stochastic structure of the model, it is impossible to categorize countries in a nontrivial way. In the case of more complex stochastic assumptions with an unrestricted covariance matrix Σ we can distinguish 10 groups of countries in both periods with statistically similar return on education parameter. In the first group with the lowest return on education we have only Denmark in both periods. Norway and Sweden with relatively low returns to education are included in the second group. In 2010 Iceland has returns to education that are statistically different than any other country's and in 2014 is included into the group with Switzerland and Ireland. Estonian case is similar to the Netherlands', a country which constituted a one member group in 2014 and belonged to a joint group with Ireland and Finland in 2010. When we look at the countries with highest returns to education and the case of the Zellner estimator then in 2014 we have the same group (Bulgaria, Portugal, Romania) as in the case of the diagonal matrix. In 2010 these three countries are split into two subgroups: the first one consisting of Romania and Portugal and the second one containing Bulgaria alone. The rest of the countries is split into four groups, separable from the statistical point of view and to some extent geographically or culturally homogenous.

The procedure of parameter testing can be conducted on the basis of estimated average returns on work experience. We split countries into groups with statistically similar returns to seniority using the parallel method as in the case of returns to education.

In 2010 we can distinguish 6 groups in the case of the diagonal covariance matrix and 4 in the case of the unrestricted one. In 2010 and in the case of model M_0, the following countries are included in the group with the highest average returns to work experience: Italy, Portugal, Austria, Spain, Germany and the Netherlands. The other group with relatively high returns to work seniority consists of Croatia, Switzerland, France, Belgium, Slovenia and Ireland. The countries in these two groups form a group under M_1 model assumptions. The rest of countries in 2010 assuming the diagonal covariance matrix are split into four groups which are separable from the statistical point of view.

Estonia, Latvia and Bulgaria are in the first group, Lithuania, Slovakia and Iceland form the second group, whereas Romania, the Czech Republic, Hungary, Poland and Sweden constitute the third one. The last group consists of Finland, the United Kingdom, Norway, Macedonia and Denmark. The unrestricted covariance matrix makes it possible to divide the rest into three groups: the first one consisting of Estonia alone, the second one containing Latvia, Bulgaria, Lithuania, Slovakia, Iceland, Romania and the Czech Republic, and the third one including Hungary, Poland, Sweden, Finland, the United Kingdom, Norway, Macedonia and Denmark.

Analyses conducted for 2014 give qualitatively similar conclusions. The M_0 model separates five groups whereas M_1 divides countries into four groups. The first distinct two groups under the diagonal matrix assumption consists of CEE countries. The third group covers four Nordic countries and Poland, Ireland, the United Kingdom and Macedonia. Croatia, Denmark, Switzerland, Slovenia and France constitute the fourth group. The last group with the highest returns to work experience consists of selected members of the EU15, namely Germany, Spain, Austria, the Netherlands, Belgium, Italy and Portugal. In 2014 and in the case of more complex stochastic assumptions with an unrestricted covariance matrix the first group stays unchanged comparing to 2010. In comparison to 2010, the second group is enhanced by Iceland, Poland and Ireland. Scandinavian countries, Switzerland, United Kingdom and two SEE countries form the third group. The rest of countries constitute the last, fourth group.

In our analyses, due to the same matrix of explanatory variables, estimates are equivalent for the OLS procedure and Zellner methods. The comparison of the explanatory power of specifications in both the analysed periods is presented in Table 9. The log-likelihood values clearly indicate that model M_1 receives decisive data support in comparison to model M_0. Additionally, the empirical importance of an unrestricted covariance matrix is greater than the explanatory power of Mincerian explanatory variables under diagonal covariance matrix assumptions.

4 Conclusions

The main goal of the paper was to estimate the Mincer equation without imposing the assumption of constancy of parameters across countries. The variability of parameters describing the impact of years of schooling and experience on wages was obtained by the application of a system of seemingly unrelated regression equations. We tested formally the differences between parameters of interest in two settings. Initially, no contemporaneous correlations between error terms in the system were imposed, while in the second approach an unrestricted covariance matrix was considered.

A preliminary analysis showed the statistical significance of the impact of the level of skills on the wage level in the analyzed set of countries. The rate of the estimated returns to education vary from 17–20% in Scandinavian countries to at least 40% and more in Portugal, Bulgaria and Romania. Furthermore, the estimated returns to education do not change significantly between the two years under study (2010 and 2014).

In general, countries with low estimated returns to education can be characterized by higher labour force participation rates, more educated population, higher public expenditures on education and lower dispersion of wages. Moreover, in this group of countries job experience seems to be much more valuable as compared to the remaining countries.

Estimated returns to work seniority indicate that work experience plays a significant role in wage formation in most of European countries. Comparing the dynamics of average returns to work we find them unchanged between 2010 and 2014. However, their diversification among European countries is substantial. The highest returns to work experience are obtained in Southern European countries (ca. 13–14%). The lowest values of these rates (ca. 6% or less) can be found in selected CEE countries.

The conducted analyses raised legitimate concerns about the stochastic structure imposed in the analysed system of regressions. The estimates of parameters of equations describing return on education and work experience effects vary across countries. However, in many cases differences are not statistically significant when simple stochastic assumptions imposing no correlations between countries are considered. The contemporaneous correlations of error terms in the SURE system are empirically supported. Also, rich parameterisation of the covariance matrix of contemporaneous relations reduced statistical uncertainty.

Hence, the inference about return on education effect in a set of countries become more diverse. In the case of independent regressions, the results of testing the heterogeneity of the return on education effect suffer from significant uncertainty. Given a more complex stochastic structure of dependence among error terms it was possible to classify a set of countries in a nontrivial way. The testing procedure distinguishes between groups of countries with different return on education effects. Hence, the linkages between countries, expressed in the model by contemporaneous correlations of the error term are empirically important and provide much more interesting results about the interpretable functions of parameters, making the statistical inference about regression parameters unchanged. Consequently, testing the heterogeneity of parameters in Mincer regressions is not an easy task and can be performed in the system regression approach with more complicated stochastic assumptions.

The obtained regional differences as a result of complex stochastic assumptions indicate that the returns to education are higher in the CEE than in the EU15 countries. But the returns to work seniority are lower in the CEE than in the EU15.

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Annex

Table 1
ISCO-08 groups and skill levels

ISCO-08 major groups	Skill level
1 Managers	3 + 4
2 Professionals	4
3 Technicians and associate professionals	3
4 Clerical support workers	2
5 Service and sales workers	2
6 Skilled agricultural, forestry and fishery workers	2
7 Craft and related trades workers	2
8 Plant and machine operators and assemblers	2
9 Elementary occupations	1
10 Armed forces occupation	1 + 2 + 4

Source: International Standard Classifications: ISCO-08, International Labour Office, Geneva: ILO, 2012, vol. 1.

Table 2

Descriptive statistics of hourly wages in selected EU countries in 2010 and 2014 (in PPS)

Country	Mean		Minimum		Maximum		Coefficient of variation	
	2010	2014	2010	2014	2010	2014	2010	2014
Austria	15.44	16.69	7.08	8.26	46.57	48.83	0.508	0.479
Belgium	18.07	19.42	10.13	11.53	42.66	47.17	0.418	0.447
Bulgaria	5.06	5.31	2.35	2.45	13.12	14.00	0.526	0.543
Croatia	9.34	9.21	4.39	4.21	21.41	23.32	0.490	0.512
Czech Republic	7.70	8.71	3.96	4.25	20.25	23.94	0.469	0.485
Denmark	19.64	20.15	12.58	12.85	35.80	39.79	0.257	0.284
Estonia	7.14	7.72	3.41	3.92	17.68	17.30	0.449	0.389
Finland	15.54	16.46	8.97	9.80	35.30	37.52	0.382	0.390
Macedonia	7.37	5.72	3.48	3.02	15.87	13.01	0.424	0.446
France	14.52	16.00	8.15	9.08	40.69	41.25	0.447	0.424
Germany	16.98	18.71	7.58	8.46	40.31	49.40	0.470	0.503
Hungary	7.77	8.39	3.87	4.70	20.29	21.97	0.511	0.488
Iceland	11.93	14.06	7.27	9.12	25.14	32.29	0.331	0.359
Ireland	18.61	18.37	10.30	11.39	40.79	33.97	0.404	0.320
Italy	15.37	15.65	7.73	7.94	43.47	45.56	0.587	0.590
Latvia	4.17	6.39	2.23	3.46	9.29	14.59	0.385	0.392
Lithuania	5.63	6.03	2.85	3.31	12.12	13.25	0.409	0.414
Netherlands	15.43	16.06	7.08	7.46	31.76	34.95	0.360	0.386
Norway	18.39	20.35	11.57	12.87	33.68	38.49	0.262	0.271
Poland	8.41	9.51	4.15	5.04	22.97	27.24	0.526	0.525
Portugal	10.45	10.05	4.06	4.46	31.20	33.04	0.701	0.668
Romania	5.76	5.55	2.55	2.69	15.66	13.61	0.606	0.555
Slovakia	7.38	7.84	3.83	4.12	19.16	20.30	0.481	0.446
Slovenia	11.80	11.49	5.71	5.94	33.62	34.11	0.573	0.540
Spain	13.73	13.66	7.32	7.72	35.73	33.97	0.483	0.439
Sweden	14.24	16.30	9.49	10.92	27.87	31.72	0.280	0.287
Switzerland	20.26	21.92	10.78	13.58	43.73	44.83	0.389	0.336
United Kingdom	14.61	14.11	7.19	7.39	34.46	32.23	0.449	0.436

Table 3

Returns on education and work experience in 2010 and in 2014 (in percentage points)

Country	Estimated return on education		Estimated return on work experience	
	2010	2014	2010	2014
Austria	33.64	31.17	11.86	11.67
Belgium	29.38	29.33	9.86	12.21
Bulgaria	43.52	43.74	-2.03	-2.37
Croatia	36.43	38.04	9.28	7.56
Czech Republic	35.74	36.34	2.77	3.03
Denmark	16.17	17.73	7.18	7.96
Estonia	36.44	31.32	-3.86	-2.73
Finland	26.91	27.56	5.16	5.39
Macedonia	32.65	33.21	6.31	6.52
France	30.19	28.69	9.61	9.74
Germany	34.42	36.62	11.47	9.97
Hungary	39.24	36.31	4.43	2.92
Iceland	24.38	24.82	1.48	4.19
Ireland	26.78	24.08	10.11	5.01
Italy	35.28	35.16	14.09	12.97
Latvia	33.03	31.78	-2.04	-3.25
Lithuania	34.56	33.87	0.11	-1.09
Netherlands	25.25	26.94	10.89	11.82
Norway	18.90	19.24	5.63	6.53
Poland	39.77	38.98	4.48	4.86
Portugal	49.17	42.96	12.50	14.05
Romania	47.22	43.80	1.56	2.08
Slovakia	35.98	33.19	1.27	1.49
Slovenia	40.04	37.27	10.02	9.18
Spain	33.50	30.93	11.72	10.32
Sweden	19.44	19.84	4.66	5.12
Switzerland	28.59	22.85	9.32	8.92
United Kingdom	34.85	34.07	5.61	5.47

Note: shaded areas indicate statistically insignificant (at any reasonable level) values.

Table 4

Groups of countries with the same returns to education rates, the case of restricted and unrestricted covariance matrix in 2010

M_0		M_1	
1	Denmark Norway Sweden	1	Denmark
		2	Norway Sweden
2	Iceland Netherlands	3	Iceland
3	Ireland Finland Switzerland Belgium France	4	Netherlands Ireland Finland
		5	Switzerland Belgium France
4	Macedonia Latvia Spain Austria Germany Lithuania United Kingdom	6	Macedonia Latvia Spain Austria
5	Italy Czech Republic Slovakia Croatia Estonia Hungary Poland Slovenia	7	Germany Lithuania United Kingdom Italy Czech Republic Slovakia Croatia Estonia
		8	Hungary Poland Slovenia
6	Bulgaria Romania Portugal	9	Bulgaria
		10	Romania Portugal

Table 5
Groups of countries with the same returns to education rates, the case of restricted and unrestricted covariance matrix in 2014

	M_0		M_1
1	Denmark Norway Sweden	1	Denmark
		2	Norway Sweden
2	Switzerland Ireland Iceland	3	Switzerland Ireland Iceland
3	Netherlands Finland France Belgium	4	Netherlands
		5	Finland France
4	Spain Austria Estonia Latvia Slovakia Macedonia Lithuania United Kingdom	6	Belgium Spain Austria Estonia Latvia
		7	Slovakia Macedonia Lithuania United Kingdom
5	Italy Hungary Czech Republic Germany Slovenia Croatia Poland	8	Italy Hungary Czech Republic Germany
		9	Slovenia Croatia Poland
6	Portugal Bulgaria Romania	10	Portugal Bulgaria Romania

Table 6
Groups of countries with the same returns to work seniority, the case of diagonal and unrestricted covariance matrix in 2010

M_0		M_1	
1	Estonia	1	Estonia
	Latvia	2	Latvia
	Bulgaria		Bulgaria
2	Lithuania		Lithuania
	Slovakia		Slovakia
	Iceland		Iceland
3	Romania		Romania
	Czech Republic		Czech Republic
	Hungary	3	Hungary
	Poland		Poland
	Sweden		Sweden
4	Finland		Finland
	United Kingdom		United Kingdom
	Norway		Norway
	Macedonia		Macedonia
	Denmark		Denmark
5	Croatia	4	Croatia
	Switzerland		Switzerland
	France		France
	Belgium		Belgium
	Slovenia		Slovenia
	Ireland		Ireland
6	Netherlands		Netherlands
	Germany		Germany
	Spain		Spain
	Austria		Austria
	Portugal		Portugal
	Italy		Italy

Table 7

Groups of countries with the same returns to work seniority, the case of diagonal and unrestricted covariance matrix in 2014

	M_0		M_1
1	Latvia Estonia Bulgaria Lithuania	1	Latvia Estonia Bulgaria Lithuania
2	Slovakia Romania Hungary Czech Republic	2	Slovakia Romania Hungary Czech Republic Iceland Poland Ireland
3	Iceland Poland Ireland Sweden Finland United Kingdom Macedonia Norway	3	Sweden Finland United Kingdom Macedonia Norway Croatia Denmark Switzerland
4	Croatia Denmark Switzerland Slovenia France	4	Slovenia France Germany Spain Austria Netherlands Belgium Italy Portugal
5	Germany Spain Austria Netherlands Belgium Italy Portugal		

Table 8
The results of estimation of parameters in Mincer equations in a set of countries

Country	**2010**				**2014**			
	α_{0i}	α_{1i}	α_{2i}	α_{3i}	α_{0i}	α_{1i}	α_{2i}	α_{3i}
Austria	0.9221***	0.3364***	0.3619****	-0.0315**	1.0211***	0.3117***	0.3958***	-0.0362***
Belgium	1.4165***	0.2938***	0.2696***	-0.0222**	1.4109***	0.2933***	0.2818***	-0.0207**
Bulgaria	0.1008	0.4352***	0.2094*	-0.0298**	0.1295	0.4374***	0.2207*	-0.0317**
Croatia	0.7211***	0.3643***	0.1731	-0.0104	0.5615**	0.3804***	0.2549**	-0.0232
Czech Republic	0.5374**	0.3574***	0.2704**	-0.0315**	0.5604**	0.3634***	0.3154***	-0.0369**
Denmark	1.6901***	0.1617***	0.4135***	-0.0443***	1.6278***	0.1773***	0.4292***	-0.0453***
Estonia	0.6161***	0.3644***	0.2548**	-0.0380**	0.7173***	0.3132***	0.3158***	-0.0445***
Finland	1.3792***	0.2691***	0.3081***	-0.0333***	1.3816***	0.2756***	0.3270***	-0.0354***
Macedonia	0.8064***	0.3265***	0.0895	-0.0034	0.2707	0.3321***	0.2458**	-0.0234*
France	1.2950***	0.3019***	0.1996**	-0.0134	1.4233***	0.2869***	0.2053***	-0.0140
Germany	0.7418***	0.3442***	0.5235***	-0.0530***	0.8289***	0.3662***	0.5106***	-0.0533***
Hungary	0.6987***	0.3924***	0.0969	-0.0068	0.9260***	0.3631***	0.0769	-0.0062
Iceland	1.3051***	0.2438***	0.2869***	-0.0353***	1.2452***	0.2482***	0.3756***	-0.0433***
Ireland	1.0948***	0.2678***	0.5157***	-0.0537***	1.5185***	0.2408***	0.3751***	-0.0421***
Italy	0.8476***	0.3528***	0.3358***	-0.0253*	0.8284***	0.3516***	0.3751***	-0.0318**
Latvia	0.3836**	0.3303***	0.1137	-0.0174	0.7629***	0.3178***	0.1765*	-0.0271**
Lithuania	0.6403***	0.3456***	0.0838	-0.0107	0.5065***	0.3387***	0.2318**	-0.0315***
Netherlands	0.9508***	0.2525***	0.5090***	-0.0519***	0.8472***	0.2694***	0.5523***	-0.0563***
Norway	1.7110***	0.1890***	0.3408***	-0.0369***	1.7708***	0.1924***	0.3475***	-0.0366***
Poland	0.3926*	0.3977***	0.3138***	-0.0349**	0.4413**	0.3898***	0.3668***	-0.0412***
Portugal	-0.0015	0.4917***	0.3840***	-0.0336*	0.1361	0.4296***	0.3658**	-0.0292
Romania	-0.0393	0.4722***	0.2508*	-0.0305*	0.0295	0.4380***	0.2454**	-0.0291**
Slovakia	0.5619**	0.3598***	0.2456**	-0.0302**	0.6273***	0.3319***	0.2898***	-0.0356***
Slovenia	0.8127***	0.4004***	0.1818*	-0.0106	0.8494***	0.3727***	0.2044*	-0.0146
Spain	1.2385***	0.3350***	0.1107	0.0008	1.1799***	0.3093***	0.2099**	-0.0138
Sweden	1.5458***	0.1944***	0.2902***	-0.0316***	1.6545***	0.1984***	0.2930***	-0.0314***
Switzerland	1.4349***	0.2859***	0.3488***	-0.0331***	1.7762***	0.2285***	0.2943***	-0.0266***
United Kingdom	0.7577***	0.3485***	0.5001***	-0.0575***	0.8641***	0.3407***	0.4328***	-0.0490***

Note: ***p < 0.01; **p < 0.05; *p < 0.1 (p-values for the zero restriction test of a particular parameter).

Table 9
Criteria for model selection

	2010	2014
	Log-likelihood	
M_0 without explanatory variables	-895.581	-840.068
M_0	755.177	793.063
M_1 without explanatory variables	2516.578	2655.414
M_1	2818.804	2943.759
	LR test (M_0 vs. M_1)	
χ^2 statistics	4127.253	4301.392
p-value	0.000	0.000
No. of restrictions	378	378

Figure 1
Returns to education in 2010 and 2014

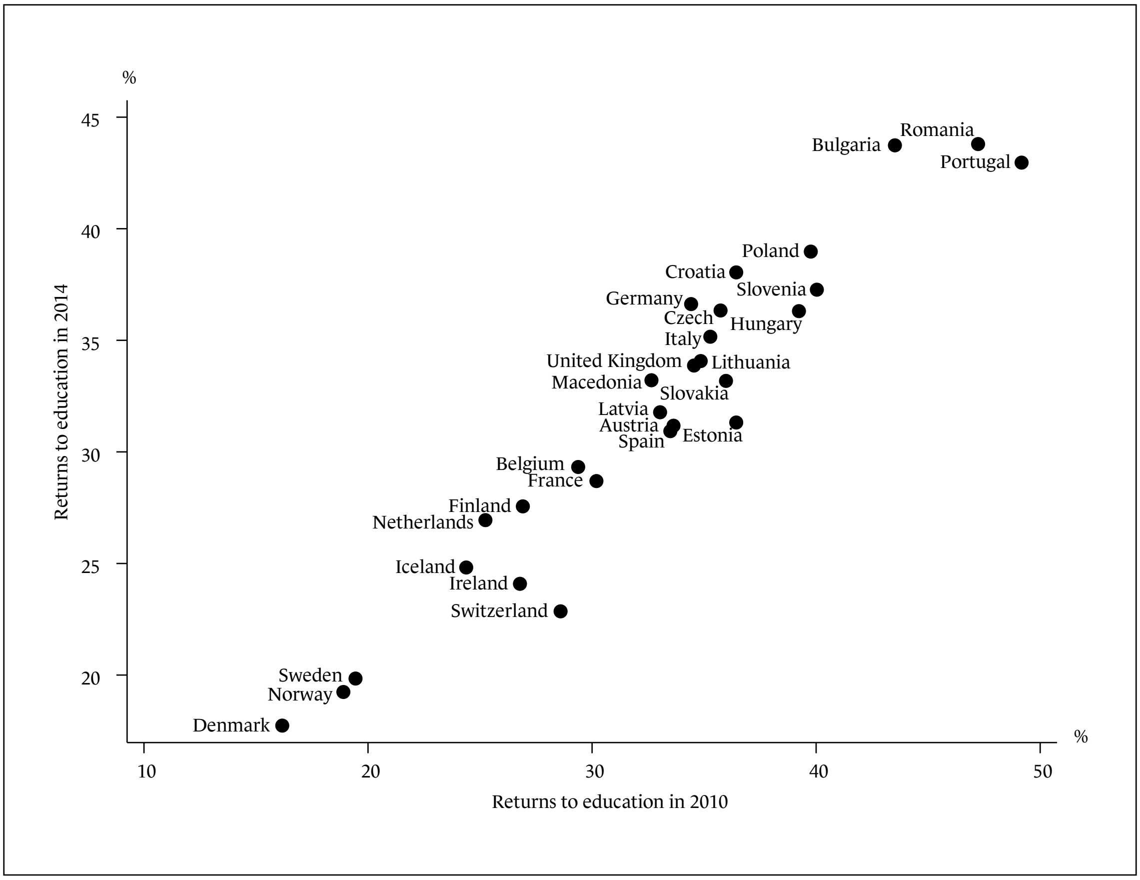

Figure 2
Returns to work experience in 2010 and 2014