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DOES EDUCATION AFFECT WAGES DURING AND AFTER ECONOMIC CRISIS? EVIDENCE FROM LATVIA 2006–2012

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ABBREVIATIONS

AMECO – Annual macro-economic database
CSB – Central Statistical Bureau of Latvia
EC – European Commission
EU – European Union
EU-SILC – EU Statistics on Income and Living Conditions
IT – information technology
IV – instrumental variable
ISCED – International Standard Classification of Education
ISCO – International Standard Classification of Occupations
ISSP – International Social Survey Programme
LFS – Labour Force Survey
NUTS – Nomenclature of Territorial Units for Statistics
OECD – Organisation for Economic Co-operation and Development
OLS – ordinary least squares
USSR – Union of Soviet Socialist Republics
UK – United Kingdom
2SLS – two-stage least squares

SUMMARY

We employ EU-SILC micro data for Latvia to study how returns to education have changed during the economic crisis of 2008–2009 and afterwards. We found that returns to education increased significantly during the crisis and decreased slightly during the subsequent economic recovery. The counter-cyclical effect of education on wages was particularly strong for males; it was evident in majority of sectors and all age groups (except youth, for citizens of Latvia, resident non-citizens and other country citizens as well as in all regions of the country, particularly outside the capital city region. The share of career component (better access to higher paid occupations, sectors and positions) in the Mincer coefficient remained broadly constant over time. After the crisis, education became even more associated with a longer working week and higher chances to be employed. Furthermore, we show that returns to education in Latvia are generally higher in the capital city and its suburbs than outside the capital city region, for citizens of Latvia than for resident non-citizens and citizens of other countries, but lower for males and young people. Wage differential models reveal a relatively large wage premium for higher education and rather small for secondary education. In line with the previous findings for other countries, the estimates obtained with instrumental variable models significantly exceed the Mincer coefficient.

Key words: returns to education, Mincer coefficient, wage differentials model, higher education wage premium, instrumental variables

JEL codes: I26, J31

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INTRODUCTION

During the last two decades Latvia experienced growing popularity of higher education. In 2014, people with higher education accounted for 34% of Latvian employment, compared to only 22% in 2002. Despite growing popularity, media highlights anecdotal evidence that higher education does not guarantee a higher wage in Latvia (Db.lv, 2013). Whether this anecdotal evidence represents outliers or education in Latvia indeed ceased to promote wages after the economic crisis will be addressed in this paper.

Several papers get mixed results on whether there exists a trend in returns to education over time. For instance, Trostel et al. (2002) do not find significant changes in returns to education for most countries. In turn, Montenegro and Patrinos (2014) report a downward trend in returns to education reflecting an increase in education attainment. There is a gap in the literature, however, on how returns to education may change over the business cycle. A typical human capital theory would suggest that individuals choose education attainment to maximize net present value of their income (minus costs of education) over the life span. Therefore, changes of return to education over such a short period as a typical business cycle is cannot be related to investment in education. Instead, the degree of labour market tightness may vary between high-skilled and low-skilled occupations during different phases of the business cycle, thus affecting returns to education estimates.

Latvia may be considered a unique case to study how returns to education have changed over the business cycle. The Latvian economy, being one of the most overheated in 2007, lost one fifth of its output during the crisis, but recovered quickly afterwards[1]. Before the crisis, labour shortage in Latvia was most pronounced in the low-skilled sector of labour market. For instance, during 2006 and 2007, the vacancy rate was the highest within ISCO 7–9 occupational group, while the unemployment rate was broadly similar across occupational groups (see Charts A1 and A2). The real estate bubble promoted strong growth of employment and wages in the construction sector where formal education is not a prerequisite. During the economic crisis, however, the demand decreased most for low-skilled employees as evidenced by the skyrocketing unemployment rate and sharp drop in the vacancy rate, particularly in ISCO 7–9 occupational group. Even nowadays, the unemployment rate in ISCO 7–9 group remains three times higher than in ISCO 1–3 group, while the vacancy rate is the lowest[2]. This would suggest that returns to education might have risen during the crisis.

Measuring returns to education takes roots in the mid-20th century, with Mincer's paper (1974) being one of the most famous contributions. While during the following decades consensus that more educated people receive higher wages was achieved, both the methodology and results tend to differ (see, e.g. Card (1999) and Blundell et al. (2001)).

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[1] Output gap estimates reveal that Latvia's GDP exceeded potential by 11% in 2007, was by 12% lower than potential in 2010, and returned to potential by 2013 (EC AMECO, cited on 3 September 2015).

[2] Ideally, we need unemployment and vacancy rate by education level, but the latter indicator is not available, therefore we proxy education level with ISCO occupation group. Unemployment rate by education level shows a similar picture as unemployment rate by occupation.

A large part of this research is based on the Mincer model (1974) in which wage is a function of years of schooling and job experience. The main outcome of the model – the Mincer coefficient – shows the percent increase in wage for each additional year of schooling. Despite its popularity, the Mincer model has also been criticised: first, for its linearity assumption stating that returns to each additional year of schooling are the same, and second, for claiming that individual's choice of years of schooling is exogenous, i.e. not dependent on other variables.

Linearity assumption is relaxed in the wage differentials model, which allows each education level to have a different impact on wage (Blundell et al. (2001)). In turn, the endogeneity issue is often addressed with the IV method (Angrist and Krueger (2001), Hoogerheide et al. (2012)). Both methods will be employed in this paper.

Returns to education in Latvia have already been estimated in several papers.

Trostel et al. (2002) used the data from International Social Survey Programme (ISSP) and estimated the Mincer coefficient for hourly wage in Latvia as being 6.7% for males and 7.8% for females in 1995. Estimates for Latvia were higher than the 28 country sample average. However, caution should be taken when comparing these results with those in other papers: in the case of Latvia, the dataset contained only 331 observations (141 males and 190 females).

Hazans (2003) used the micro data from the Labour Force Survey (LFS) 2000 to estimate a wage differentials model for Latvia, Estonia and Lithuania. He concluded that, by international standards, the Baltic States have a relatively large (monthly) wage premium for higher education, but rather small for secondary education. In all three Baltic countries, especially in Latvia, returns to education are larger for females than for males. Moreover, in Estonia ethnic minority employees gain less from higher education than ethnic Estonians, while in Latvia and Lithuania the ethnic gap is not statistically significant.

DAIF (2006) used Latvia's LFS 2003–2004 micro data and included education as one of the factors affecting wage differences among individuals. It concluded that about a half of wage premium reflects the direct impact of education on wages, while the other half mirrors a better access to higher paid jobs (career component).

Flabbi et al. (2007) used the ISSP data for eight Eastern European countries during the transition period. Latvia was placed in the "medium" returns group, with the Mincer coefficient increasing somewhat during the transition period (from 6.7% in 1995 to 7.8% in 2002). Returns to education (using monthly wage) in the private sector were higher than in the public sector during the early transition period, but later on this difference diminished to an insignificant level.

Romele (2014) used Latvia's LFS micro data to study returns to education (annual wage). Particularly, she found that in 2011 compared with 2010 the Mincer coefficient decreased both for males (from 7.9% to 7.1%) and females (from 8.1% to 6.8%). She also concluded that before the crisis returns to education were higher in the public sector, but since the crisis they became higher in the private sector.

Montenegro and Patrinos (2014) estimated a standard Mincer model in 139 economies all over the world. The results for Latvia show that the Mincer coefficient after increasing by half in 2006 was broadly stable at 10%–12% in the next six years.

To sum up, previous papers measuring returns to education in Latvia either used data for the period prior to the EU accession (Trostel et al. (2002), Hazans (2003), DAIF (2006), Flabbi et al. (2007)) or were limited to the standard Mincer model only (Romele (2014), Montenegro and Patrinos (2014)). Therefore, we will particularly address the gap in the literature on how returns to education have changed during the economic crisis and afterwards by using extended Mincer and wage differential models. Returns to education have been measured for different ethnicities (Hazans (2003)), genders (Trostel et al. (2002), Hazans (2003), Romele (2014)) and institutional sectors (Flabbi et al. (2007), Romele (2014)). In addition, we will estimate possible differences in returns to education by citizenship, country of birth, region, economic sector and age group. Moreover, the authors have used different dependent variables in their papers, e.g. hourly wage (Trostel et al. (2002)), monthly wage (Hazans (2003), Flabbi et al. (2007)) and annual wage (Romele (2014)). We will use hourly wage in the base specification and alternative wage definitions as a robustness check. Despite possible endogeneity bias, all previous papers on Latvia, to the best of our knowledge, relied solely on ordinary least squares (OLS) estimates. Therefore, this paper fills the gap by using the IV method and comparing its results with the outcome of the Mincer model.

Consequently, the contribution of our paper is threefold. First, we focus on how returns to education have changed over the recent business cycle. Second, we study how education affects wages in different population groups (by gender, age, citizenship and country of birth), sectors and regions. Third, we estimate three IV models using parental education, spouse's education and binary variable indicating whether the most recent education level was obtained in the USSR or after the restoration of Latvia's independence. In addition, we include family background variables (parents and spouse's education) as additional factors to control for unobservable ability.

This paper is structured as follows. Section 1 reviews the methodology of Mincer model, wage differentials model (standard specifications as well as specifications extended with exogenous and endogenous variables) and IV model. Section 2 examines the EU-SILC micro data used in the study and the shifts of wage distribution and average years of schooling over time. In Section 3, we present the main empirical results for the total economy. Section 4 provides an overview of the performed robustness check, while Section 5 discusses the differences in returns to education for several population groups and regions. Finally, the last Section concludes.

1. METHODOLOGY

The Mincer model (1974) is often used as a starting point in measuring returns to education and as a benchmark for comparing the obtained results with those of more sophisticated models. This model approximates human capital accumulation of individual i with the linear function of years of schooling and quadratic function of job experience:

$$y_i = \alpha_0 + \beta_0 S_i + \tau_0 X_i + \tau_1 X_i^2 + \varepsilon_i \quad (1)$$

where y_i is log wage of individual i, S is years of schooling and X is job experience (years). The famous Mincer coefficient β_0 implies a percentage wage increase for each additional year of formal education.

Wage differentials model relaxes the linearity assumption by allowing each educational level to have different impact on wages:

$$y_i = \alpha_0 + \beta_1 S_{1i} + \beta_2 S_{2i} + \cdots + \beta_j S_{ji} + \tau_0 X_i + \tau_1 X_i^2 + \varepsilon_i \quad (2)$$

where binary variable S_{ji} equals 1, if the highest level of education for person i is j. For instance, wage premium for education level j (e.g. higher education), ceteris paribus, reflects relative differences in wages for people with higher education and people in the control group (e.g. secondary education). It is calculated as follows:

$$\text{Wage premium of education level } j = \left(e^{\beta_j} - 1\right) * 100 \quad (3).$$

Mincer and wage differentials models can be supplemented with vectors of other wage determinants, which may be both exogenous and endogenous to education level (denoted as C_i and F_i respectively):

$$y_i = \alpha_0 + \beta_0 S_i + \tau_0 X_i + \tau_1 X_i^2 + \mathrm{C}_i \omega' + \varepsilon_i \quad (4),$$

$$y_i = \alpha_0 + \beta_0 S_i + \tau_0 X_i + \tau_1 X_i^2 + \mathrm{C}_i \omega' + \mathrm{F}_i \mu' + \varepsilon_i \quad (5).$$

When the Mincer model is supplemented only with variables that are exogenous to education level (see equation (4)), e.g. gender and ethnicity, the interpretation of the Mincer coefficient remains the same. However, if the model includes variables that are endogenous to education (see equation (5)), e.g. occupation, sector and position, the Mincer coefficient may be smaller, reflecting only the direct impact of education on wages, i.e. for people working in the same occupation, sector and position. The difference of the Mincer coefficient estimate in equations (4) and (5) reflects the indirect impact of education on wages (career component), i.e. better education promotes employment in higher paid occupations, sectors and positions.

There are, however, some reasons why estimates of returns to education may be biased: two of them relate to possible endogeneity issue and the last one – to possible measurement error of education variable.

An endogeneity issue may arise if individuals are different in their ability not related to the formal education. Ability may be indeed correlated with education attainment, because, for instance, individuals with higher ability may choose to obtain higher education levels in order to signal their potential employers about their skills. In this case, the Mincer coefficient may be biased upwards. For instance, Leigh and Ryan

(2008) claim that the ability bias accounts for about 30% of the Mincer coefficient value. However, the magnitude of this bias may depend on country and time.

Another endogeneity issue may arise if returns to education differ among individuals (β_i *instead of* β_0). Individuals with higher returns are likely to choose a higher education level (Blundell et al. (2005)), thus causing error term ε to be correlated with years of schooling.

Considering the estimated model given in equation (1), the true model may be written as:

$$y_i = \alpha_0 + (a_i - a_0) + \beta_i S_i + \tau_0 X_i + \tau_1 X_i^2 + \varepsilon_i \quad (6)$$

where a_i reflects ability of individual i (population average a_0) and β_i represents returns to schooling for individual i (population average β_0). Rearranging, we obtain:

$$y_i = \alpha_0 + \beta_0 S_i + \tau_0 X_i + \tau_1 X_i^2 + (a_i - a_0) + (\beta_i - \beta_0) S_i + \varepsilon_i \quad (7).$$

Neither a_i nor β_i are directly observable. Therefore error ε_i is correlated with education variable S_i, and β_0 estimate is likely to be biased:

$$\begin{cases} y_i = \alpha_0 + \beta_0 S_i + \tau_0 X_i + \tau_1 X_i^2 + \varepsilon_i \\ \varepsilon_i = (a_i - a_0) + (\beta_i - \beta_0) S_i + \vartheta_i \end{cases} \quad (8).$$

A third possible source of bias arises when the education variable is measured with error. The education variable is truncated, so people with low-level education are more likely to overstate it, while people with high-level education are more likely to understate it. Therefore, education level variance in the data set may be smaller than in reality, leading to a downward bias of the Mincer coefficient estimate. At least partly, it may compensate for a possible upward ability bias discussed above. For instance, Ashenfelter and Zimmerman (1997) claim that both biases are of similar magnitude; hence the total bias of Mincer coefficient is not large.

There are several options how to solve the endogeneity issue. One option is to include a proxy variable for individual's ability in the Mincer model. For instance, Harmon et al. (2000) included individuals' test scores obtained before they started to acquire formal education (at the age of 7). Badescu et al. (2011) included parental education as a control variable. Both papers, however, showed that the inclusion of ability variable does not change the estimate of returns to education significantly. It means that either endogeneity bias is not large or the proposed variables are not able to capture ability well enough.

Another option is to find an IV which is correlated with the education variable but is not correlated with the Mincer model's error term. Some examples used in papers are parental education (Hogerheide et al. (2012)), spouse's education (Trostel et al. (2002)) and education system reforms (Card (2001), Leigh and Ryan (2008), Meghir and Palme (2005)).

IV models could be empirically estimated with the 2SLS method:

$$\hat{S}_i = \alpha_2 + \pi_0 Z_i + n_i$$
$$y_i = \alpha_0 + \beta_0 \hat{S}_i + v_i \quad (9).$$

The first step calculates expected education $\hat{S}_i$ by employing strong correlation between the instrumental factor and education variable (relevance condition). The second step expresses log wage as a function of expected education estimate. If the IV impacts wages only through education and does not have any direct impact on it (exclusion restriction), β_0 reflects the true coefficient of returns to education.

Inappropriate instrumental factors may bias results substantially, especially if the instruments are weak. As relevance condition can be tested with ease, weak instrumental factors should be avoided. Unfortunately, the exclusion restriction cannot be tested directly as it involves an unobservable residual. That is why researchers pay extra attention to convincing the reader that the chosen variable fits the exclusion restriction. Some papers argue that family education variables are not appropriate instrumental factors. It is possible that both parental and spouse's education is correlated with household income and wealth, which may in turn affect individual's employment choice and hence also wage. Moreover, parental education may be correlated with unobservable ability, and, therefore, also with the Mincer model error (Card (1999)). As noted by Trostel et al. (2002), individuals with a high ability level may try to find a spouse with similarly high ability. Furthermore, parents with high education may use their professional relations to help their children obtain better paid jobs (Badescu et al. (2011)). Besides, the education level of family members may be subject to a larger measurement error than the education level of respondent himself. However, as the EU-SILC data set includes education attainment of household members, in this paper we will use the parental (and spouse) education variable first as an IV and afterwards as a control variable.

In most cases, estimates of returns to education are larger when using IV models. Evidence shows that compared with OLS estimates, the difference may be between 20% and 250% (Card (2001), Harmon and Walker (1995), Harmon et al. (2000)). It is possible that IVs explain only part of the education variable variance (Angrist and Kreuger (2001). For instance, using changes of compulsory education level as an IV, one estimates the variation of years of schooling only for those individuals who abandon studies as soon as possible. Therefore, the estimated returns to schooling are not attributable to each year of formal schooling but rather to those years that are affected by the instrumental factor (Angrist and Kreuger (2001), Devereux and Fan (2011), Card (2001)). We will use the transition to market economy as an IV possibly influencing the education choice.

2. DATA

To estimate returns to education in Latvia we used anonymised micro data from the EU-SILC survey (carried out in 2007–2013, thus reflecting the situation during 2006–2012), obtained from the CSB. The EU-SILC survey is carried out annually and focuses on income and living conditions of households. It is a rich set of data that includes information about individuals' gender, age, education and earnings. Importantly, contrary to the LFS, earnings and age are given as precise numbers rather than intervals. Therefore, it is often used in estimating returns to education for other countries (for instance, Badescu et al. (2011)).

The choice of research period (from 2006 to 2012) was determined by the availability of data. EU-SILC data for Latvia are available as from 2004, but the first two years employed somewhat different classification of education attainment which is not directly comparable to the subsequent years. This seven-year period allows us to measure how returns to education have changed during and after the period of economic crisis.

The survey sample was narrowed to the working age population (15–64). Moreover, observations with missing education level, wage, average hours worked per week or months worked per year were excluded. The resulting sample consists of the total of 29 499 observations for the period of 2006–2012 or from 3 690 to 4 433 observations per year.

We use log of hourly wage as a dependent variable in our base models. Since hourly wage is not directly observable in the data set, it was calculated from annual wage, taking into account average hours worked per week and the number of months worked in the year. To avoid possible heteroskedasticity, we used robust standard errors to estimate the statistical significance of all coefficients. Moreover, alternative wage definitions (monthly wage, annual wage) were used as a robustness check.

The dynamics of hourly wage broadly captures the aggregate figure for average wage change for full-time job from the CSB business survey, except for 2007 and 2009. EU-SILC data point to steeper wage growth in 2007 and sharper decline in 2009. In both cases, however, EU-SILC data are closer to national accounts (compensation of employees divided by hours worked by employees) than the business survey data (see Chart A3).

The years of schooling variable is not directly observable. It was calculated from the highest level of education (ISCED) attained. Transformation of the education level variable to the years of schooling variable and vice versa is often used in the literature (e.g. Fersterer and Winter-Ebmer (2003), Strauss and de la Maisonneuve (2010)). It should be noted that our data set posted all higher education as ISCED 5, so it was not possible to distinguish between bachelor, master and doctoral degrees. Also, the data set contained information only on highest completed education level, thus underestimating years of schooling for those with unfinished degrees or currently in studies. Average years of schooling tended to rise until 2010 and to stabilise afterwards (see Chart A4).

We distinguish three education levels in the wage differentials model: less than secondary, secondary and higher education. Individuals with secondary education are used as a control group. Chart A5 presents the total economy wage distribution, while wage distribution by education level is reflected in Charts A6–A8. It seems that there are no substantial differences in wage distribution between employees with secondary or lower than secondary education. In turn, employees with higher education have a higher average wage. In addition, at the end of the research period, higher education was associated with less peaked wage distribution.

It seems that the shape of wage distribution for employees with higher education did not change substantially over time (see Chart A9). For other employees, wage distribution became more peaked, particularly for those with lower than secondary education between 2009 and 2012 (see Charts A10 and A11).

The job experience variable was directly observed in our database. However, in order to check robustness, we also used other experience variables that are often dealt with in the literature (such as age and potential experience; see Mincer (1974)).

The Mincer model and wage differentials model were extended with the following exogenous binary variables: gender, marriage, citizenship, region, current education status, health (whether person suffers from long-term illness), number of employees in a company, and whether a person has changed employer during the last year. Moreover, the models were extended with binary variables that are endogenous to education, taking into account occupation, sector and position of a person.

Empirical estimation was carried out with STATA 13 software. As particular weight was assigned to each observation, "pweight" function was used for each regression.

3. EMPIRICAL RESULTS FOR TOTAL ECONOMY

First, we present the estimates of the Mincer model, followed by wage differentials model and IV model.

3.1 Mincer model results

Our results show that in Latvia better education is positively and statistically significantly correlated with higher wages. The standard Mincer model reveals that, on average, each additional year of education is associated with a higher wage (by 7.7%; see Table 1). This finding is similar to Hanushek et al. (2015) result for OECD countries (7.5% on average) as well as to findings by Psacharopoulos and Patrinos (2004) for the high income country group (7.4%) and Montenegro and Patrinos (2014) for Eastern European countries (7.4%). It is also similar to the previous estimates of Mincer coefficient for Latvia: 7.8% (Flabbi et al. (2007)), 6.7%–7.8% (Trostel et al. (2002)), 6.8%–8.1% (Romele (2014)) and 6.5%–11.9% (Montenegro and Patrinos (2014)).

The negative coefficient of quadratic experience term suggests that marginal returns to job experience decrease with each additional year of experience. These findings are also in line with the previous research (DAIF (2006)).

Contrary to the result of Flabbi et al. (2007), we do not find any evidence of increasing education returns over time. Possibly, the result of Flabbi et al. (2007) was obtained due to the inclusion of early transition period which is not covered in the data set herein.

Instead, we found that returns to education in Latvia were counter-cyclical. They rose significantly during the period of economic crisis (from 6.9% in 2007 to 8.9% and 9.3% in 2008 and 2009 respectively) and decreased afterwards (to 7.4% in 2010; see Chart 1). It means that during the economic crisis returns to education were higher than in the other phases of business cycle.

Table 1
Mincer model results (2006–2012)

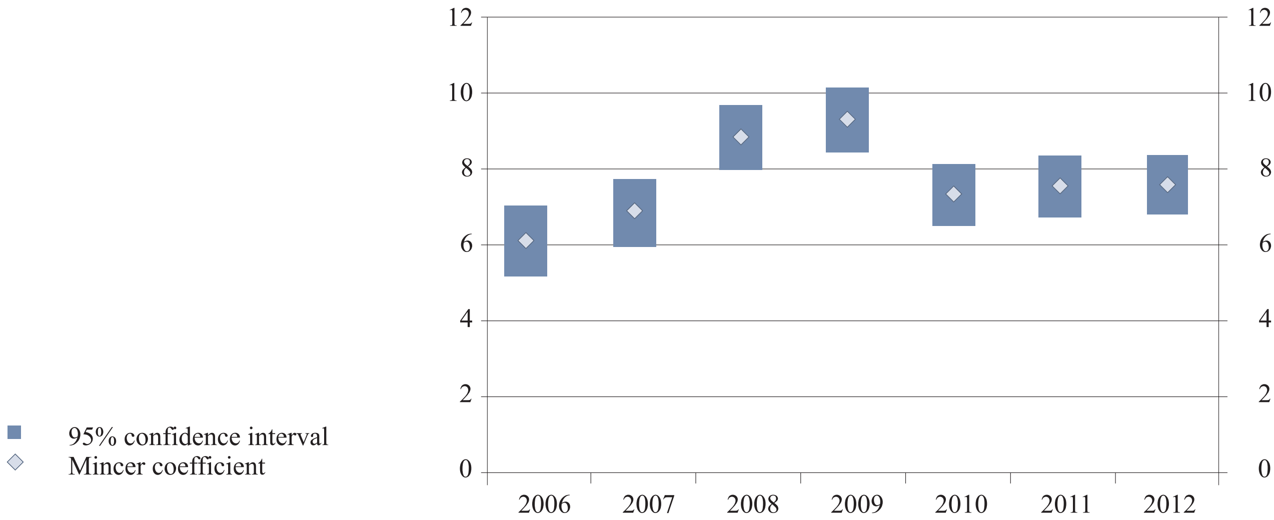
Independent variables / Model	Standard	Extended with exogenous variables	Extended with both exogenous and endogenous variables
Experience	0.0082*** (0.0012)	0.0119*** (0.0012)	0.0099*** (0.0011)
Experience^2	–0.0003*** (0.0000)	–0.0003*** (0.0000)	–0.0003*** (0.0000)
Years of schooling	**0.0769*** (0.0016)**	**0.0800*** (0.0016)**	**0.0382*** (0.0019)**
Male		0.2664*** (0.0073)	0.2173*** (0.0083)
Married		0.0467*** (0.0073)	0.0292*** (0.0069)
Latvian citizen		0.1075*** (0.0095)	0.0791*** (0.0091)
In studies		0.0959*** (0.0155)	0.0288* (0.0152)
Long-term illness		–0.0816*** (0.0088)	–0.0679*** (0.0084)
Self-employed		–0.3728*** (0.0209)	–0.3603*** (0.0212)
Employees <10		–0.0398*** (0.0084)	–0.0309*** (0.0083)
Employees >50		0.1234*** (0.0075)	0.0990*** (0.0072)
Job change		–0.0266** (0.0143)	–0.0106 (0.0139)
Region		Included	Included
Sector			Included
Occupation			Included
Manager			0.0568*** (0.0109)
Time (year)	Included	Included	Included
Constant	–0.5370*** (0.0269)	–0.7865*** (0.0312)	0.1192** (0.0507)
R^2	0.1597	0.2797	0.3569
Observations	29 499	29 470	29 470

Notes: Dependent variable: log hourly wage.
***, **, *: statistically significant with 99%, 95% and 90% confidence level respectively.
Standard errors in parentheses.
Source: Authors' calculations using EU-SILC micro data for Latvia.

The extension of Mincer model with exogenous variables did not change the returns to education estimate significantly (8.0%), which is in line with Harmon et al. (2000). Furthermore, the impact of exogenous control variables on wages is in line with the literature (DAIF (2006)).

The adding of control variables improved the model's fit: these variables proved to be significant wage determinants. For instance, males earned 31% [$\left(e^{0.2664}-1\right)\cdot 100$] more on average than females, with all other factors remaining constant. The wage of married persons was almost 5% higher. Latvian citizens earned 11% more than Latvian resident non-citizens and citizens of other countries (two latter groups cannot be divided in our data set), which may reflect the impact of state language proficiency on wages. Employees currently engaged in formal education earned 10% more, possibly reflecting a positive signalling effect. Long-term illness decreased wages by about 8% on average, possibly reflecting the negative impact of poor health on labour productivity and, consequently, on wages.

Chart 1
Mincer coefficient and its 95% confidence interval (2006–2012)
(annually; %)



Source: Authors' calculations using EU-SILC micro data for Latvia.

Furthermore, there is a positive link between wages and company size. Hourly wage for self-employed and in small companies was respectively by 31% and 4% smaller than in medium-sized companies. In large companies in turn employees earned 13% more. This may reflect higher labour productivity in large companies, due to, for instance, greater specialisation opportunities or higher capital to labour ratio, which may stem from a better access to external financing (see Fadejeva and Krasnopjorovs (2015)). Alternatively, this may reflect a higher labour income share in large firms, possibly owing to wider collective bargaining coverage (see Fadejeva and Krasnopjorovs (2015)). According to DAIF (2006), firms with collective wage contracts generally pay higher wages, all other factors holding constant. Also we found that employees earn 3% less if they changed employer during the past year. This result is in line with the evidence that the wage of a newly hired worker tends to be smaller than the wage of incumbent workers even after controlling for experience and task assignment (Fadejeva and Krasnopjorovs (2015)). Finally, region of residence proved to be a significant wage determinant, with the highest wages posted in Riga and the lowest in Latgale.

Further extending the Mincer model with factors endogenous to years of schooling reveals that about a half of the impact of education on wages in Latvia comes from a career component, i.e. better access to higher paid occupations, sectors and positions (in line with DAIF (2006)). The other half reflects direct wage premium: each additional year of schooling increases the wage on average by 3.8% for employees working in the same occupation, sector and position.

The share of career component in the Mincer coefficient remained roughly constant over time. In 2008, the increase in Mincer coefficient was primarily attributed to rising direct wage premium, while in 2007 and 2009 it rose due to the career component. Both parts of returns to education decreased in 2010 and mingled afterwards (see Chart A12).

Employees in managerial positions earn 6% more on average than others. Also, occupation proved to be a significant wage determinant, with the highest wages (all other factors held constant) received by managers (ISCO 1) and the lowest – by agricultural, forestry and fishery workers (ISCO 6). Regarding sectors, the highest wages (all other factors held constant) are found in financial intermediation (K) and the lowest in agriculture, industry and energy (A–E) as well as trade (G).

3.2 Wage differentials model results

Our results show that employees with higher education earn significantly more than those with secondary education (control group). Moreover, employees with lower than secondary education earn significantly less. The wage differentials model reveals that from 2006 to 2012 on average higher education wage premium was 48% but secondary education wage premium was 9% (see Table 2).

These results are broadly in line with the previous studies. For instance, Hazans (2003) and Romele (2014) obtained higher education wage premium to be 48% and 44% respectively, which is not statistically significantly different from the results in this paper. In Estonia, higher education wage premium was estimated between 40% and 51%, but in Lithuania – between 59% and 74% (Badescu et al. (2011), Hazans (2003)). The average indicator for OECD countries is about 55% (Strauss and de la Maisonneuve (2010)), which is not statistically significantly different from this study's result for Latvia either.

Also, wage premium for secondary education is in line with the previous studies. The estimates for Latvia by Romele (2014) and Hazans (2003) are 4% and 14% respectively. They are broadly similar to the results for Lithuania (14% and 13% found by Badescu et al. (2011) and Hazans (2003) respectively), but somewhat smaller than for Estonia (19% and 23% found by Badescu et al. (2011) and Hazans (2003) respectively). The results for the Baltic countries, however, are lower than for some other European countries, e.g. Poland (34%) and the UK (42%); (see Strauss and de la Maisonneuve (2010)). Thus, our results are in line with Hazans (2003) who showed that wage premium for secondary education in the Baltics is relatively low.

Changes in wage premium for secondary education over time were not statistically significant. In turn, wage premium for higher education changed counter-cyclically, similar to the Mincer coefficient. From 40% in 2006, it rose to 55% and 58% in 2008 and 2009 respectively. Afterwards, it decreased towards the 2007 level (see Chart 2).

Table 2
Wage differentials model results (2006–2012)

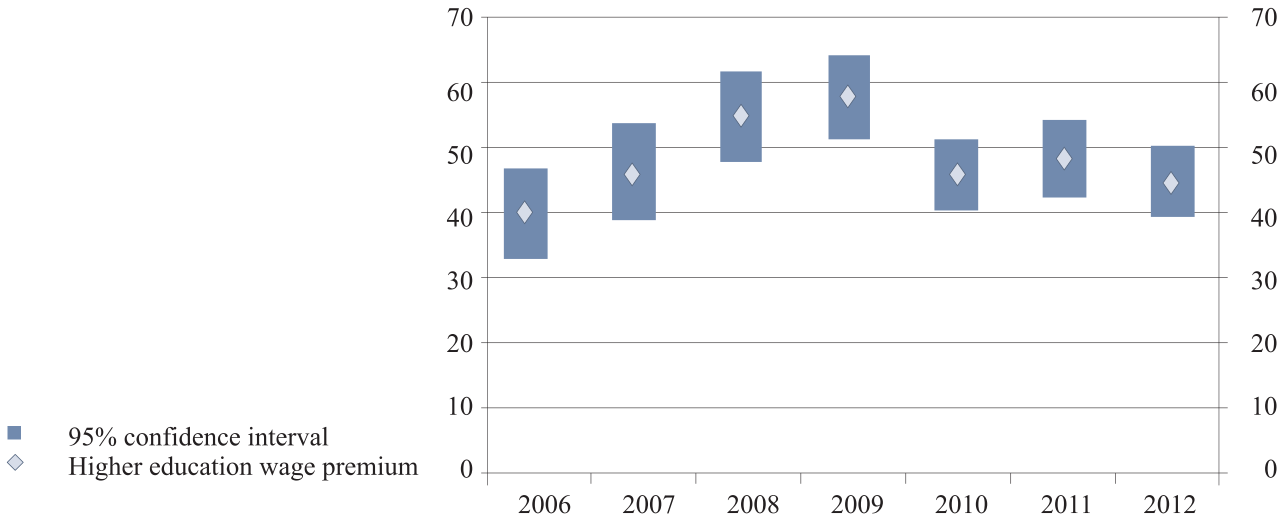
Independent variables / Model	Standard	Extended with exogenous variables	Extended with both exogenous and endogenous variables
Experience	0.0098*** (0.0012)	0.0135*** (0.0012)	0.0109*** (0.0011)
Experience^2	–0.0003*** (0.0000)	–0.0003*** (0.0000)	–0.0003*** (0.0000)
Higher education	**0.3930*** (0.0082)**	**0.3984*** (0.0080)**	**0.2095*** (0.0096)**
Lower than secondary education	**–0.0904*** (0.0123)**	**–0.1121*** (0.0116)**	**–0.0436*** (0.0114)**
Male		0.2635*** (0.0072)	0.2158*** (0.0083)
Married		0.0500*** (0.0072)	0.0311*** (0.0069)
Citizen of Latvia		0.0961*** (0.0095)	0.0754*** (0.0091)
In studies		0.1129*** (0.0155)	0.0419*** (0.0153)
Long-term illness		–0.0827*** (0.0087)	–0.0680*** (0.0084)
Self-employed		–0.3714*** (0.0208)	–0.3576*** (0.0212)
Employees <10		–0.0367*** (0.0083)	–0.0305*** (0.0082)
Employees >50		0.1216*** (0.0075)	0.0983*** (0.0071)
Job change		–0.0296** (0.0142)	–0.0128 (0.0139)
Region		Included	Included
Sector			Included
Occupation			Included
Manager			0.0564*** (0.0109)
Time (year)	Included	Included	Included
Constant	0.4845*** (0.0146)	0.2907*** (0.0213)	0.6157*** (0.0421)
R2	0.1696	0.2877	0.3599
Observations	29 499	29 470	29 470

Notes: Dependent variable: log hourly wage.
***, **, *: statistically significant with 99%, 95% and 90% confidence level respectively.
Standard errors in parentheses.
Source: Authors' calculations using EU-SILC micro data for Latvia.

Extending the wage differentials model with exogenous control factors does not statistically significantly change wage premiums for higher and secondary education. Also, the impact of other control variables on wages is similar to that estimated in the Mincer model. Consequently, the choice of education variable does not change the estimated impact of other factors on wages in statistically significant way.

About half of wage premiums for higher and secondary education are attributed to career component, while the other half (23% and 4%) reflect higher wages for employees within the same occupation, sector and position. The share of career component in wage premiums remained roughly constant over time. Therefore, during the period of economic crisis, education became an even more significant determinant of access to better paid sectors, occupations and positions. In this respect, the result of wage differentials model is similar to that of the Mincer model.

Chart 2
Higher education wage premium and its 95% confidence interval (2006–2012)
(annually; %)



Source: Authors' calculations using EU-SILC micro data for Latvia.

3.3 Instrumental variable model results

Next, we added family background (parental education, spouse's education) as control variables, in order to account for unobserved abilities, and as IVs, to exploit its possible linkage with education choice. Moreover, we used a binary variable as an instrumental factor which indicates whether a higher education level was obtained in the USSR or after the restoration of Latvia's independence.

In Latvia, parental education is highly correlated with individual's education, thus fulfilling the relevance condition of IV. IV estimates of returns to education (14.4% in standard model and 12.1% in the model extended with exogenous factors) are 2–3 times higher than the Mincer coefficient (see Table 3).

Table 3
Returns to education: parents' years of schooling as instrumental and control variables (2006–2012)

Model	Standard model	Extended model (with exogenous factors)
Mincer model	0.0588*** (0.0033)	0.0639*** (0.0033)
Mincer model with parents' education as control variable	0.0509*** (0.0034)	0.0589*** (0.0034)
IV model	0.1440*** (0.0113)	0.1214*** (0.0108)

Notes: Dependent variable: log hourly wage.
***, **, *: statistically significant with 99%, 95% and 90% confidence level respectively.
Standard errors in parentheses.
Source: Authors' calculations using EU-SILC micro data for Latvia.

These results are broadly in line with papers on other countries' finding that the IV model estimate of returns to education significantly exceeds the Mincer coefficient (Ashenfelter and Zimmerman (1997), Card (1999), Trostel et al. (2002)). However, in the case of Latvia, this difference tends to be particularly large.

Inclusion of the parents' years of schooling variable as a control factor decreases the value of Mincer coefficient by about 10%. The decrease, however, is not statistically significant. The results herein are in line with Badescu et al. (2011), who find that the inclusion of parental education control variable does not alter the estimate of returns to education in a significant way.

Note that information on parental education was available only for those individuals who lived in one household with their parents (23% of sample; most of them relatively young). Therefore, these results should not be attributed to the whole population.

Spouse's education is also highly correlated with individual's education. IV coefficients (19.2% in standard model and 14.8% in model extended with exogenous factors) exceed Mincer coefficient estimates considerably (see Table 4).

Table 4

Returns to education: spouses' years of schooling as instrumental and control variables (2006–2012)

Model	Standard model	Extended model (with exogenous factors)
Mincer model	0.0794*** (0.0021)	0.0835*** (0.0021)
Mincer model with spouses' education as control variable	0.0636*** (0.0022)	0.0739*** (0.0022)
IV model	0.1917*** (0.0064)	0.1479*** (0.0059)

Notes: Dependent variable: log hourly wage.
***, **, *: statistically significant with 99%, 95% and 90% confidence level respectively.
Standard errors in parentheses.
Source: Authors' calculations using EU-SILC micro data for Latvia.

In turn, the inclusion of spouses' years of schooling in a Mincer model decreases the Mincer coefficient by 10%–20%. Moreover, unlike the parental education case, the decrease of Mincer coefficient is statistically significant.

Again, a caveat should be made that this model narrowed the sample to married individuals (62% of sample); therefore, the results should not be attributed to the whole population.

As noted before, education of parents (and spouse) is likely to have a direct impact on individual's wages, thus not meeting the exclusion restriction and not being a valid instrument.

When Latvia regained its independence, various social and economic transformations took place. One of them, the transition to market economy, may have increased returns to education and hence also the individuals' choices of education. However, there is no motivation to assume that the ability (or any other characteristic that may impact wages) of those who finished their education in the Soviet times was different from the ability of those who did it after 1990. Therefore, the variable indicating when the highest level of education was obtained should satisfy the exclusion restriction and may be used as an instrumental factor.[3]

[3] We could have used more than one instrumental factor and test for over-identification; however, as education of parents and spouse is unlikely to be a valid instrument, testing would not give us any insight on the validity of reform variable.

We define IV to be a binary variable that is equal to 1, if an individual finished education before 1990. The IV model estimate (15.1% in standard and 14.3% in extended model) is twice as large as the Mincer coefficient (see Table 5).

Table 5
Returns to education: binary variable = 1 if individual finished education before 1990 as IV (2006–2012)

Model	Standard model	Extended model (with exogenous factors)
Mincer model	0.0769*** (0.0016)	0.0800*** (0.0016)
IV model	0.1507*** (0.0049)	0.1428*** (0.0051)

Notes: Dependent variable: log hourly wage.
***, **, *: statistically significant with 99%, 95% and 90% confidence level respectively.
Standard errors in parentheses.
Source: Authors' calculations using EU-SILC micro data for Latvia.

These results are broadly in line with findings for other countries. Papers that used natural experiments as IVs generally obtain estimates of returns to education that are statistically significantly higher than the Mincer coefficient (see, e.g. Card (2001), Harmon et al. (2000), Harmon and Walker (1995), Oreopoulos (2006)).

It is possible that this IV estimate is not attributable to the whole population either. Secondary education was compulsory in Soviet times as it is nowadays; therefore, a change of political and economic system may have influenced educational choices only in respect to higher education. Thus, the obtained IV estimate may reflect only the percentage change in wages to each additional year spent in higher education.

We check this with a wage differentials model by allowing each ISCED education level to have a different impact on wages. The returns to one additional year of schooling of education level j compared with education level a may be calculated as follows:

$$\beta_t = \left(\frac{\beta_j}{\beta_a}\right)^{\frac{1}{(T_j - T_a)}} - 1 \qquad (10).$$

Our results show that each additional year of schooling in ISCED 5 (higher education) increases the wage by about 12%, which statistically significantly exceeds the respective estimate for ISCED 3 and ISCED 4 levels (see Table 6). This is broadly similar to the IV model estimate herein, which may imply that the transition to market economy increased incentives to acquire higher education without markedly promoting secondary education acquisition.

Table 6
Returns to additional year of schooling by ISCED levels (2006–2012)

Model	ISCED 3	ISCED 4	ISCED 5
Standard model	0.0303	0.0056	0.1290
Model extended with exogenous variables	0.0365	0.0405	0.1206
Model extended with both exogenous and endogenous variables	0.0151	–0.0043	0.0695

Source: Authors' calculations using EU-SILC micro data for Latvia.

To sum up, this paper's IV estimates significantly exceed the Mincer coefficient, which is in line with the literature. This, however, lacks intuition, since it was expected that unobservable ability might overestimate the Mincer coefficient. Moreover, family background may not be valid instruments, and IV models could be employed only in samples that do not represent the whole population. Therefore, we conclude that the results of IV models in the case of Latvia are not preferable to Mincer and wage differentials model's estimates.

4. ROBUSTNESS CHECK

We performed two types of robustness checks. First, we replaced hourly wage with monthly wage and annual wage to check whether this change alters our results. Second, we replaced the experience variable with age and potential experience, and excluded experience variable altogether.

4.1 Alternative wage variable

In the case of Latvia, several wage variables have been used (hourly wage (Trostel et al. (2002)), monthly wage (Hazans (2003), Flabbi et al. (2007)) and annual wage (Romele (2014)). However, none of the papers above tested the sensitivity of the results in respect to the choice of wage variable. For instance, if education increases hours worked per week and employment prospects, the impact of education on monthly and annual wage will exceed its impact on hourly wage. In order to check it, we followed Card (1999) to decompose the impact of education on annual wage into three parts: it's impact on hourly wage, impact on hours worked per week, and impact on months worked per year.

Using annual wage, the Mincer coefficient appeared to be higher (8.4%) than using monthly wage (7.9%) or hourly wage (7.7%). The results are similar when supplementing the Mincer model with exogenous control factors (see Table 7). Therefore, an additional year of schooling is associated with longer working hours (by 0.2%) and more months worked per year (by 0.5%).

The impact of education on hours worked per week during and after the crisis was larger than before the crisis (see Chart 3). Employees with a low level of education experienced a steeper decline of working hours. Also, the impact of education on months worked per year increased during the crisis, reflecting growing unemployment differentials among employees with different levels of education.

Table 7

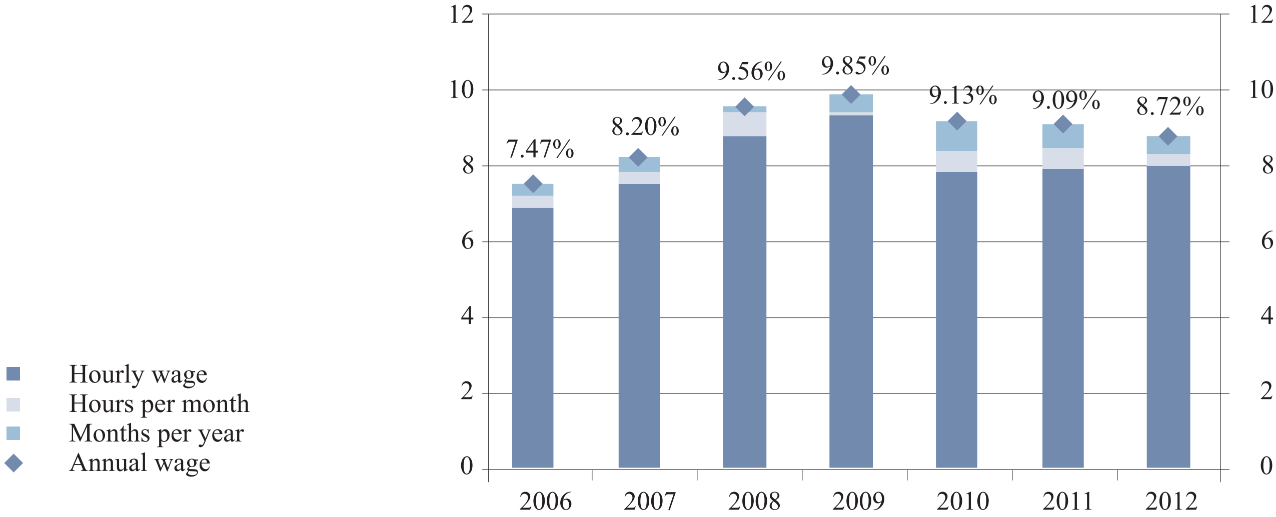
Mincer coefficient on annual wage decomposition (2006–2012)

Dependent variable	Hourly wage (1)	Hours worked per month (2)	Monthly wage (3) = (1) + (2)	Months worked per year (4)	Annual wage (5) = (3) + (4)
Mincer model	0.0769*** (0.0016)	0.0017*** (0.0006)	0.0786*** (0.0017)	0.0049*** (0.0007)	0.0835*** (0.0019)
Extended Mincer model	0.0800*** (0.0016)	0.0039*** (0.0007)	0.0840*** (0.0017)	0.0046*** (0.0007)	0.0886*** (0.0018)

Notes: ***, **, *: statistically significant with 99%, 95% and 90% confidence level respectively.
Standard errors in parentheses.
Source: Authors' calculations using EU-SILC micro data for Latvia.

The results of wage premium decomposition reveal that both higher and secondary education can be associated with an increase of hours worked per week and employment probability. Secondary education has a particularly large impact on working hours. Employees with secondary education in comparison with those with lower level of education worked longer hours (by 2.3%) and more months per year (by 1.9%). Likewise, employees with higher education in comparison with those with secondary education worked longer hours (by 1.2%) and more months per year (by 1.7%; see Table A1).

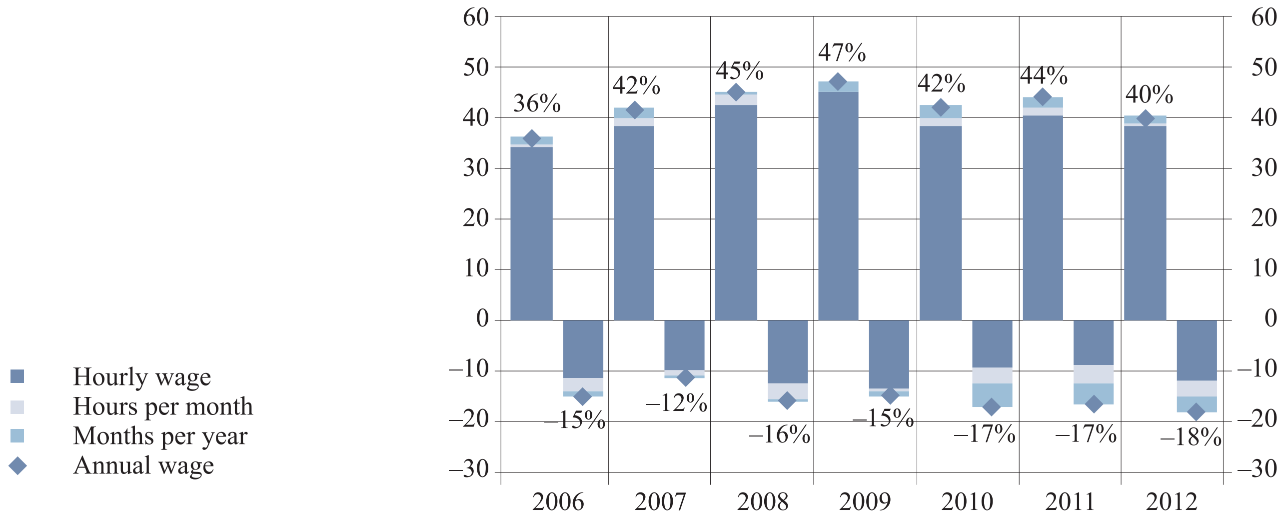
Chart 3
Decomposition of Mincer coefficient on annual wage (2006–2012)
(extended Mincer model; annually; %)



Source: Authors' calculations using EU-SILC micro data for Latvia.

The impact of higher education on hourly wage was counter-cyclical, while it had broadly constant impact on hours worked per week and months worked per year. Meanwhile, the impact of secondary education on hourly wage was broadly similar over time, while its impact on hours worked per week and months worked per year increased substantially during the crisis (see Chart 4). This may reflect a situation when employees with lower than secondary education level were involuntary transferred to part-time jobs during the crisis.

Chart 4
Decomposition of wage premium for higher education (left) and penalty for not obtaining secondary education (right; 2006–2012)
(extended wage differentials model; annually; %)



Source: Authors' calculations using EU-SILC micro data for Latvia.

Further, we decomposed the wage differentials model extended with sector, occupation and position variables to check whether increased hours worked per week and months worked per year can be associated with the career component. The results show that there is no direct impact of higher education or secondary education on the number of months worked per year (see Table A2). Therefore, higher employment probability because of better education is attributable to career component. It seems that one advantage of education is opportunity to work in more stable sectors, occupations and positions.

To sum up, we found that returns to education are slightly, but statistically significantly higher when dependent variable switches from hourly wage to monthly or annual wage. It implies that better educated workers not only earn higher wages but also have higher employment probability and face longer working hours.

Note that longer working hours and better employment prospects are not necessarily caused by education. Strauss and de la Maisonneuve (2010) suggest that working hours do not depend on education but rather are a result of voluntary choice. Thus, our results may suggest that some unobserved personal characteristics may exist that promote both longer working hours and higher levels of education. In addition, education can also promote access to some employment opportunities not possible without a certain education level.

4.2 Alternative experience variable

In our base specification, we used years spent in employment (provided in the data set) as a variable for job experience. Taking into account the fact that Mincer coefficient estimates may be sensitive to the experience variable (Harmon et al. (2000)), we used alternative proxy variables for experience as a robustness check. First, we follow Hazans (2003) and use age. This intrinsically assumes that all individuals, irrespective of their education level, start working at the same age. Second, we follow Mincer (1974) by calculating potential experience by subtracting years of schooling and starting age of formal education (6) from individual's age. This assumes that individuals, irrespective of their age, start working at the same time after graduation. Third, we exclude the experience variable, given some ambiguity about whether experience is a likely wage determinant (especially, given that the maximum wage level in Latvia in comparison with international standards is achieved in early stages of career; see Hazans (2005) and Krasnopjorovs (2012)).

The Mincer coefficient estimates appeared robust subject to alternative experience definitions. The differences between models that use different experience variables or drop the experience variable are not statistically significant (see Table A3).

5. HOW EDUCATION AFFECTS WAGES IN DIFFERENT POPULATION GROUPS, SECTORS AND REGIONS

Next, we check whether returns to education differ subject to gender, age, sector of employment, region, citizenship and country of birth. Particularly, we investigate the sources of counter-cyclicality of Mincer coefficient. For instance, it may be driven either by increasing Mincer coefficient during the crisis in separate sectors or by structural changes in the labour market (e.g. with layoffs concentrated more in sectors with a low Mincer coefficient).

5.1 Returns to education by gender

Wage distribution of males has a higher mode and is less peaked (see Chart A13). Furthermore, the higher the education level, the less peaked wage distribution is, particularly among females (see Charts A14 and A15). Therefore, it seems that higher education is a prerequisite but not a guarantee for high wages. Although for both genders the employees with higher education have higher mode wages, this evidence is particularly strong for females. Thus, returns to education may be higher among females than among males. In addition, females have slightly higher average years of schooling than males (see Chart A16).

Estimating the Mincer coefficient separately for males and females, we found that returns to education for females are larger than for males. Moreover, gender differences are statistically significant (the average value of Mincer coefficient for 2006–2012 is 10.0% for females and 8.0% for males; see Table A4).

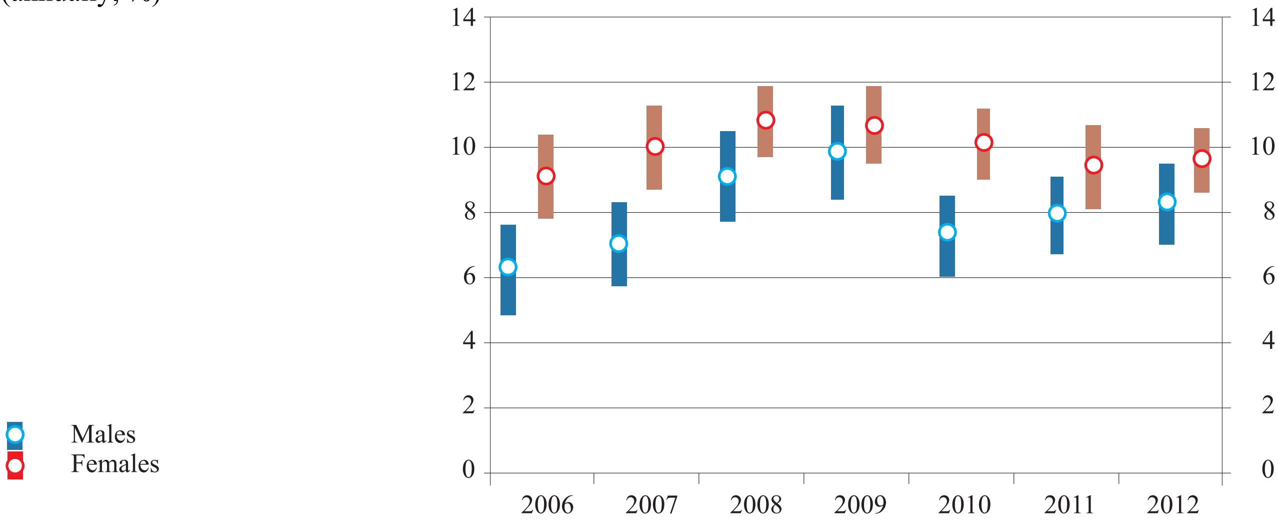
The results are in line with general findings in the literature, which imply higher returns to education for females (Arrazola and de Hevia (2006), Montenegro and Patrinos (2014)). For Latvia, it was previously shown by Trostel et al. (2002), Hazans (2003) and Romele (2014).

Our results also do not statistically significantly differ from the world average estimates (9.8% for females and 8.7% for males) by Psacharopoulos and Patrinos (2004). However, our results are somewhat lower than world average estimates (11.7% for females and 9.6% for males) by Montenegro and Patrinos (2014).

Our finding for males is similar to the previous findings for Latvia (7.9% and 7.1% in 2010 and 2011 respectively; Romele (2014)) and for other European countries, e.g. the UK (7.8%; Devereux and Fan (2011)) and Austria (7.6%; Fersterer and Winter-Ebmer (2003)). The result herein for females, however, is somewhat higher than in other studies. For Latvia, Romele (2014) estimated the Mincer coefficient to be 8.1% and 6.8% in 2010 and 2011 respectively. As for other countries, it was 7.4% for Spain (Arrazola and de Hevia (2006)) and 7.5% for Austria (Fersterer and Winter-Ebmer (2003)).

Gender differences in the Mincer coefficient were statistically significant in 2006, 2007 and 2010 (see Chart 5). Before the economic crisis, returns to education for females were significantly higher than for males, but during it the differences became insignificant.

Chart 5
Mincer coefficients and their 95% confidence intervals for males and females (2006–2012)
(annually; %)



Source: Authors' calculations using EU-SILC micro data for Latvia.

Mincer coefficient changes over time for males are statistically significant and exhibit larger counter-cyclicality. Adding exogenous control variables does not alter the results significantly.

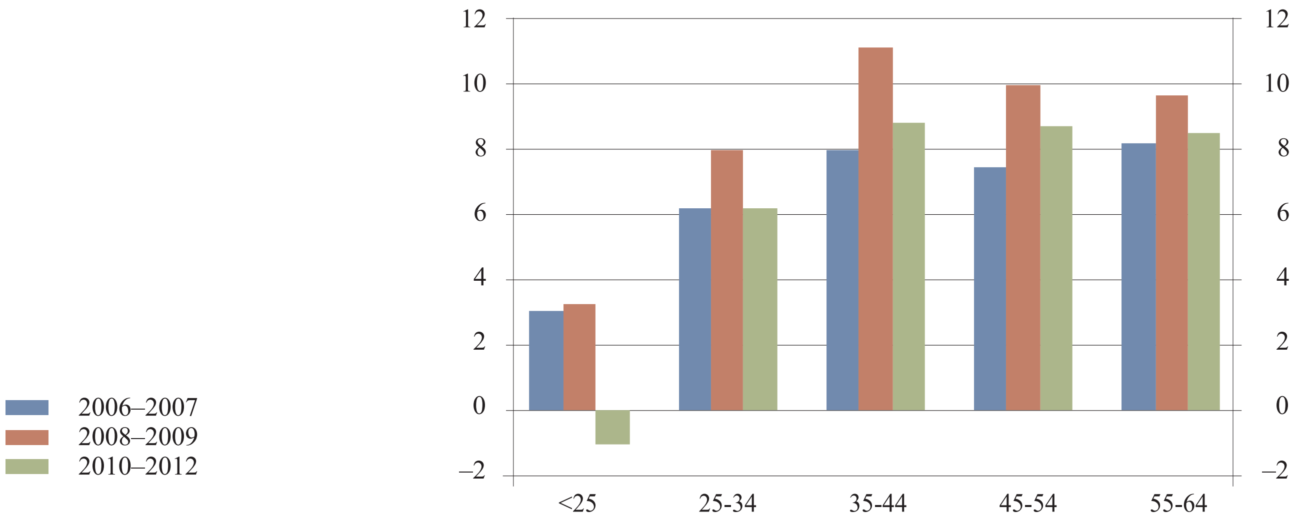
5.2 Returns to education by age

Wage distribution of young employees (less than 25 years of age) is more peaked and has considerably thinner right tail in comparison with the other age groups (see Chart A17). Consequently, high wages are less prevalent among young employees. Average years of schooling are only slightly (albeit statistically significantly) lower among young employees, many of whom have not finished to acquire their desired level of formal education (see Chart A18). Therefore, considerably lower prevalence of high wages among youth may reflect lower returns to education in comparison with other age groups. Differences of average years of schooling in other wage groups are not statistically significant.

Regression analysis confirms that returns to education for young people are lower (albeit highly statistically significant) than in other age groups. For the age group 15–24, the estimate of Mincer coefficient (2006–2012) was 1.7%, against 6.7% in the age group 25–34 and about 9% in subsequent age groups (see Table A5). It is possible that either education is not instantaneously reflected in labour productivity, or productivity is not instantaneously reflected in wages. This is in line with Andini (2013) who notes that returns to education may rise with experience; accordingly, the Mincer coefficient is relatively low for employees who just begin their careers.

During the economic crisis, returns to education increased in all age groups, except for youth. Furthermore, the Mincer coefficient estimate for the age group 15–24 was not statistically significant after the crisis period (see Chart 6).

Chart 6
Mincer coefficients by age group and business cycle period
(%)



Source: Authors' calculations using EU-SILC micro data for Latvia.

These results may agree with Hanushek et al. (2015) findings: in OECD countries, math skills have the biggest impact on wages in the age group 35–54 but the lowest in the age group 25–34 (employees younger than 25 were not considered). However, Estonia, which was the only Baltic State in their paper, does not show any statistically significant differences among age groups.

5.3 Returns to education by sectors

According to the EU-SILC micro data, the highest wages are recorded in financial intermediation (see Chart A19). This is in line with the CSB business survey data claiming financial intermediation to have the highest monthly wage for full-time work. The evidence is further confirmed by national accounts: the compensation of employees to hours worked by employees ratio is the highest in this sector.

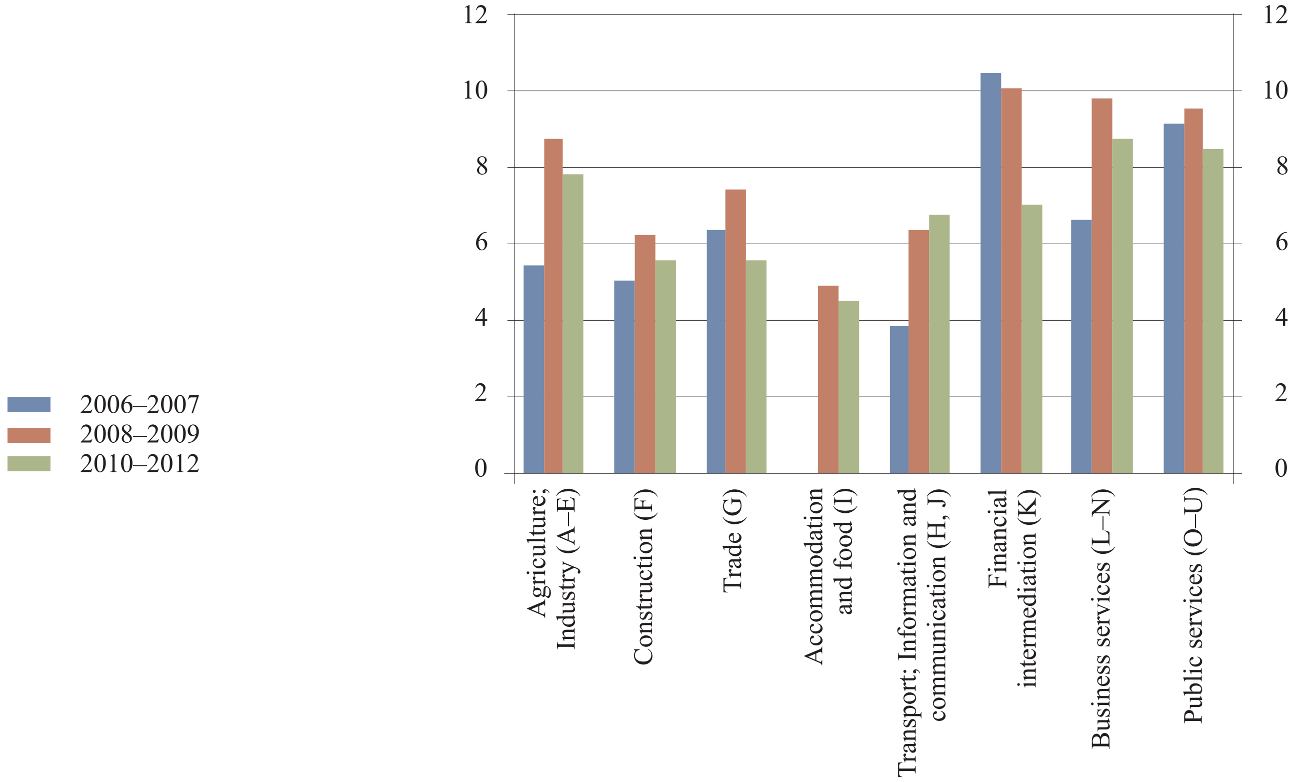
Financial intermediation leads also in terms of average years of schooling, followed by business services and public services (see Chart A20). Thus, education attainment of employees in services is generally higher than that of employees in the goods sector. When interpreting the differences in returns to education across sectors, one should bear in mind that sector-of-employment choices may not be exogenous in respect to education and unobservable ability.

The regression results show that years of schooling have a statistically significant impact on wages in each sector of the economy. The highest Mincer coefficient is found in public administration, education and healthcare (8.9%; O–U; see Table A6), followed by real estate, science and administrative services (8.8%; L–N) and financial intermediation (8.8%; K). Meanwhile, the lowest Mincer coefficients were recorded in accommodation and food services (3.4%; I) as well as construction (5.4%; F).

Differences in the Mincer coefficient across sectors may reveal why returns to education are lower for males than for females. According to the CSB data, about of 90% employees in construction were males (2008–2013, on average). Also in other sectors with relatively low returns to education, males constitute the lion's share of employment (for instance, 73% in transport and 61% in information and communication). In financial intermediation (sector with the highest Mincer coefficient), on the other hand, only 32% of employees were males.

During the economic crisis, returns to education increased in every sector of the economy, except financial intermediation (see Chart 7). After the crisis, the Mincer coefficient decreased in all sectors, except transport and information and communication. As a result, counter-cyclicality of Mincer coefficient is evident not only in aggregate data (which may stem from changes in the economic structure owing to the business cycle) but is also present in the majority of sectors.

Chart 7
Mincer coefficients by sector and business cycle period
(%)



Source: Authors' calculations using EU-SILC micro data for Latvia.

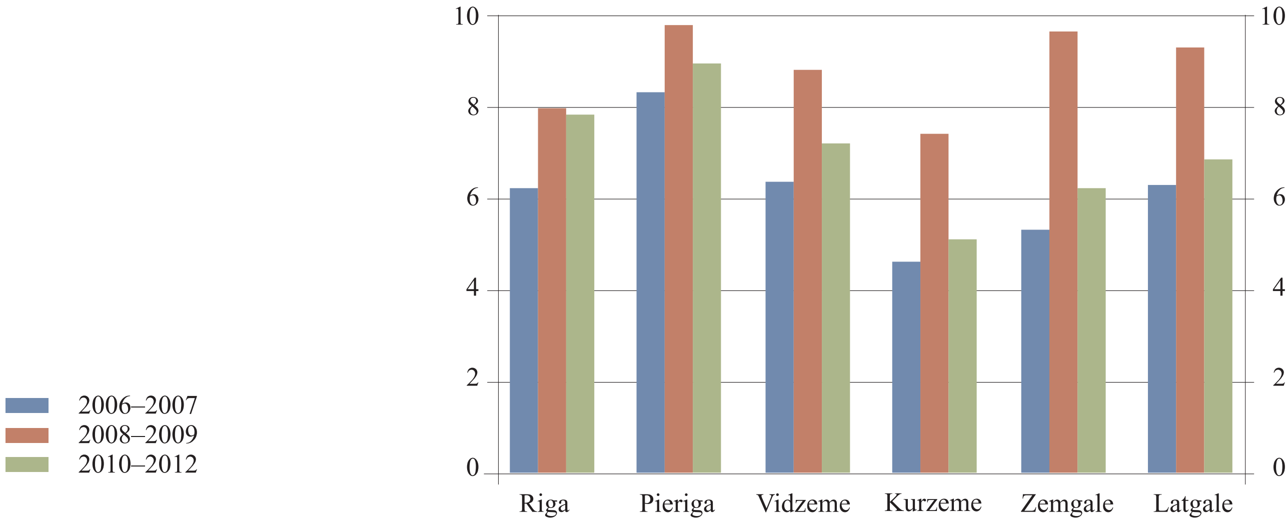
5.4 Returns to education by region

EU-SILC micro data reveals that the highest wages are earned in Riga (see Chart A21), which is in line with CSB business survey data, reflecting the highest GDP per capital level in the capital city. However, average years of schooling in Latgale (region with the lowest average wage) are broadly on a par with the capital city (see Chart A22).

Given that returns to education may differ across regions (see, e.g. Furno (2014)), and that there is no empirical evidence for Latvia as yet, we estimated Mincer coefficient separately for Latvia's NUTS-3 regions.

During 2006–2012, the highest average Mincer coefficient was recorded in Pieriga (suburbs of Riga; 9.0%) and the lowest in Kurzeme (western part of the country; 5.2%; see Table A7). During the crisis, Mincer coefficient increased in all regions, however the increase was smaller in Riga and Pieriga (see Chart 8). Therefore, the counter-cyclicality of returns to education was particularly present outside the capital city region. During the period of economic crisis, the differences in Mincer coefficient between the capital city and other regions decreased.

Chart 8
Mincer coefficients by region and business cycle period (2006–2012)
(%)



Source: Authors' calculations using EU-SILC micro data for Latvia.

5.5 Returns to education by citizenship and country of birth

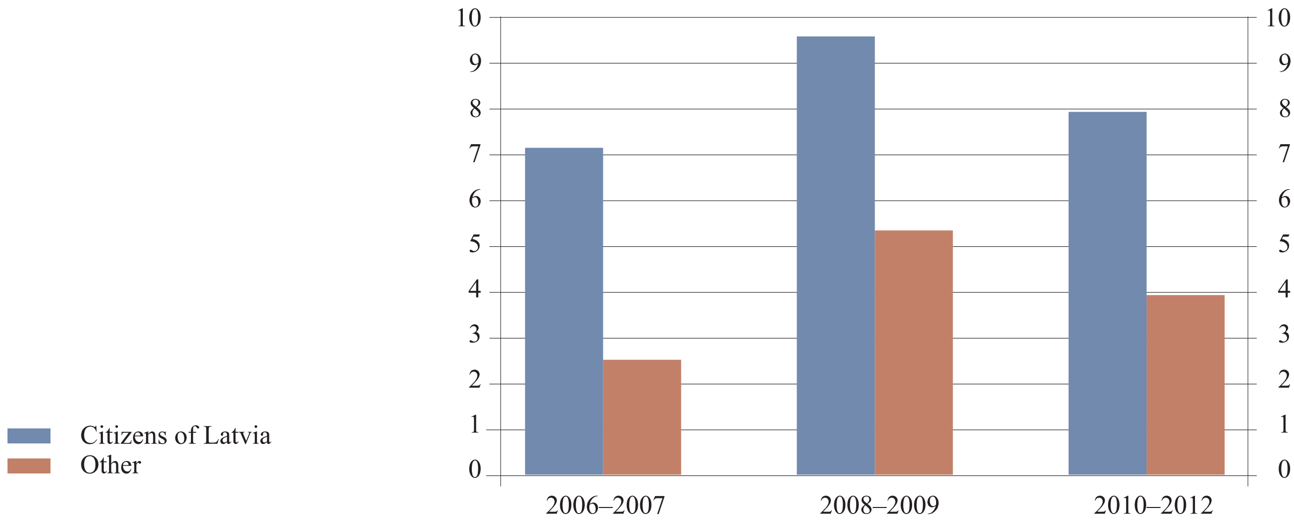
In Latvia, citizens earn higher average wage than non-citizens and citizens of other countries. This, to a large extent, is a result of thicker right tail in wage distribution of citizens (see Chart A23). Thus, even if citizenship does not guarantee high wages by itself (modes of the two wage distributions are similar), citizenship of Latvia may be a prerequisite to receive high wages. It should also be noted that education attainment among citizens is higher than among non-citizens (see Chart A24).

The Mincer model estimate reveals that among citizens of Latvia returns to education are more than two times higher than among Latvia's non-citizens and citizens of other countries (8.1% and 3.8% respectively; see Table A8; non-citizens of Latvia cannot be separated from citizens of other countries in the present data set). Among those employees who were born in Latvia, the Mincer coefficient is somewhat higher than among those born in other countries (7.9% and 5.9% respectively). Hence it seems that citizenship has a stronger impact on education returns than country of birth.

During the period of economic crisis, the Mincer coefficient increased for Latvia's citizens, non-citizens and citizens of other countries (see Chart 9). Accordingly, returns to education behaved counter-cyclically, irrespective of the citizenship.

The results for other countries generally suggest that ethnicity with the largest share in population has higher returns to education (see, e.g. Hanushek et al. (2015)). In the papers so far, Latvia's Mincer coefficient differences were estimated by ethnicity, not by citizenship. Hazans (2003) concluded that from the three Baltic States ethnic differences in returns to schooling exist only in Estonia: Estonians have higher returns to education than non-Estonians. We were not able to test the impact of ethnicity and language skills on returns to education, since these variables were not available in our data set.

Chart 9
Mincer coefficients by citizenship and business cycle period (2006–2012)
(%)



Source: Authors' calculations using EU-SILC micro data for Latvia.

CONCLUSIONS

We employ EU-SILC micro data for Latvia to study how returns to education have changed during and after the economic crisis of 2008–2009. We found that returns to education increased significantly during the crisis and decreased slightly during the subsequent economic recovery. The counter-cyclical effect was particularly strong for males: it was evident in the majority of sectors, for all age groups (except youth), for citizens of Latvia, resident non-citizens and citizens of other countries, as well as in all regions of the country, particularly outside the capital city region.

The returns to education, measured by standard and extended Mincer and wage differentials models, are statistically significant. Mincer models reveal that during 2006–2012 on average, each additional year of schooling was associated with higher wages by about 8%. Wage differential models show that employees with higher education earned 48% more than employees with secondary education; in turn, employees with lower than secondary education earned 9% less. A half of the impact came via career component, i.e. better access to higher paid occupations, sectors and positions; the share of career component in the Mincer coefficient remained broadly constant over time.

After the economic crisis, education became even more associated with a longer working week and better employment prospects. Thus, rendering the impact of education is higher on annual and monthly wage than on hourly wage.

Furthermore, we show that returns to education in Latvia are generally higher in the capital city and its suburbs than outside the capital city region, for citizens of Latvia than for non-citizens and citizens of other countries, albeit being lower for males and young people.

In line with the previous findings for other countries, IV models give higher estimates of returns to education than standard and extended Mincer models. However, none of the IV estimates leads to convincing results. For instance, education of spouse and parents is likely to have a direct impact on individual's wages, thus turning them into invalid instruments; besides, it restricts the sample towards married individuals and those living in the same household with their parents. In turn, transition to the market economy was likely to increase motivation to acquire higher education, without markedly promoting secondary education acquisition. Therefore, the IV model estimate may only indicate the returns to each year spent in higher education. We conclude that in the case of Latvia Mincer and wage differential models provide more relevant results than IV models.

Regarding policy implications, it should be noted that the results in this study do not imply that raising average years of schooling by one year will increase wages (and/or labour productivity) by about 8%. Education choice may be endogenous to unobserved individual ability that may bias the Mincer coefficient estimate. Similarly, Mincer coefficient cross-country comparisons should not be treated as a proxy for quality of education, since the Mincer coefficient estimate may depend also on economic and population structure, demand and supply of respective labour category, education and employment choices as well as many other factors. Statistically significant changes of Mincer coefficient over time (and its counter-cyclicality) may be viewed as a caveat for making far-reaching conclusions from the Mincer coefficient cross-country comparisons during a short period of time.

However, the current study presents robust evidence that education in Latvia is indeed associated with higher wages and that returns to education even rose during the recent economic crisis.

APPENDIX

Table A1

Decomposition of education-wage premiums: wage differentials model extended with exogenous variables (2006–2012)

Dependent variable	Hourly wage (1)	Hours worked per month (2)	Monthly wage (3) = (1) + (2)	Months worked per year (4)	Annual wage (5) = (3) + (4)
Higher education	0.3984*** (0.0080)	0.0120*** (0.0033)	0.4104*** (0.0082)	0.0167*** (0.0032)	0.4271*** (0.0088)
Lower than secondary education	–0.1121*** (0.0116)	–0.0227*** (0.0056)	–0.1349*** (0.0121)	–0.0192*** (0.0069)	–0.1541*** (0.0139)

Notes: ***, **, *: statistically significant with 99%, 95% and 90% confidence level respectively.
Standard errors in parentheses. Time (year) dummies included in each model.
Source: Authors' calculations using EU-SILC micro data for Latvia.

Table A2

Decomposition of education–wage premiums: wage differentials model extended with both exogenous and endogenous variables (2006–2012)

Dependent variable	Hourly wage (1)	Hours worked per month (2)	Monthly wage (3) = (1) + (2)	Months worked per year (4)	Annual wage (5) = (3) + (4)
Higher education	0.2095*** (0.0096)	0.0165*** (0.0042)	0.2260*** (0.0098)	0.0050 (0.0042)	0.2310*** (0.0106)
Lower than secondary education	–0.0436*** (0.0114)	–0.0177*** (0.0057)	–0.0614*** (0.0118)	–0.0115 (0.0071)	–0.0729*** (0.0137)

Notes: ***, **, *: statistically significant with 99%, 95% and 90% confidence level respectively.
Standard errors in parentheses. Time (year) dummies included in each model.
Source: Authors' calculations using EU-SILC micro data for Latvia.

Table A3

Mincer coefficients depending on experience variable

Year	Without experience variable	Experience	Potential experience	Age
2006	0.0609*** (0.0047)	0.0617*** (0.0046)	0.0567*** (0.0034)	0.0631*** (0.0047)
2007	0.0690*** (0.0046)	0.0692*** (0.0031)	0.0646*** (0.0045)	0.0711*** (0.0046)
2008	0.0899*** (0.0043)	0.0886*** (0.0043)	0.0859*** (0.0044)	0.0896*** (0.0043)
2009	0.0947*** (0.0045)	0.0934*** (0.0045)	0.0918*** (0.0045)	0.0936*** (0.0045)
2010	0.0747*** (0.0041)	0.0736*** (0.0041)	0.0718*** (0.0042)	0.0736*** (0.0041)
2011	0.0769*** (0.0041)	0.0760*** (0.0041)	0.0729*** (0.0040)	0.0759*** (0.0041)
2012	0.0769*** (0.0039)	0.0762*** (0.0039)	0.0724*** (0.0039)	0.0761*** (0.0039)

Notes: Dependent variable: log hourly wage.
***, **, *: statistically significant with 99%, 95% and 90% confidence level respectively.
Standard errors in parentheses. Time (year) dummies included in each model.
Source: Authors' calculations using EU-SILC micro data for Latvia.

Table A4
Mincer model results by gender (2006–2012)

Gender	Experience	Experience^2	Years of schooling	Constant	R^2	Number of observations
Males	0.0085*** (0.0017)	–0.0003*** (0.0000)	0.0800*** (0.0025)	–0.4834*** (0.0412)	0.1508	14 192
Females	0.0070*** (0.0015)	–0.0002*** (0.0000)	0.1000*** (0.0022)	–1.0457*** (0.0378)	0.2351	15 307

Notes: Dependent variable: log hourly wage.
***, **, *: statistically significant with 99%, 95% and 90% confidence level respectively.
Standard errors in parentheses. Time (year) dummies included in each model.
Source: Authors' calculations using EU-SILC micro data for Latvia.

Table A5
Mincer model results by age group (2006–2012)

Age group	Experience	Experience^2	Years of schooling	Constant	R^2	Number of observations
<25	0.0514** (0.0260)	–0.0037 (0.0037)	0.0168*** (0.0062)	0.1125 (0.1081)	0.0763	1 830
25–34	0.0371*** (0.0087)	–0.0009* (0.0005)	0.0667*** (0.0030)	–0.4003*** (0.0636)	0.1588	6 014
35–44	0.0575*** (0.0091)	–0.0016*** (0.0003)	0.0917*** (0.0034)	–1.0700*** (0.0860)	0.1846	7 632
45–54	0.0572*** (0.0091)	–0.0010*** (0.0002)	0.0868*** (0.0033)	–1.8667*** (0.1276)	0.1648	8 545
55–64	0.0556*** (0.0164)	–0.0007*** (0.0002)	0.0873*** (0.0039)	–1.9273*** (0.2855)	0.2040	5 478

Notes: Dependent variable: log hourly wage.
***, **, *: statistically significant with 99%, 95% and 90% confidence level respectively.
Standard errors in parentheses. Time (year) dummies included in each model.
Source: Authors' calculations using EU-SILC micro data for Latvia.

Table A6
Mincer model results by sector (2006–2012)

	Experience	Experience^2	Years of schooling	Constant	R^2	Number of observations
Agriculture; Industry (A–E)	–0.0058** (0.0027)	0.0001 (0.0001)	0.0727*** (0.0038)	–0.3360*** (0.0600)	0.1206	7 032
Construction (F)	0.0130*** (0.0045)	–0.0004*** (0.0001)	0.0542*** (0.0065)	–0.1612 (0.1055)	0.1148	2 454
Trade (G)	0.0050* (0.0027)	–0.0002*** (0.0001)	0.0643*** (0.0046)	–0.4377*** (0.0716)	0.1372	4 308
Accommodation and food (I)	0.0069 (0.0061)	–0.0003* (0.0001)	0.0336* (0.0188)	–0.0376 (0.2788)	0.0685	717
Transport; Information and communication (H, J)	0.0213*** (0.0034)	–0.0006*** (0.0001)	0.0628*** (0.0049)	–0.3340*** (0.0858)	0.1735	3 259
Financial intermediation (K)	0.0663*** (0.0082)	–0.0017*** (0.0002)	0.0878*** (0.0173)	–0.8077*** (0.3071)	0.3010	656
Business services (L–N)	0.0132*** (0.0023)	–0.0004*** (0.0001)	0.0880*** (0.0031)	–0.6460*** (0.0621)	0.1711	6 539
Public services (O–U)	0.0110*** (0.0032)	–0.0003*** (0.0001)	0.0886*** (0.0041)	–0.9010*** (0.0791)	0.1919	4 534

Notes: Dependent variable: log hourly wage.
***, **, *: statistically significant with 99%, 95% and 90% confidence level respectively.
Standard errors in parentheses. Time (year) dummies included in each model.
Source: Authors' calculations using EU-SILC micro data for Latvia.

Table A7
Mincer model results by region (2006–2012)

Region	Experience	Experience^2	Years of schooling	Constant	R^2	Number of observations
Riga	0.0159*** (0.0020)	0.0004*** (0.0000)	0.0726*** (0.0027)	–0.4466*** (0.0468)	0.1690	9 592
Pieriga	0.0119*** (0.0029)	–0.0004*** (0.0001)	0.0902*** (0.0038)	–1.0586*** (0.0619)	0.2070	5 067
Vidzeme	0.0018 (0.0041)	–0.0002* (0.0001)	0.0744*** (0.0059)	–0.4051*** (0.0969)	0.1603	2 741
Kurzeme	0.0184*** (0.0034)	–0.0005*** (0.0001)	0.0522*** (0.0047)	–0.4164*** (0.0696)	0.1121	3 863
Zemgale	–0.0008 (0.0031)	–0.0001 (0.0001)	0.0686*** (0.0043)	0.4135*** (0.0734)	0.1303	4 137
Latgale	–0.0025 (0.0031)	0.0000 (0.0001)	0.0743*** (0.0043)	–0.5958*** (0.0766)	0.1660	4 099

Notes: Dependent variable: log hourly wage.
***, **, *: statistically significant with 99%, 95% and 90% confidence level respectively.
Standard errors in parentheses. Time (year) dummies included in each model.
Source: Authors' calculations using EU-SILC micro data for Latvia.

Table A8
Mincer model results by citizenship and country of birth (2006–2012)

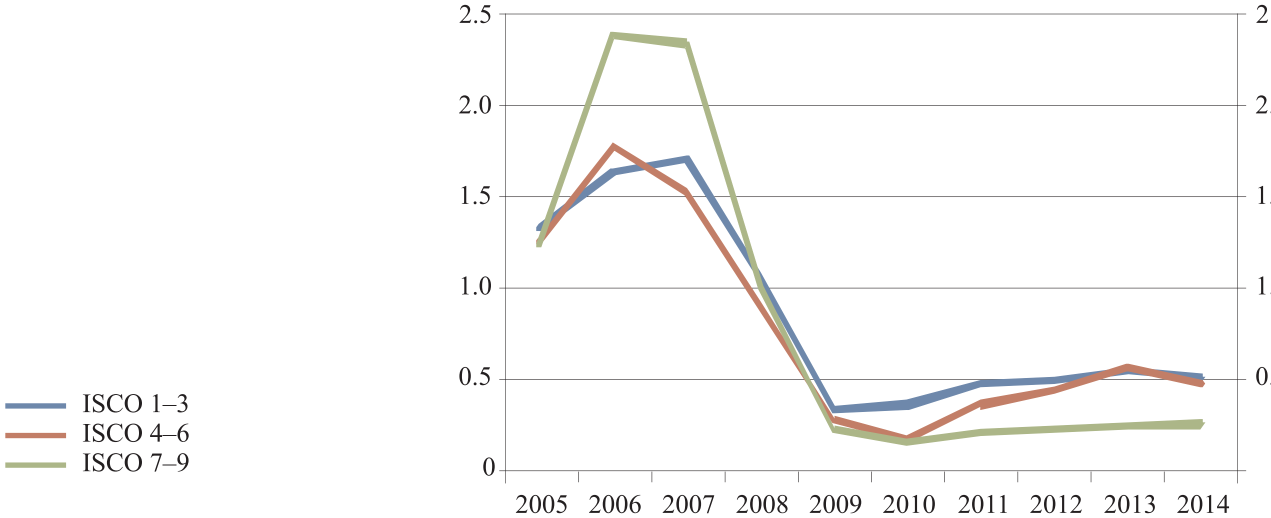
	Experience	Experience^2	Years of schooling	Constant	R^2	Number of observations
Citizens of Latvia	0.0097*** (0.0013)	–0.0003*** (0.0000)	0.0809*** (0.0018)	–0.9647*** (0.0300)	0.1657	25 353
Non-citizens of Latvia; other country citizens	0.0023 (0.0034)	–0.0001 (0.0001)	0.0378*** (0.0045)	0.0337 (0.0731)	0.1135	4 146
Born in Latvia	0.0094*** (0.0013)	–0.0003*** (0.0000)	0.0790*** (0.0017)	–0.4421*** (0.0290)	0.1625	26 132
Born in other countries	0.0078 (0.0048)	–0.0002** (0.0001)	0.0586*** (0.0050)	–0.3059*** (0.1016)	0.1489	3 367

Notes: Dependent variable: log hourly wage.
***, **, *: statistically significant with 99%, 95% and 90% confidence level respectively.
Standard errors in parentheses. Time (year) dummies included in each model.
Source: Authors' calculations using EU-SILC micro data for Latvia.

Chart A1
Unemployment rate by occupation
(% of economically active population)

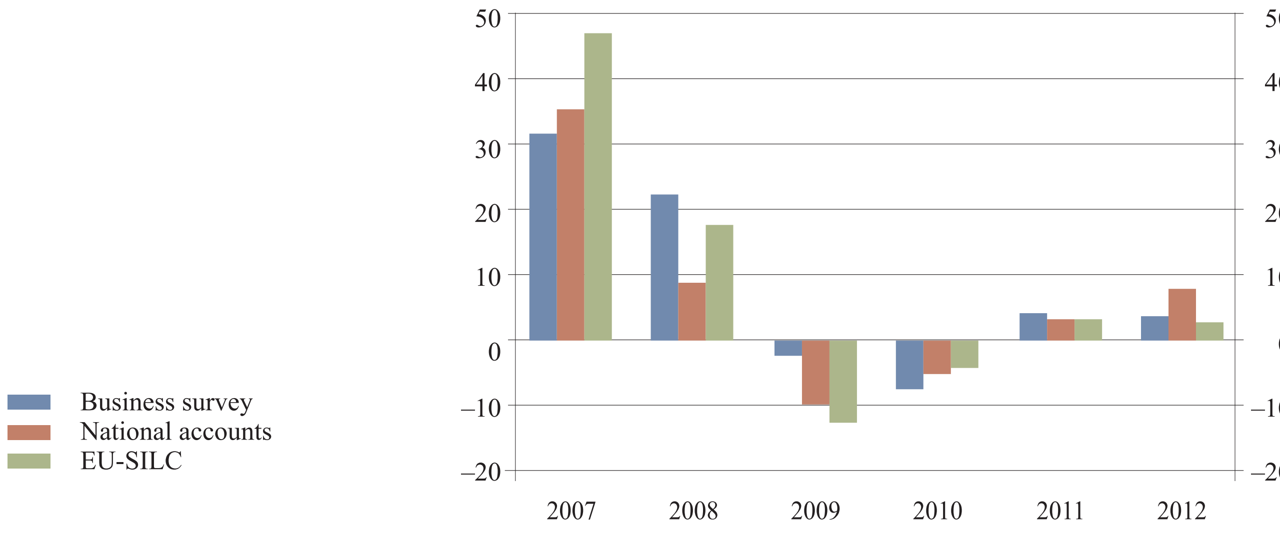
Notes: ISCO 1–3: Managers, professionals, technicians and associate professionals.
ISCO 4–6: Clerical support, service and sales workers; skilled agricultural, forestry and fishery workers.
ISCO 7–9: Craft and related trade workers, plant and machine operators and assemblers, elementary occupations.
Unemployed persons, who stopped work within the past 8 years and whose last job was corresponding occupation, were included.
Sources: CSB data and authors' calculations.

Chart A2
Vacancy rate by occupation
(% total posts)



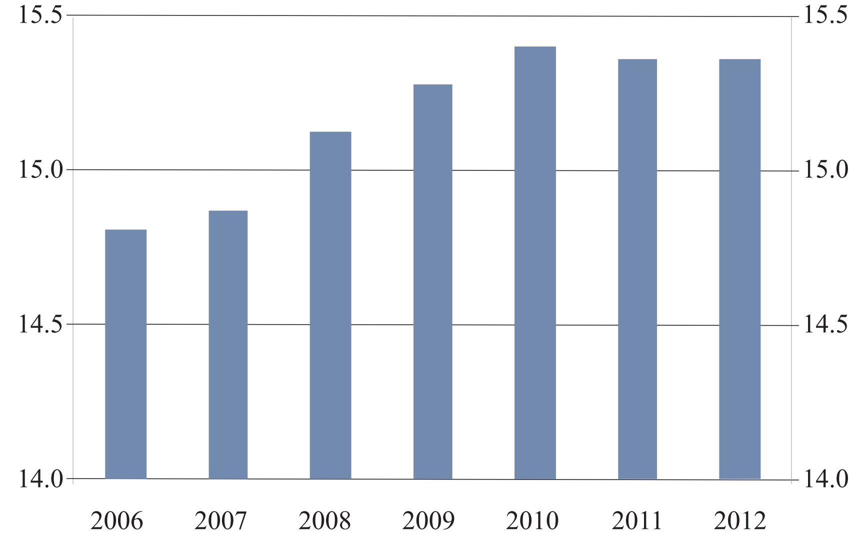
Note: Vacancy rate calculated as a ratio of unfilled posts to total posts.
Sources: CSB data and authors' calculations.

Chart A3
Average hourly wage growth according to various statistical data sources (2007–2012)
(%)



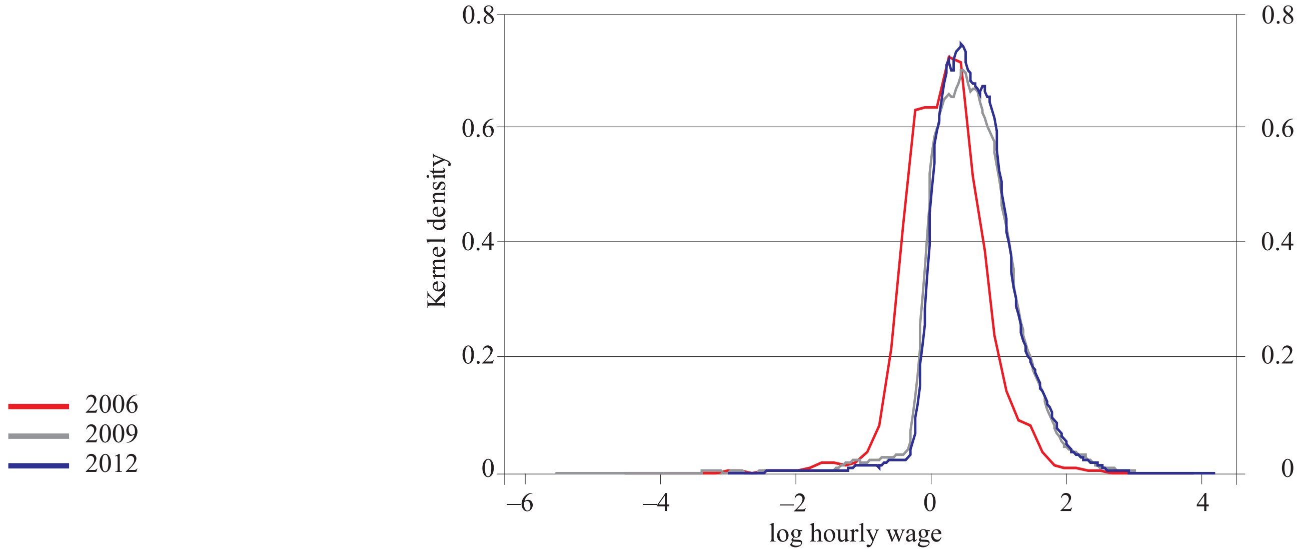
Sources: CSB data and authors' calculations.

Chart A4
Average years of schooling (2006–2012)
(employed population; annually)



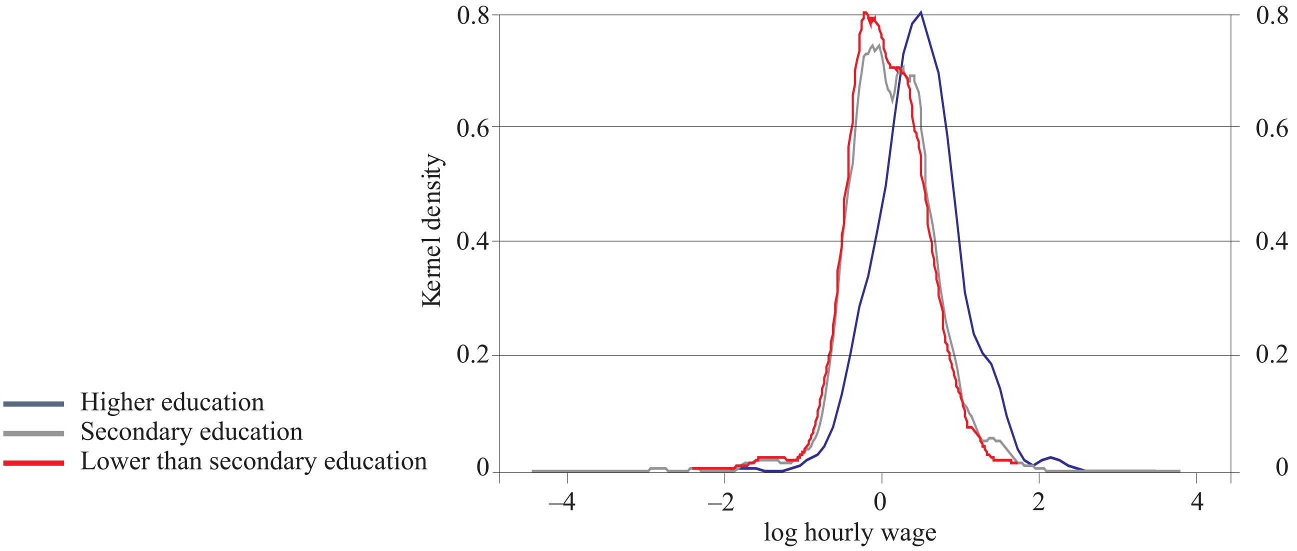
Source: Authors' calculations using EU-SILC micro data for Latvia.

Chart A5
Log hourly wage distribution in 2006, 2009 and 2012



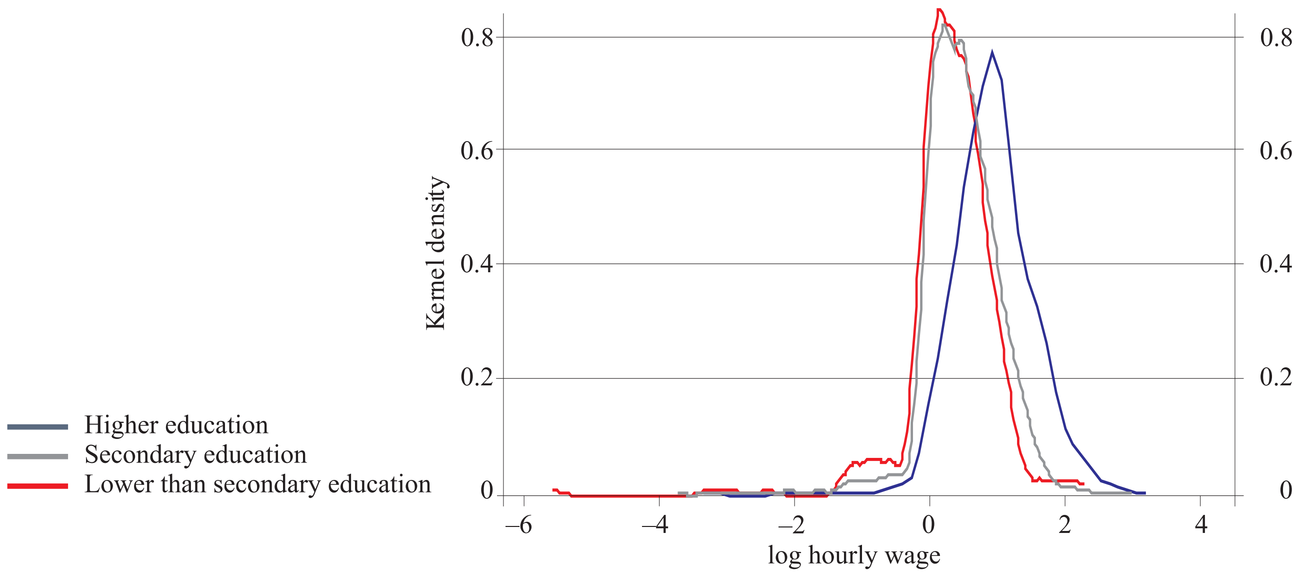
Source: Authors' calculations using EU-SILC micro data for Latvia.

Chart A6
Log hourly wage distribution by education level in 2006



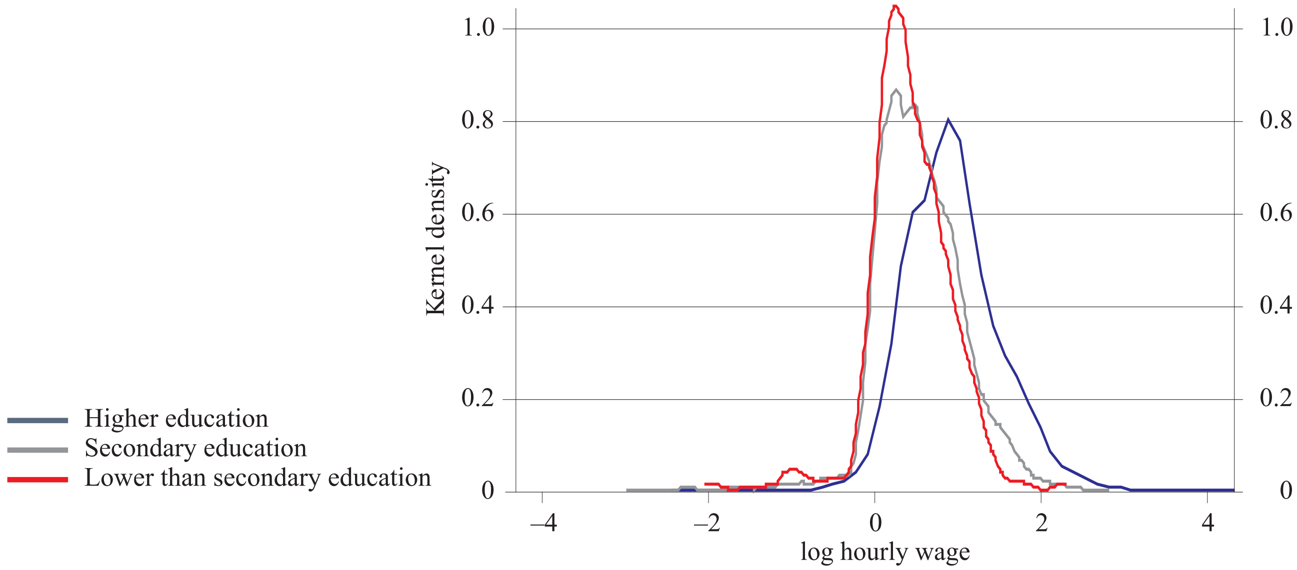
Source: Authors' calculations using EU-SILC micro data for Latvia.

Chart A7
Log hourly wage distribution by education level in 2009



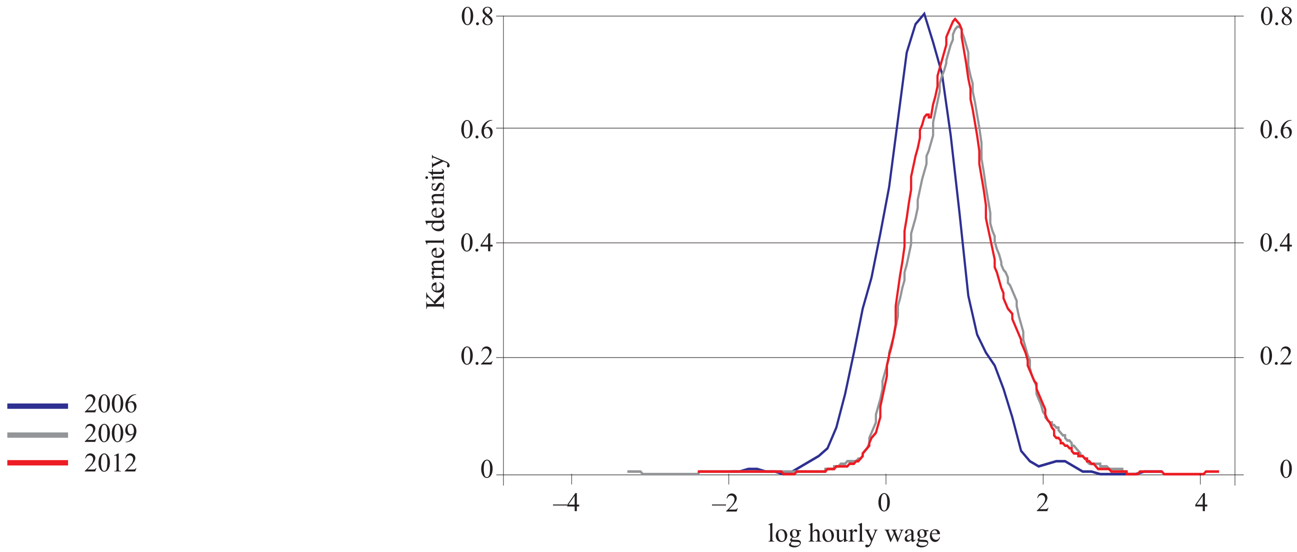
Source: Authors' calculations using EU-SILC micro data for Latvia.

Chart A8
Log hourly wage distribution by education level in 2012



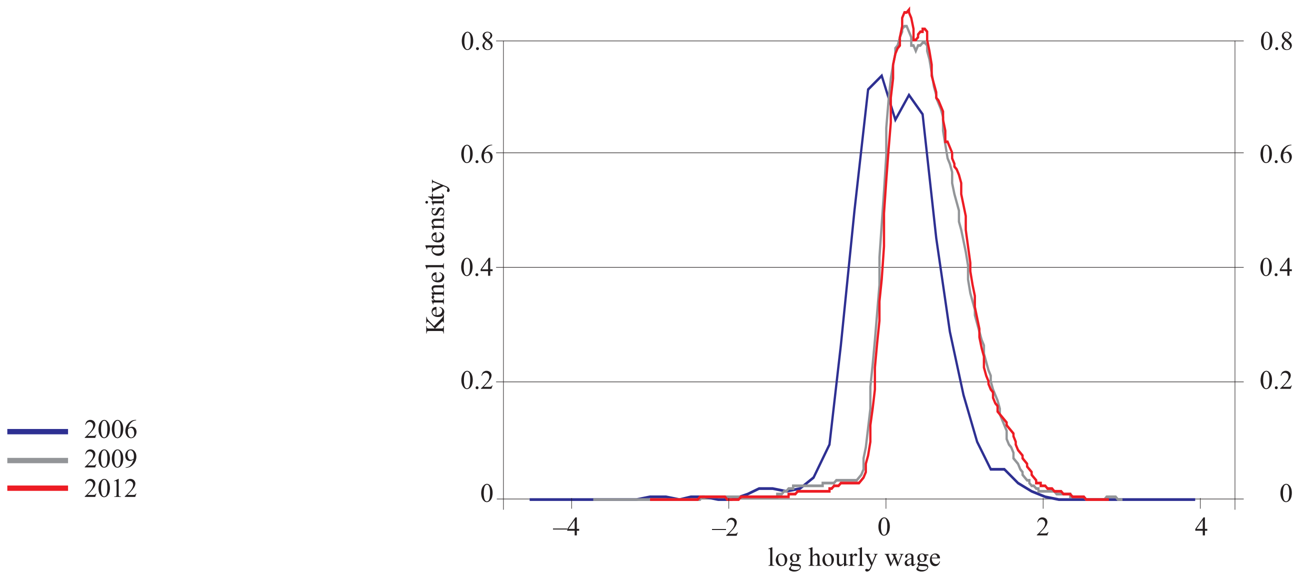
Source: Authors' calculations using EU-SILC micro data for Latvia.

Chart A9
Log hourly wage distribution by year (higher education)



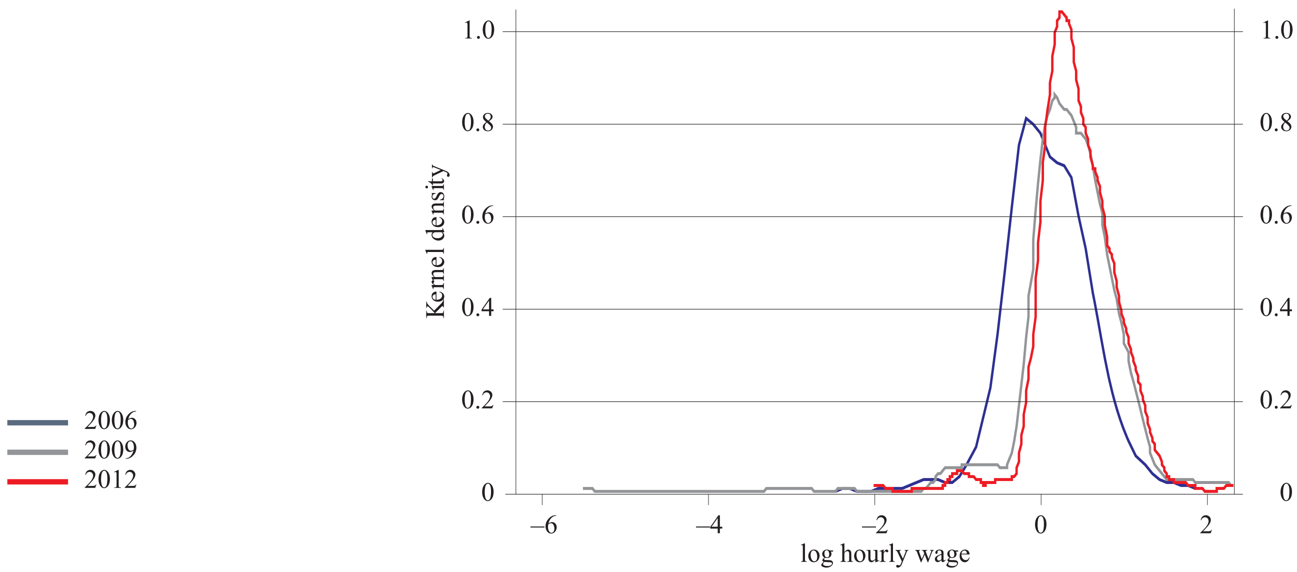
Source: Authors' calculations using EU-SILC micro data for Latvia.

Chart A10
Log hourly wage distribution by year (secondary education)



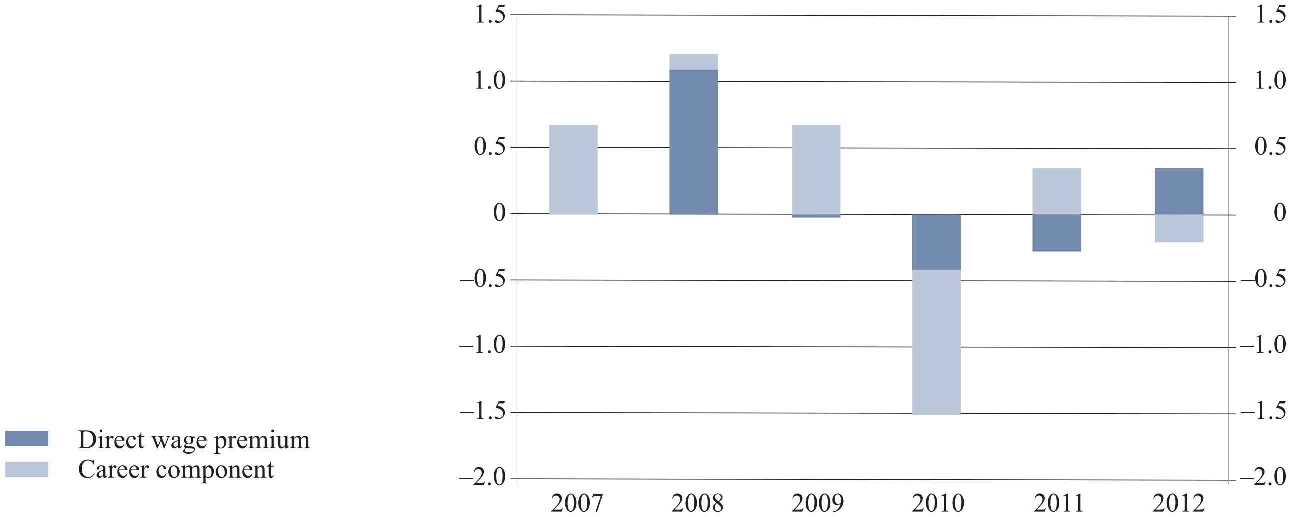
Source: Authors' calculations using EU-SILC micro data for Latvia.

Chart A11
Log hourly wage distribution by year (lower than secondary education)



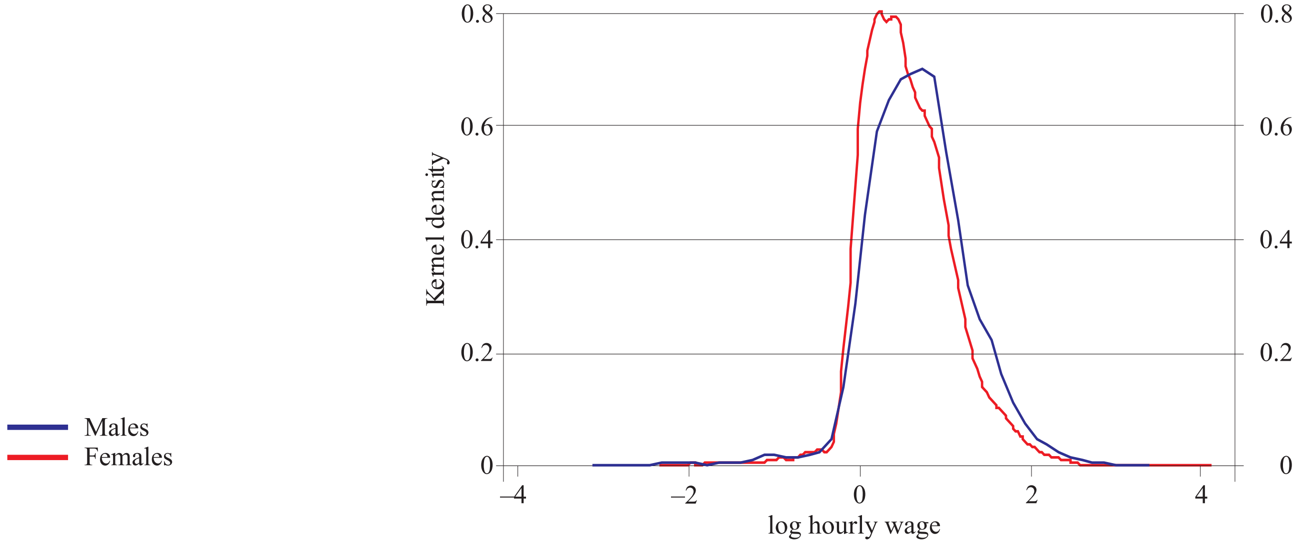
Source: Authors' calculations using EU-SILC micro data for Latvia.

Chart A12
Decomposition of Mincer coefficient change into direct wage premium and career component (2007–2012)
(annually; percentage points)



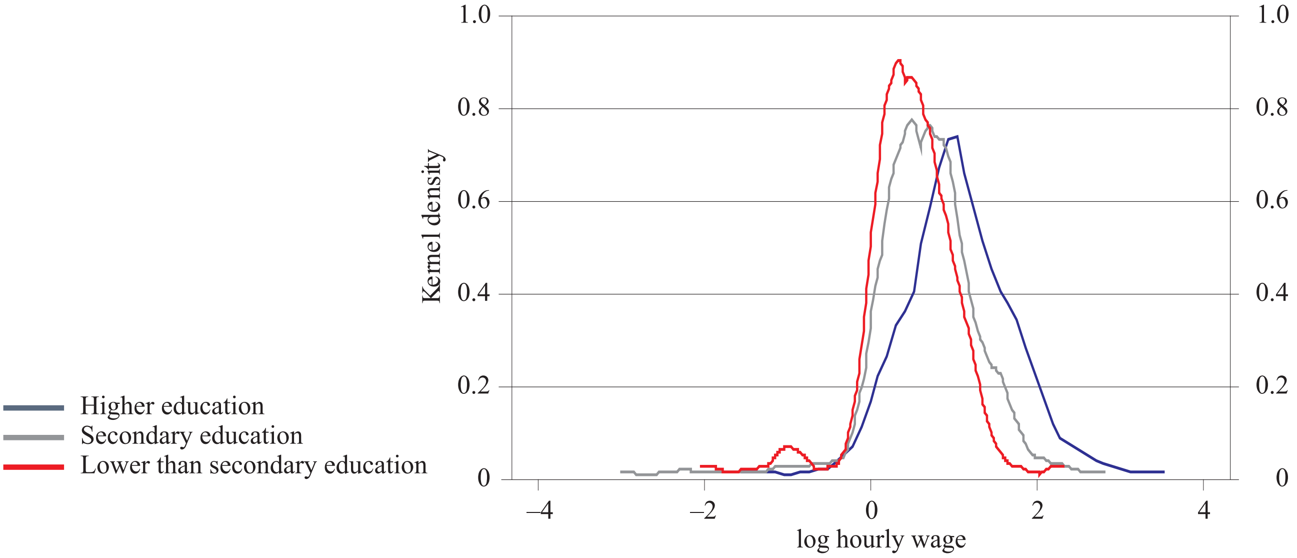
Source: Authors' calculations using EU-SILC micro data for Latvia.

Chart A13
Log hourly wage distribution by gender in 2012



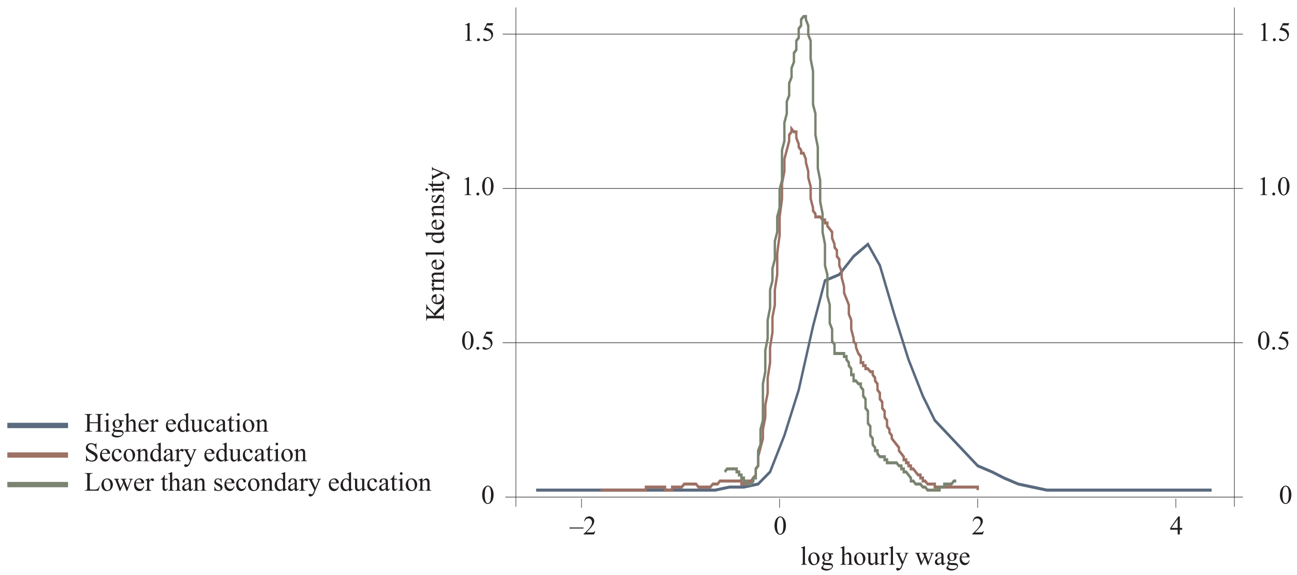
Source: Authors' calculations using EU-SILC micro data for Latvia.

Chart A14
Log hourly wage distribution of males by education level in 2012



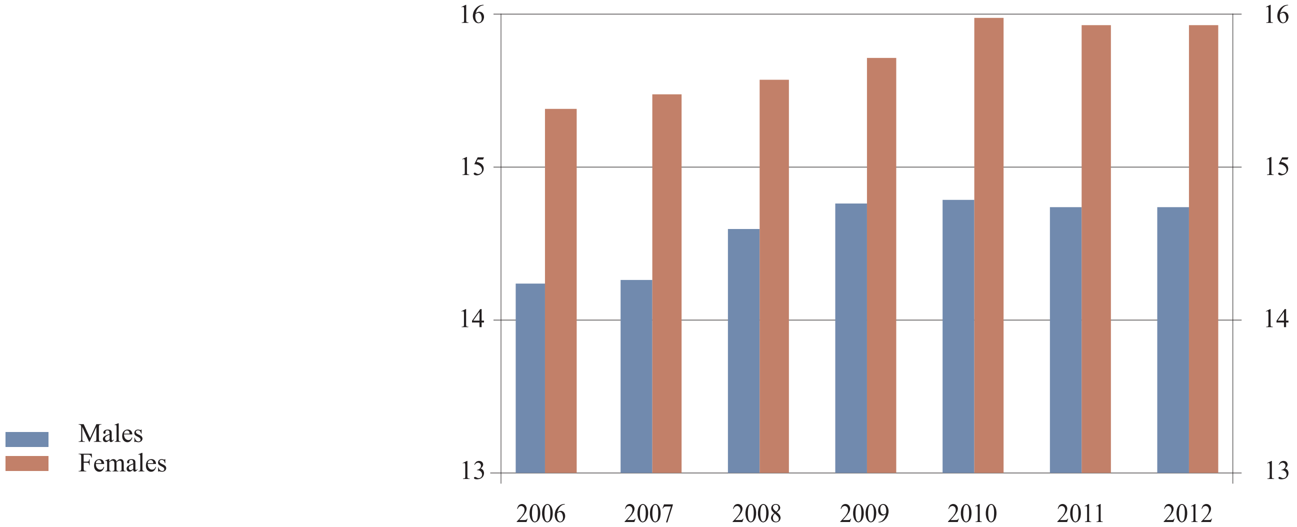
Source: Authors' calculations using EU-SILC micro data for Latvia.

Chart A15
Log hourly wage distribution of females by education level in 2012



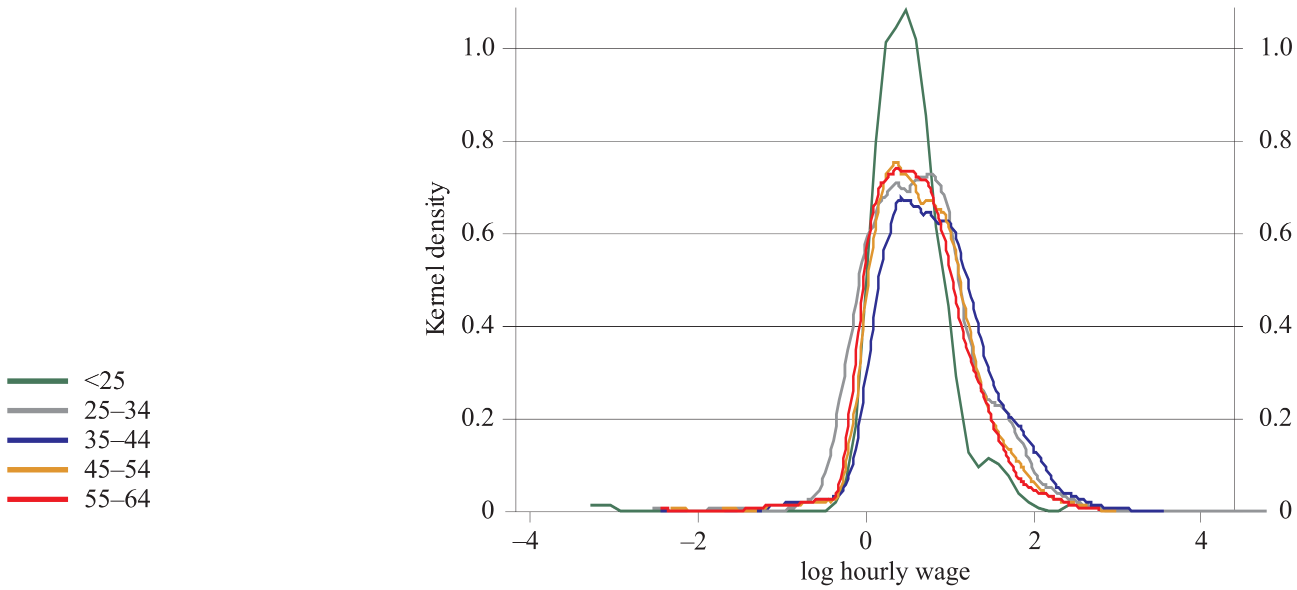
Source: Authors' calculations using EU-SILC micro data for Latvia.

Chart A16
Average years of schooling by gender (2006–2012)
(employed population; annually)



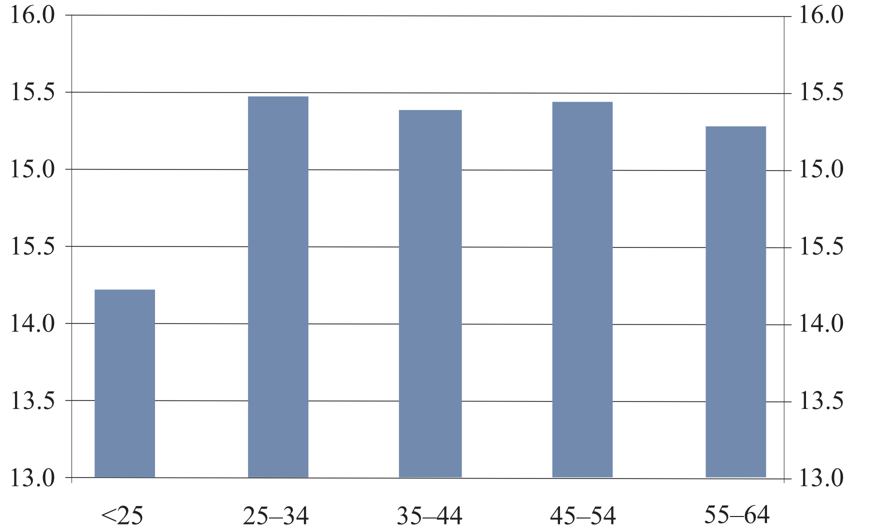
Source: Authors' calculations using EU-SILC micro data for Latvia.

Chart A17
Log hourly wage distribution by age group in 2012



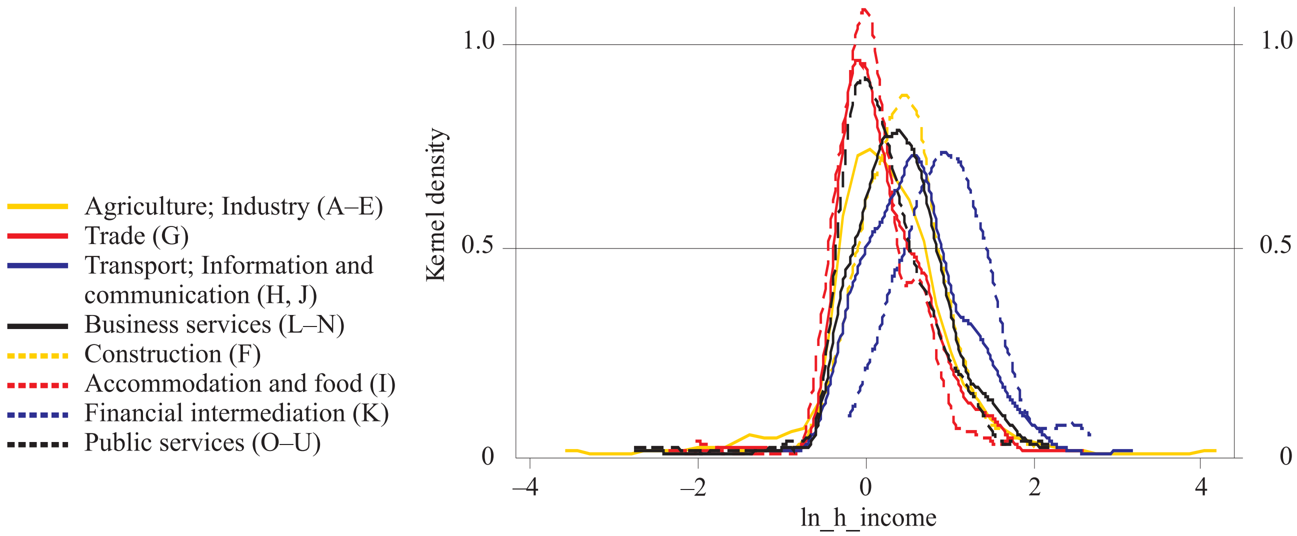
Source: Authors' calculations using EU-SILC micro data for Latvia.

Chart A18
Average years of schooling by age group in 2012
(employed population)



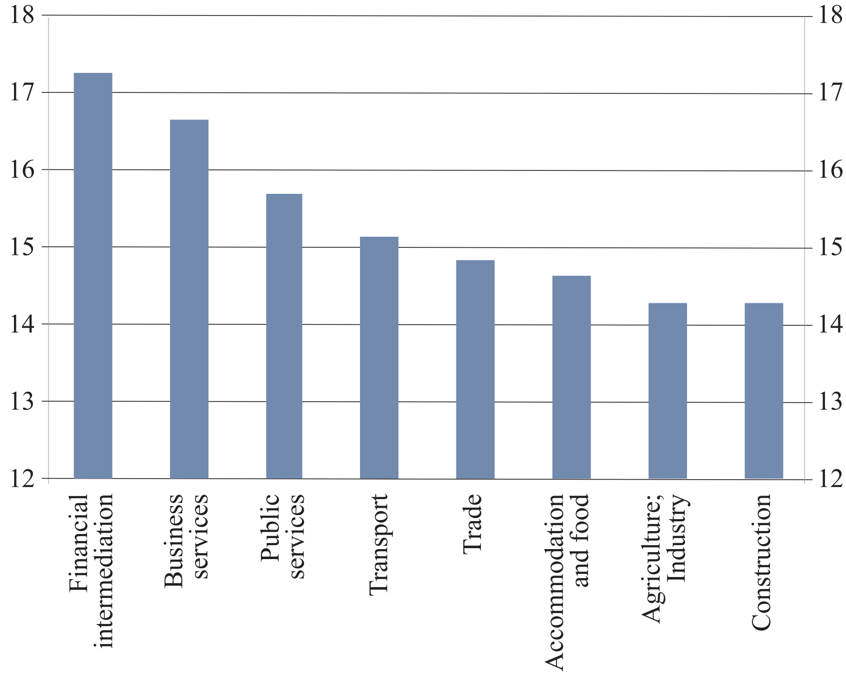
Source: Authors' calculations using EU-SILC micro data for Latvia.

Chart A19
Log hourly wage distribution by sector in 2012



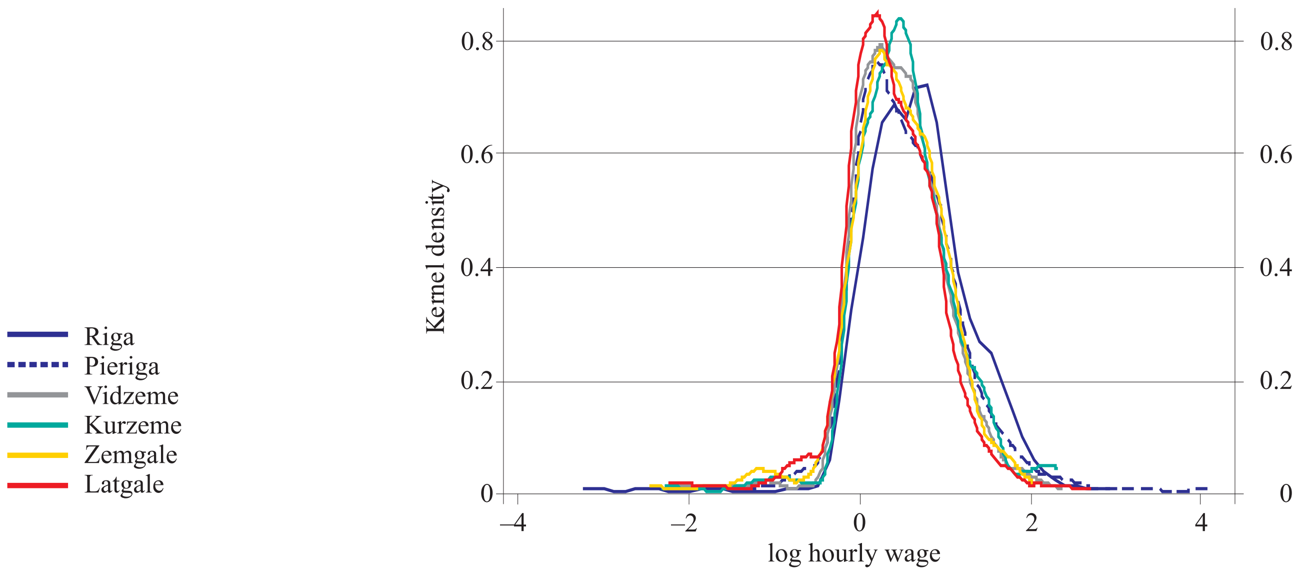
Source: Authors' calculations using EU-SILC micro data for Latvia.

Chart A20
Average years of schooling by sector of employment in 2012
(employed population)



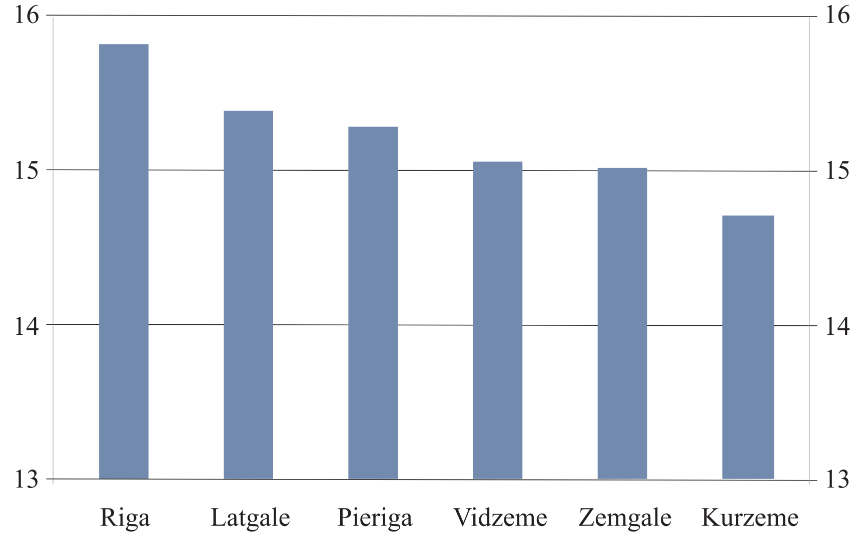
Source: Authors' calculations using EU-SILC micro data for Latvia.

Chart A21
Log hourly wage distribution by region in 2012



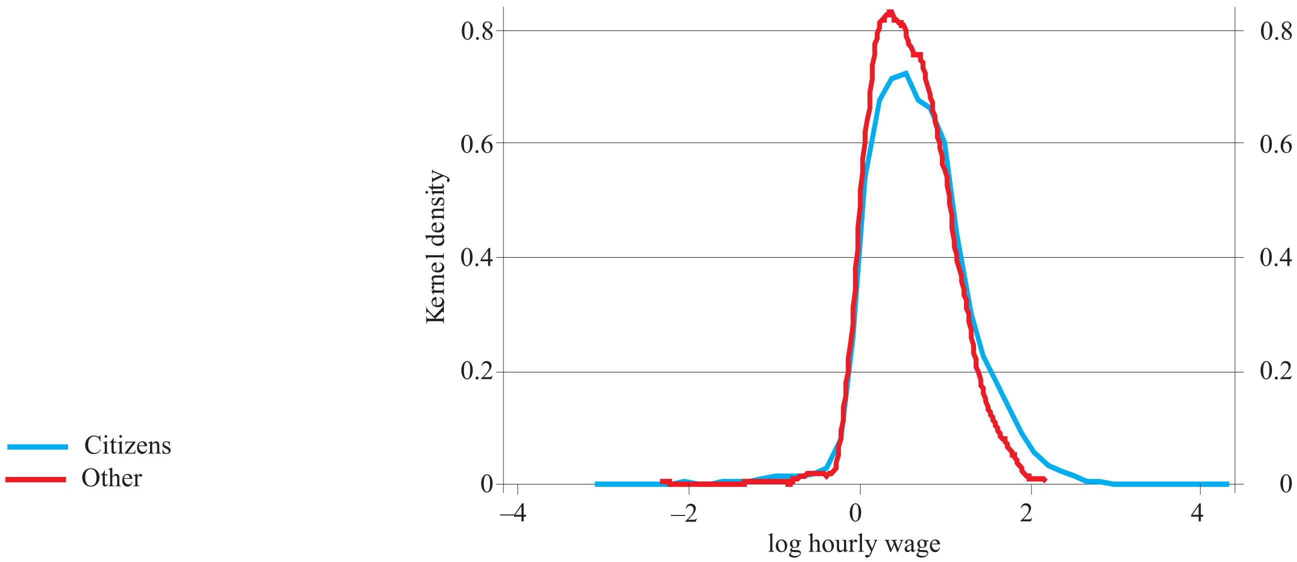
Source: Authors' calculations using EU-SILC micro data for Latvia.

Chart A22
Average years of schooling by region in 2012
(employed population)



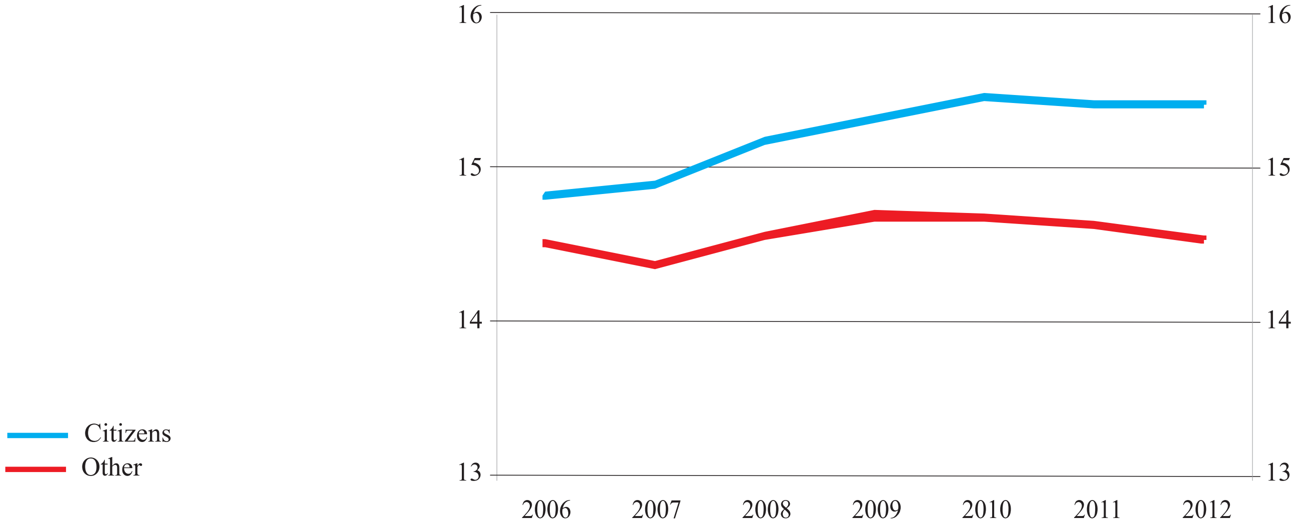
Source: Authors' calculations using EU-SILC micro data for Latvia.

Chart A23
Log hourly wage distribution by citizenship in 2012



Source: Authors' calculations using EU-SILC micro data for Latvia.

Chart A24
Average years of schooling by citizenship (2006–2012)
(employed population; annually)



Source: Authors' calculations using EU-SILC micro data for Latvia.

BIBLIOGRAPHY

ANDINI, Corrado (2013) – Earnings Persistence and Schooling Returns. *Economics Letters*, vol. 118, issue 3, March, pp. 482–484. DOI: 10.1016/j.econlet.2012.12.025.

ANGRIST, Joshua, KRUEGER, Alan (2001) – Instrumental Variables and the Search for Identification: From Supply and Demand to Natural Experiments. *Journal of Economic Perspectives*, vol. 15, No. 4, Fall, pp. 69–85. DOI: 10.1257/jep.15.4.69.

ARRAZOLA, María, DE HEVIA, José (2006) – Gender Differentials in Returns to Education in Spain. *Education Economics*, vol. 14, issue 4, pp. 469–486. DOI: 10.1080/09645290600854151.

ASHENFELTER, Orley, ZIMMERMAN, David John (1997) – Estimates of the Returns to Schooling from Sibling Data: Fathers, Sons, and Brothers. *Review of Economics and Statistics*, vol. 79, No. 1, February, pp. 1–9. DOI: 10.1162/003465397556421.

BADESCU, Mircea, D'HOMBRES, Béatrice, VILLALBA, Ernesto (2011) – *Returns to Education in European Countries*. Ispra Italy, European Commission – JRC. 62 p. (cited 04.09.2015).
Available: *http://publications.jrc.ec.europa.eu/repository/bitstream/JRC65411/reqno_jrc65411_eur_24850_en_web.pdf%5B1%5D.pdf*.

BLUNDELL, Richard, DEARDEN, Lorraine Margaret, SIANESI, Barbara (2005) – Evaluating the Effect of Education on Earnings: Models, Methods and Results from the National Child Development Survey. *Journal of the Royal Statistical Society: Series A (Statistics in Society)*, vol. 168, issue 3, July, pp. 473–512. DOI: 10.1111/j.1467-985X.2004.00360.x.

BLUNDELL, Richard, DEARDEN, Lorraine Margaret, SIANESI, Barbara (2001) – *Estimating the Returns to Education: Models, Methods and Results.* University College London and Institute for Fiscal Studies, October. 61 p. (cited 22.12.2014). Available: *http://cee.lse.ac.uk/ceedps/ceedp16.pdf*.

CARD, David (2001) – Estimating the Return to Schooling: Progress on Some Persistent Econometric Problems. *Econometrica*, vol. 69, No. 5, September, pp. 1127–1160. DOI: 10.1111/1468-0262.00237.

CARD, David (1999) – The Causal Effect of Education on Earnings. ***In:*** *Handbook of Labor Economics*, vol. 3, part A, pp. 1801–1863. DOI: 10.1016/S1573-4463(99)03011-4.

DAIF (2006) – Eiropas Savienības struktūrfondu Nacionālā programma "Darba tirgus pētījumi" (2006). Projekts *Darba algas un to ietekmējošie faktori* (Labklājības ministrijas pētījums, Nr. VPD1/ESF/NVA/04/NP/3.1.5.1./0001/0003). Rīga, Latvija. 214 p. [cited 08.02.2015]. Available:
http://www.lm.gov.lv/upload/darba_tirgus/darba_tirgus/petijumi/darba_algas_faktori.pdf.

Db.lv (2013) – Augstskolas diploms negarantē lielu algu. *Dienas bizness*, 25.06.2013 [cited 04.09.2015]. Available:

http://www.db.lv/finanses/makroekonomika/laikraksts-augstskolas-diploms-negarante-lielu-algu-396257.

DEVEREUX, Paul, FAN, Wen (2011) – Earnings Returns to the British Education Expansion. *Economics of Education Review*, vol. 30, issue 6, December, pp. 1153–1166. DOI: 10.1016/j.econedurev.2011.03.004.

FADEJEVA, Ludmila, KRASNOPJOROVS, Oļegs (2015) – *Labour Market Adjustment during 2008–2013 in Latvia: Firm Level Evidence*. Latvijas Banka Working Paper No. 2/2015. 177 p. [cited 05.11.2015]. Available: *https://www.macroeconomics.lv/working-paper-labour-market-adjustment-during-2008-2013-latvia-firm-level-evidence.*

FERSTERER, Josef, WINTER-EBMER, Rudolf (2003) – Are Austrian Returns to Education Falling Over Time? *Labour Economics*, vol. 10, issue 1, pp. 73–89. DOI: 10.1016/S0927-5371(02)00105-7.

FLABBI, Luca, PATERNOSTRO, Stefano, TIONGSON, Erwin R. (2007) – Returns to Education in the Economic Transition: A Systematic Assessment Using Comparable Data. *Economics of Education Review*, vol. 27, issue 6, September, pp. 724–740. DOI: 10.1016/j.econedurev.2007.09.011.

FURNO, Marilena (2014) – Returns to Education and Gender Gap. *International Review of Applied Economics*, vol. 28, issue 5, May, pp. 628–649. DOI: 10.1080/02692171.2014.907243.

HANUSHEK, Eric, SCHWERDT, Guido, WIEDERHOLD, Simon, WOESSMANN, Ludger (2015) – Returns to Skills Around the World: Evidence from PIAAC. *European Economic Review*, vol. 73, January, pp. 103–130. DOI: 10.1016/j.euroecorev.2014.10.006.

HARMON, Colm, OOSTERBEEK, Hessel, WALKER, Ian (2000) – *The Returns to Education. A Review of Evidence, Issues and Deficiencies in the Literature.* London School of Economics and Political Science, December. 51 p. [cited 04.09.2015]. Available: *http://cee.lse.ac.uk/ceedps/ceedp05.pdf*.

HARMON, Colm, WALKER, Ian (1995) – Estimates of the Economic Return to Schooling for the United Kingdom. *The American Economic Review*, vol. 85, No. 5, December, pp. 1278–1286 [cited 04.09.2015]. Available: *http://www.jstor.org/stable/2950988*.

HAZANS, Mihails (2003) – *Returns to Education in the Baltic Countries*. GDNet Knowledge Base Working Paper, No. DOC16801, July [cited 20.12.2014]. Available: *http://papers.ssrn.com/sol3/papers.cfm?abstract_id=699623pers.cfm?abstract_id=699623*.

HAZANS, Mihails (2005) – *Unemployment and the Earnings Structure in Latvia*. World Bank Policy Research Working Paper, No. 3504, February. 90 p. [cited 04.09.2015]. Available: *https://openknowledge.worldbank.org/bitstream/handle/10986/8907/wps3504.pdf?sequence=1*.

HOOGERHEIDE, Lennart, BLOCK, Joern, THURIK, Roy (2012) – Family Background Variables as Instruments for Education in Income Regressions: A Bayesian Analysis. *Economics of Education Review*, vol. 31, issue 5, October, pp. 515–523. DOI: 10.1016/j.econedurev.2012.03.001.

KRASNOPJOROVS, Oļegs (2012) – "Zelta jaunatne" jeb kas Latvijā saņem lielākās algas? Blog at macroeconomics.lv 20.04.2012 [cited 04.09.2015]. Available: *https://www.makroekonomika.lv/zelta-jaunatne-jeb-kas-latvija-sanem-lielakas-algas*.

LEIGH, Andrew, RYAN, Chris (2008) – Estimating Returns to Education Using Different Natural Experiment Techniques. *Economics of Education Review*, vol. 27, issue 2, pp. 149–160 [cited 04.09.2015].
Available: *http://www.andrewleigh.org/pdf/EstimatingReturnsToEducation.pdf*.

MEGHIR, Costas, PALME, Mårten (2005) – Educational Reform, Ability, and Family Background. *American Economic Review*, vol. 95, No. 1, March, pp. 414–424. DOI: 10.1257/0002828053828671.

MINCER, Jacob (1974) – *Schooling, Experience and Earnings*. New York : Columbia University Press. 167 p.

MONTENEGRO, Claudio, PATRINOS, Harry Anthony (2014) – *Comparable Estimates of Returns to Schooling Around the World*. Policy Research Working Paper Series, No. 7020, The World Bank, September. 41 p. [cited 04.09.2015]. Available:
http://documents.worldbank.org/curated/en/2014/09/20173085/comparable-estimates-returns-schooling-around-world.

OREOPOULOS, Philip (2006) – Estimating Average and Local Average Treatment Effects of Education when Compulsory Schooling Laws Really Matter. *American Economic Review*, vol. 96, No. 1, March, pp. 152–175. DOI: 10.1257/000282806776157641.

PSACHAROPOULOS, George, PATRINOS, Harry Anthony (2004) – Returns to Investment in Education: A Further Update. *Education Economics*, vol. 12, issue 2, pp. 111–134. DOI: 10.1080/0964529042000239140.

ROMELE, Linda (2014) – *Izglītības privātās un sociālās atdeves novērtējums Latvijā*. Promocijas darbs. Rīga : LU EVF Ekonomikas promocijas padome. 205 p.

STRAUSS, Hubert, DE LA MAISONNEUVE, Christine (2010) – The Wage Premium on Tertiary Education: New Estimates for 21 OECD Countries. *OECD Journal: Economic Studies*, vol. 2009, issue 1, January, pp. 1–29. DOI: 10.1787/eco_studies-v2009-art7-en.

TROSTEL, Philip, WALKER, Ian, WOOLLEY, Paul (2002) – Estimates of the Economic Return to Schooling for 28 Countries. *Labour Economics*, vol. 9, No. 1, February, pp. 1–16. DOI: 10.1016/S0927-5371(01)00052-5.