EMIGRATION AND WAGES: THE EU ENLARGEMENT EXPERIMENT

Benjamin Elsner

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Emigration and Wages: The EU Enlargement Experiment

Benjamin Elsner[*,†]

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Abstract

This paper studies the impact of a large emigration wave on real wages in the source country. Following EU enlargement in 2004, a large share of the workforce of the Central and Eastern Europe emigrated to Western Europe. Using data from Lithuania for the calibration of a factor demand model I show that emigration had a significant short-run impact on real wages in the source country. In particular, emigration led to a change in the wage distribution between young and old workers. The wages of young workers increased by 6%, whereas the wages of old workers decreased by around 1%. On the contrary, I find no effect on the wage distribution between workers of different education levels.

Keywords: Emigration, EU Enlargement, European Integration, Wage Distribution
JEL codes: F22, J31, O15, R23

[*]Trinity College Dublin, Department of Economics and IIIS. Email: elsnerb@tcd.ie, Webpage: www.benjaminelsner.com .

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1 Introduction

Migration affects both receiving and sending countries. While there is a vast literature on the effect of migration on the labor markets in the receiving country, little is known about its impact on the sending country.[1] This paper studies the enlargement of the European Union (EU) in 2004, which was followed by substantial migration movements from Central and Eastern Europe to Western Europe. From 2004 to 2007, 5-9% of the workforce of Latvia, Lithuania, Poland and Slovakia received a work permit in Ireland and the UK.[2] The aim of this paper is to analyze the impact of this emigration wave on the wage distribution in the source country and to quantify the gains and losses for different groups of workers.

Based on data from Lithuania, I find that emigration significantly changed the wage distribution. First, among those workers who stay in the home country, young workers gain from emigration while old workers lose. Second, the gains for young workers exceed the losses for old workers. This distributional impact is driven by two opposite effects. Groups of workers with a high share of emigrants become a more scarce resource in the labor market, which leads to an increase in their wages. Since most emigrants were young, this effect dominated for young workers. Moreover, old and young workers are complements in the aggregate production process, so that the emigration of young workers lowers the labor demand for old workers and causes a decrease in their wages.

The analysis is based on a factor demand model, which follows Card & Lemieux (2001), Borjas (2003) and Ottaviano & Peri (2011). The workforce consists of skill groups defined by the observable characteristics *education* and *work experience*. The model generates a labor demand framework which accounts for differences in substitutability between these skill groups. Using Lithuanian microdata, I estimate the structural parameters that characterize the labor market in this model. To overcome simultaneity bias in the iden-

[1] See Kerr & Kerr (2011) for a review of the literature on the wage effects of immigration.

[2] Own calculations based on work permit data from Ireland and the UK. See Figure 1.

tification of the labor demand curves, *birth cohort size* serves as an instrument for labor supply. Based on these estimates I calibrate the model and simulate the post-2004 emigration wave on the Lithuanian labor market. The number of emigrants per skill group is taken from census and work permit data in the the main destination countries, Ireland and the UK. Based on the model predictions I find that wages of the youngest cohort increased by 6-8%, while the oldest cohort saw their wages decrease by around 1%.

These findings are broadly consistent with the literature on the long-run effects of migration on wages. Moreover, this study contributes to the literature by introducing an old-young dimension to the analysis and by focusing on the short run. Mishra (2007) uses data on Mexican emigration to the US and finds that for an emigration of 10% of the workforce wages increased on average by 8% over the period from 1970-2000. Aydemir & Borjas (2007) apply a factor demand model to the same case and show that the wage increases were higher for workers with a high-school degree and some college education and lower for college graduates and high-school dropouts. Batista (2007) considers the EU accession of Portugal and shows in a macro model that emigration led to an increase in wages in the long run, but the impact of emigration is much smaller than the impact of capital inflows. Elsner (2010) shows that emigration can also have an impact on wages in the short run. He finds that emigration from Lithuania after EU enlargement in 2004 increased by 6.6% for every 10% emigration of the workforce.

This paper extends the existing literature as it shows that emigration can have a significant impact on the wage distribution *in the short run*. In particular, it adds an age dimension to the analysis. In the long run, this dimension is less important, since the cohorts change over time. The youngest cohort today becomes an older cohort in 10 years' time. However, in the short run the cohorts are fixed so that the emigration of workers from the young cohort directly affects the wages of stayers from the same cohort.

The wage effects in this paper are significantly larger than those found in other studies on the wage effect of immigration, e.g. Borjas (2003) or Manacorda *et al.* (2011). As such, the wage effect of emigration reflects more than a mirror image of the wage effects in the receiving countries. The labor markets in sending countries like Lithuania or Poland are fundamentally different from those in developed receiving countries like the US or Germany. The young and the old generations in former socialist countries acquired their skills under different economic systems. Consequently, young and old workers are less substitutable in these countries, which translates into stronger own-wage and complementarity effects.

The remainder of the paper is structured as follows: Section 2 gives a historical overview of the emigration wave following EU enlargement. Sections 3 to 6 describe the structural model, the estimation of the structural parameters and the simulation of the post-2004 emigration wave. Section 7 concludes.

2 EU Enlargement, Migration and Wages: Stylized Facts

In 2004 eight former socialist countries from Central and Eastern Europe joined the EU. For workers from these countries, the high wage differentials between Western European countries and the accession countries at that time created a large incentive to emigrate to Western Europe.[3] *Freedom of Movement*, a basic principle of the EU, would guarantee every worker from the New Member States the right to migrate to any EU country and take up employment. However, most countries in Western Europe feared negative consequences for their labor markets as well as their welfare states and restricted the access for workers from the New Member States for a period of up to 7 years. Only

[3] If GDP per capita differentials in purchasing power parities can be seen as a proxy for real wages, the average wages in Poland amounted to 40% of UK wages. In Lithuania, this share was 37%. Source: Eurostat.

Ireland, the UK and Sweden immediately opened their labor markets and welcomed a large number of immigrant workers. 1.2 million workers migrated between 2004 and 2007 to the UK (770,000), Ireland (416,000) and Sweden (19,000).[4] The majority of migrants went to Ireland and the UK, because both countries were experiencing an economic boom and the language barrier was lower than in Sweden.

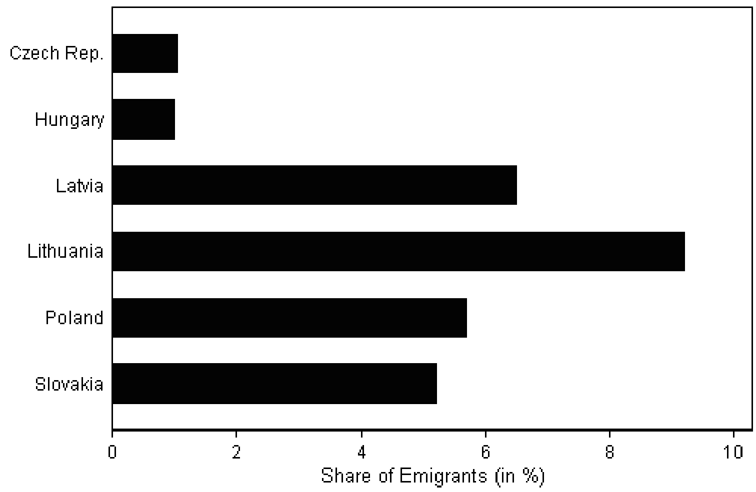

FIGURE 1 – EMIGRANT SHARES IN CENTRAL AND EASTERN EUROPE

Note: Number of emigrants 2004-2007 relative to the total workforce in 2003. Own calculation. Sources: Irish PPS, UK NINo numbers, Eurostat.

Most migrants came from Poland, Latvia, Lithuania and Slovakia. Figure 1 illustrates the magnitude of the emigration wave relative to the workforce of the source countries. Although Poland was the country with the highest number of emigrants, Lithuania and Latvia had the highest share of emigrants relative to the workforce. Around 9% of all Lithuanian workers and 6% of all Latvian workers received a work permit in Ireland or the UK between 2004 and 2007. While some workers only migrated for a short period, the majority stayed in the destination country for longer periods of time. Evidence from the Irish Central Statistics Office (2009) suggests that around 60% of migrants from the New Member States stayed for at least two years after having received a work permit.

[4] Sources: Ireland: Central Statistics Office. UK: UK Home Office. Sweden: Wadensjö (2007).

This study uses data from Lithuania, which was the country with the highest share of emigrants among the New Member States. However, the impact of emigration on the labor market should be comparable to the impacts in Latvia, Slovakia and Poland. All four countries are former socialist countries with similar economic structures and institutions. Moreover, at the time of EU enlargement these countries were in a similar economic situation with comparable levels of GDP per capita[5]

The number of work permits per year given to Lithuanian workers increased sharply from 6,400 in 2003 to 40,000 in 2006.[6] In the time around EU enlargement Lithuania experienced a phase of high GDP growth, between 7% in 2002 and 10.7% in 2005. Consequently, average wages increased considerably in the same period. Figure 2 displays the changes in average real wages, as well as the emigrant shares for workers in different education and experience groups.

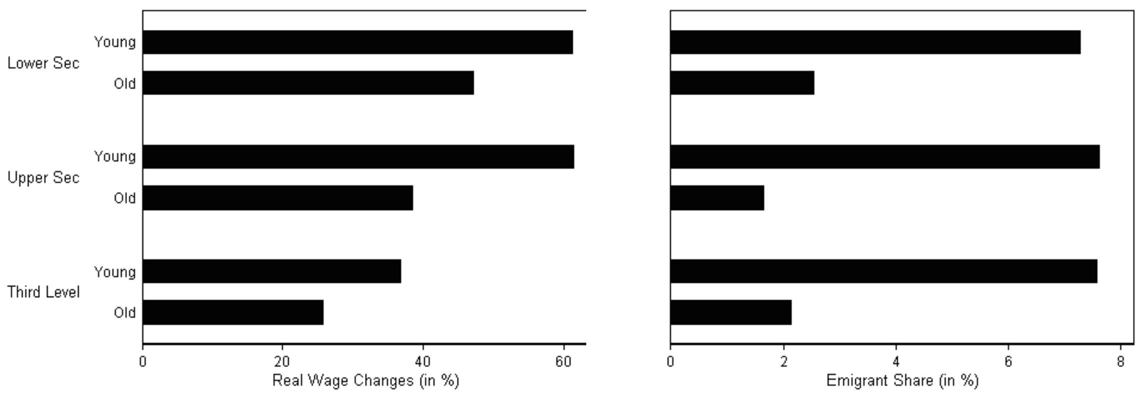

FIGURE 2 – REAL WAGE CHANGES AND EMIGRANT SHARES, LITHUANIA 2002-2006.

Notes: A skill group is defined by education and work experience. Workers with 20 years and less of work experience are defined as young, those with 21 and more years as old. The real wages are deflated by the HCPI. The emigrant share is measured as the share of the workers in a skill group that emigrated between 2002 and 2006.

Source: Own calculations from the Lithuanian HBS, the Irish Census and Work Permit Data. See Section 4 for details.

This wage increase is not surprising given the growth in GDP per capita, which amounts to 37.5% from 2002 to 2006. Clearly, the wage changes were not spread evenly

[5] In 2004 the GDP in current prices was between EUR 4,800 (Lithuania) and 6,300 (Slovakia), considerably below the average of the old member states with 26,000. Source: Eurostat.

[6] See Table 1c).

across groups of workers. Young workers with a work experience of up to 20 years gained considerably more than old workers with a work experience of more than 20 years. Additionally, workers with an education level below third-level degree saw higher wage increases than workers with a third-level degree.

Figure 2 (right graph) illustrates the magnitude of the emigration wave between 2002 and 2006 for each skill group. Similarly to the wage changes, the emigrant shares were higher for young workers than for old workers. Young workers were around 3.5 times more likely to emigrate than old workers. Surprisingly, there was no visible selection of emigrants with respect to the education groups. Workers of all three education levels had almost identical emigrant shares, which is evidence against a brain drain.

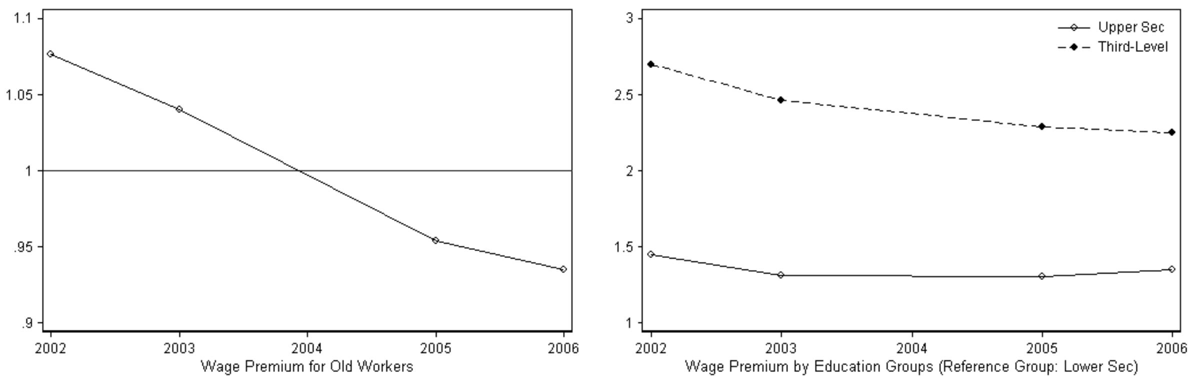

Figure 3 – Wage Premia by Work Experience and Education.
Source: Own calculations from the Lithuanian HBS.

The relative changes in real wages had a significant impact on the wage inequality between experience and education groups. In particular, the wage premium for old workers changed remarkably, as the graph on the left in Figure 3 shows. In 2002 old workers earned on average 8% more than young workers. This wage gap was reversed in 2006. The wage premium for workers with a third-level degree compared to those with a lower secondary education decreased slightly over time, while the premium of workers with an upper secondary education remained stable. Hence, the wage inequality between education groups decreased over time.

These changes in the level and the distribution of wages could be caused by numerous factors. On the supply side, emigration leads to a smaller number of workers. Given constant labor demand, the workers who did not emigrate are a more scarce resource and therefore their wages increase. On the demand side, factors like domestic and foreign investment, trade integration or TFP growth can have a positive influence on wages.

The aim of this study is to isolate the role of emigration in the total change in wages, which extends previous work by Elsner (2010) who found a positive average effect in a reduced-form approach. The current study goes a step further and aims to determine *how much* different groups of workers gained or lost from emigration, *all other things equal.*

3 Structural Model

The structural model explains how a change in labor supply affects the wages of workers with different observable skills while keeping labor demand constant. To model this heterogeneity in skills, the workforce is divided into 12 skill groups, which are defined by education and work experience. Workers with the same observable characteristics compete in the same labor market and are assumed to be perfect substitutes. Across skill groups, workers with similar skills are closer substitutes than workers with fundamentally different skills. Emigration of workers of a particular skill group shifts the labor supply and, given a downward-sloping labor demand curve, increases the wages of the stayers in this skill group. However, due to the interdependency of labor markets for different skill groups, a change in the labor supply of one skill group affects the wages of all other skill groups through changes in labor demand. The extent of these general equilibrium effects depends on the degree of substitutability between skill groups and needs to be determined empirically.

Following the works of Card & Lemieux (2001), Borjas (2003) and Ottaviano & Peri (2011), I model aggregate production in the economy with a nested CES production function, into which each skill group enters as a distinct labor input. Assuming that labor markets clear and each skill group is paid its marginal product, the model generates a relative labor demand curve for each education and experience group. The model set-up allows for an econometric identification of the labor demand curves while accounting for heterogeneity in the skills of the workforce.

The aggregate production function consists of three building blocks: first, physical capital and labor are combined to produce an aggregate output. As this study focuses on the short-run effect of emigration on wages, I assume that capital is fixed. The second building block is a CES aggregate of three education groups, which reflects the fact that workers with different education are imperfect substitutes in the labor market. The third building block combines workers with the same education but different work experience in a CES aggregate. Workers within the same education group may differ in their human capital. This difference makes them imperfect substitutes, especially when they have different levels of work experience.

3.1 Aggregate Production

The notation and analysis in this section closely follow Borjas (2003) and Ottaviano & Peri (2011). Aggregate production in the economy is described by the Cobb-Douglas production function

$$Q_t = A_t L_t^{\alpha} K_t^{1-\alpha}. \tag{1}$$

Aggregate output Q_t is produced using total factor productivity A_t, physical capital K_t and labor L_t. $\alpha \in (0, 1)$ is the share of labor in aggregate income. The price of the aggregate output is normalized to one. The labor force L_t consists of three different education groups L_{it} where i denotes lower secondary education (10 years of schooling or less), upper secondary education (11-14 years of schooling) and third-level degree (equivalent to B.Sc degree or higher). The aggregate labor input L_t is represented by the CES aggregate

$$L_t = \left[\sum_i \theta_{it} L_{it}^{\frac{\sigma_{ED}-1}{\sigma_{ED}}} \right]^{\frac{\sigma_{ED}}{\sigma_{ED}-1}}. \tag{2}$$

σ_{ED} denotes the elasticity of substitution between workers of different education groups. The higher the value of this parameter, the easier it is to substitute groups of workers with different education in the production process. The relative productivity parameters θ_{it} have the property $\sum_i \theta_{it} = 1$ and capture the difference in relative productivity between education groups.

Each education group consists of four work experience groups L_{ijt}:

$$L_{it} = \left[\sum_j \gamma_{ijt} L_{ijt}^{\frac{\sigma_{EXP}-1}{\sigma_{EXP}}} \right]^{\frac{\sigma_{EXP}}{\sigma_{EXP}-1}}. \tag{3}$$

The elasticity of substitution σ_{EXP} measures the degree of substitutability of workers with the same education but different work experience. γ_{ijt} denotes the relative productivity of workers in experience group j and education group i with $\sum_j \gamma_{ijt} = 1$.

For the division of an education group into experience groups (j) I choose intervals of 10 years of work experience (0-10 years, 11-20 years, 21-30 years, 31+ years). This choice is the result of a trade-off between many skill groups and many observations *per skill group*, given the dataset. Shorter intervals allow for a more differentiated picture of the labor market, but they come at the cost of a loss in precision. With a given number of observations, a high number of skill groups means that the calculation of the average wage and labor input per skill group are based on a small number of observations. As a consequence, the averages become less precise. Aydemir & Borjas (2011) show that this *attenuation bias* can have a significant impact on the estimates of the structural parameters. Given the available dataset, the choice of 10-year intervals is a compromise that reduces attenuation bias and yet allows for a differentiated picture of the labor supply and wage changes.[7]

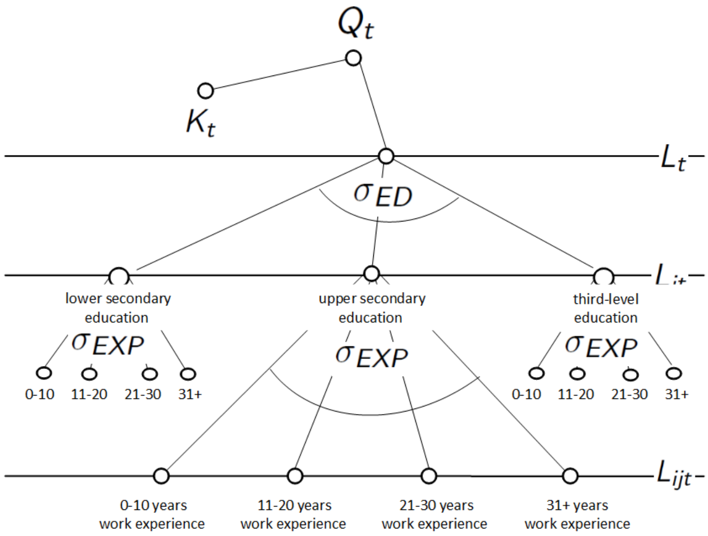

Figure 4 – Nested CES Production Function

Figure 4 illustrates the nested structure of the aggregate production function. The model compresses the different degrees of substitutability between skill groups to 2 elasticities, σ_{ED} and σ_{EXP}. This simplification is necessary for the identification of the structural parameters. Ideally, one would like to estimate a separate relative labor demand curve for every skill group, but the econometric identification of the model would be impossible. With 12 skill groups the number of parameters to be estimated would amount to $12 \cdot 11 = 132$, which cannot be estimated from the small number of observations that is typically available from aggregate labor market data. Nevertheless, σ_{ED} and σ_{EXP} can be identified and given the variation in the number of emigrants across skill groups, so that we can obtain a differentiated picture of the impact of emigration on the wages of each skill group.

7 Most of the literature, e.g. Borjas (2003), Brücker & Jahn (2011), D'Amuri *et al.* (2010), Katz & Murphy (1992), Manacorda *et al.* (2011), Ottaviano & Peri (2011) uses 5-year experience groups. In the estimation results in Section 5.1 I also report results for 5-year and 20-year cells.

3.2 Labor Market Equilibrium

Labor markets are perfectly competitive and clear in every period. Profit-maximizing firms pay each skill group L_{ijt} a real wage w_{ijt} equal to the group's marginal product $w_{ijt} = \partial Q_t / \partial L_{ijt}$. This equation is the result of a partial differentiation of equations (1)-(3) and describes the firms' labor demand for skill group ijt. The log of this equation yields a log-linear labor demand curve,

$$\begin{aligned} \log w_{ijt} = \log \alpha A_t + (1-\alpha) \log K_t + (\alpha - 1 + \frac{1}{\sigma_{ED}}) \log L_t + \log \theta_{it} \\ + (\frac{1}{\sigma_{EXP}} - \frac{1}{\sigma_{ED}}) \log L_{it} + \log \gamma_{ijt} - \frac{1}{\sigma_{EXP}} \log L_{ijt}, \end{aligned} \tag{4}$$

where $\frac{1}{\sigma_{EXP}}$ is the slope coefficient, while all other terms on the right-hand side of equation (4) are intercepts that vary along the dimensions indicated by the indices, i.e. time, education and experience. Any change in one of the factors on the right-hand side alters the marginal product, which leads to a change in the real wage *ceteris paribus*. Hence, the wage of group ij depends on its own labor supply, as well as on the labor supply of all other groups of workers. Therefore, it is not only the absolute scarcity of group ij which determines its wage, but also the relative scarcity of this group compared to all other skill groups.

From equation (4), it is possible to generate an estimating equation for σ_{EXP}, controlling for all other factors that affect the real wage. For the case of EU enlargment, these controls are particularly important, as EU accession was accompanied by increased FDI inflows, a deeper trade integration and the inflow of EU structural funds, which have an impact on labor demand and ultimately on wages. Controlling for such factors is possible because the variation in all terms on the right-hand side of equation (4) except $\left(-\frac{1}{\sigma_{EXP}} \log L_{ijt}\right)$ can be absorbed by dummies and interaction terms.

$\left(\log \alpha A_t + (1-\alpha)\log K_t + (\alpha - 1 + \frac{1}{\sigma_{ED}})\log L_t\right)$ only varies over time, so that a set of time dummies δ_t absorbs this variation. An interaction of time and education group dummies δ_{it} absorbs $\left(\log \theta_{it} + (\frac{1}{\sigma_{EXP}} - \frac{1}{\sigma_{ED}})\log L_{it}\right)$, which varies across education groups and over time. The parameters γ_{ijt} and the labor input L_{ijt} both vary along the dimensions time, education and experience, so that the inclusion of an interaction of the respective dummies would absorb all the variation and the model would be fully saturated. In this case $\frac{1}{\sigma_{EXP}}$ could not be identified. To circumvent this problem, I assume that the relative productivity of each experience group is constant over time, so that the variation of γ_{ijt} is absorbed by an interaction of education and experience dummies, δ_{ij} and an error term ε_{ijt}. This is a standard assumption in the literature[8] and in the time horizon of 5 years it is plausible that the relative productivity of an experience group does not change fundamentally. Moreover, as a robustness check in Section 5 I add an additional set of time*experience interaction terms to the estimating equation.

σ_{EXP} can be consistently estimated from

$$\log w_{ijt} = \delta_t + \delta_{it} + \delta_{ij} - \frac{1}{\sigma_{EXP}} \log L_{ijt} + \varepsilon_{ijt}. \tag{5}$$

4 Data and Descriptive Statistics

The empirical analysis requires two datasets: one for the estimation of the structural parameters that characterize the Lithuanian labor market and one for the quantification of the number of emigrants per skill group for the simulations. For the estimation of the structural parameters, I use the Lithuanian Household Budget Survey of the 2 years before and after EU enlargement: 2002, 2003, 2005 and 2006.

The number of emigrants per skill group cannot be taken from the source country, as the statistical offices usually do not keep detailed records about emigrants. An obvious

[8] See Borjas (2003), Ottaviano & Peri (2011).

reason for this lack of suitable emigration data is that in most European countries there is no legal obligation for migrants to de-register once they have emigrated. The consideration of the case of Lithuanian emigration after EU enlargement has the advantage that within the EU Lithuanians were only allowed to migrate to the UK, Ireland and Sweden, while all other old EU countries kept their labor markets closed for a transitional period up to 2011. Consequently, I can obtain the number of emigrants from the register data of the destination countries. Since the numbers of migrants to Sweden were relatively small[9], I will neglect Sweden and only use census and work permit data from Ireland and the UK.

4.1 Lithuanian Household Budget Survey

The Lithuanian Household Budget Survey (HBS) is conducted annually by the Lithuanian Statistical Office with a random sample of 7000-8000 households. The sample is representative at the individual level and includes all people aged 18 or older, for which information on their age, education, income from employment, and personal characteristics such as marital status, number of children and place of residence are available. The HBS does not contain information on the sector the respondents are employed in or their occupation.

To obtain the monthly real wages I deflate the variable *income from employment* using the harmonized consumer price index (HCPI).[10] Table 1a) displays the summary statistics for the HBS. The average real wages increase for all groups between 2002 and 2006. The magnitude of the standard errors of the average wages indicates a considerable variation of wages within each skill group.

Income data are self-reported, which can be subject to a misreporting bias. However, this bias should be negligible. Comparing the average wages in Table 1a) with the average

[9] See Wadensjö (2007).
[10] See Table 1d) for the HCPI.

Table 1 – Summary Statistics Lithuanian HBS

a) Lithuanian HBS

Survey Year			**2002**	**2003**	**2005**	**2006**
Number of Workers		All Workers	3950	4136	4042	3874
		Men	2322	2411	2426	2314
		Women	1628	1725	1616	1560
	Education	Lower Sec	348	431	435	384
		Upper Sec	2726	2860	2733	2614
		Third-level	876	844	874	876
Age			42.9	42.5	43.1	43.4
Experience			24.5	24.1	24.6	24.9
Real Wage		All Workers	1084	1142	1339	1533
(monthly, in LTL)			(799)	(836)	(954)	(1093)
		Men	1185	1152	1440	1688
			(856)	(913)	(981)	(1134)
		Women	940	988	1189	1303
			(684)	(686)	(890)	(985)
	Education	Lower Sec	689	768	946	1045
			(466)	(545)	(706)	(707)
		Upper Sec	952	1019	1203	1382
			(619)	(667)	(784)	(938)
		Third-Level	1653	1752	1964	2197
			(1076)	(1129)	(1203)	(1351)

b) Irish Census

			2002	2003	2005	2006
Number of Workers		All Workers	1274	-	-	11501
		Men	671	-	-	6557
		Women	603	-	-	4944
	Education	Lower Sec	211	-	-	2315
		Upper Sec	808	-	-	7166
		Third-level	255	-	-	2020
Age			29.5	-	-	30.7

c) Work Permit Data

		2002	2003	2005	2006
NINo Numbers	(UK)	1430	3140	10710	24200
PPS Numbers	(Ireland)	2709	2394	18680	16017

d) Aggregate Data, Lithuania

		2002	2003	2005	2006
Monthly Wage (in LTL)	Men	1173	1227	1420	1676
	Women	998	1029	1167	1356
HCPI	2005=100	97.334	96.291	100	103.788
Unemployment Rate		13.8%	12.4%	8.3%	5.6%

Note: Standard errors of average values in parentheses. HBS: Number of private sector workers between 18 and 64 years. Education groups and work experience are determined as described in Section 4. Real wages in Litas (LTL) are deflated by the harmonized consumer price index (HCPI).
The Irish census was conducted in 2002 and 2006 only. Data from the Irish census contain all Lithuanian workers who finished their education.
Sources: HBS and Irish census: Own calculations. Work permit data: UK Home Office, Irish Social Welfare Office. Panel d): Statistics Lithuania.

monthly wage for men and women working in the private sector from the Lithuanian live register in Table 1d), the difference between the two turns out to be minor, which indicates the absence of misreporting bias in the data.

I restrict the sample to private sector workers of working age, i.e. 18-64 years and exclude public sector workers from the sample, as wage determination in the public sector is usually not based on the market mechanism of supply and demand, but on seniority. Additionally, I drop the following observations: if the variable *disposable income* is negative, if the socioeconomic status is *pensioner* or *other*, and if workers are self-employed or own a farm.

For each worker the highest obtained degree counts for her classification into one of the education groups *lower secondary education*, *upper secondary education* and *third-level degree*. Lower secondary education includes all workers with less than a high school degree. Upper secondary school classifies all workers with a high school degree that allows them to go to college as well as workers who obtained a degree that is less than the equivalent of a B.Sc degree. Third-level degrees are all degrees that are at least equivalent to a B.Sc and would allow workers to apply for an international M.Sc programme. To make the third-level education comparable I choose the general minimum requirement for graduate admission at the London School of Economics (LSE) as a criterion. According to this definition, workers with a degree *Bakalauras*, *Magistras* or higher are classified as having a third-level degree. Workers with some college education, but a degree that requires less schooling than the two mentioned above are classified as having an upper secondary education.[11] This clustering may appear fairly broad, given that the Lithuanian education system offers a variety of educational tracks.[12] However, these broad categories are necessary to match the characteristics of the stayers with those of the emigrants.

[11] For the admission minimum requirement at the LSE, see http://www2.lse.ac.uk/study/informationForInternationalStudents/countryRegion/europeEU/lithuania.aspx .

[12] See www.euroguidance.lt for a description of the Lithuanian education system.

The HBS gives 12 education groups, while the data on the emigrants only distingiushes between 5. Furthermore, broad categories ensure that the number of observations within each group is large enough to allow for the calculation of reliable average wages and emigration numbers.[13]

The HBS does not directly give any information about the actual work experience of an individual. Therefore, I calculate the potential work experience of individual i with the formula $exp_i = age_i - education_i - 6$, in which $education_i$ represents the years of schooling it takes to obtain individual i's highest degree, age_i is i's age and 6 is subtracted because the compulsory schooling age in Lithuania is 6 years. $education_i$ equals 10 years for lower secondary education, 12 for upper secondary education and 15 for third-level degree. While this measure is appropriate for men, a caveat applies for the use of the same formula for the calculation of the work experience of women, who might have less actual work experience due to maternity leave. However, for Lithuania the use of this formula for women should not be problematic. First, the country has had low fertility rates of 1.5 children per women and less since the 1980s. Second, as is typical for a former socialist country, women between 20 and 64 years have a high employment rate with 65%, compared to the EU average of 62%.[14] Moreover, to overcome this potential problem of misclassification of women I use data on men only in a robustness check.

4.2 Irish Census

For the simulations, I use immigration data from the two main receiving countries, Ireland and the UK. The Irish Census is conducted by the Irish Central Statistics Office (CSO) every 4-5 years and contains all people living in Ireland and present in the night of the survey. For this study, I use the survey rounds in 2002 and 2006. The CSO provided me

[13] Table 8 in the appendix illustrates in detail the aggregation of the educational tracks into the three education groups.

[14] Source: Eurostat. Employment rates from 2009.

with a tabulation of the number of all Polish and Lithuanian immigrants in Ireland by gender, age and education.

The census reflects a lower bound to the number of emigrants, as it only captures migrants who are present on the survey night. People who came for a summer job or a time shorter than one year may not be included in the census.

For the calculation of the number of emigrants I only use data on migrants whose education is finished, which is 93% of Lithuanians in the census 2002 and 85% in 2006. As we can see in Table 1b) the number of workers in the Irish census increased by a factor 10 between 2002 and 2006. Interestingly, the educational distribution and the average age did not change significantly over time. The gender distribution of migrants in 2006 is slightly skewed towards men. Comparing the Lithuanian migrants in the Irish census with the workers in Lithuania, we can see that the education distribution is similar, although the migrants are on average 13 years younger than the stayers. In 2006 workers with a lower secondary education are slightly overrepresented among the migrants (20% among migrants compared to 10% among stayers), while workers with a third-level education are slightly underrepresented (18% among migrants compared to 23% among stayers). These summary statistics indicate two types of selection behavior: migrants are more likely to be young than stayers and on average less educated, although the extent of selection across education groups is minor.

4.3 Work Permit Data: PPS and NINo Numbers

The number of workers who obtained a work permit in Ireland and the UK defines an upper bound to migration from Lithuania to Ireland and the UK. Every worker who moves to Ireland or the UK and wants to take up employment has to apply for a Personal Public Service (PPS) number in Ireland or a National Insurance Number NINo in the

UK.[15] These data capture all workers that emigrated from Lithuania to one of those two countries, regardless of how long they stay in the host country. There is no obligation to de-register for workers in their home country, so it is not possible to measure, how many people returned to Lithuania and how much time they spent in the host country. Double counts are unlikely, however, as workers keep their PPS and NINo numbers, no matter how often they move back and forth between Lithuania and Ireland or between Lithuania and the UK. The PPS and NINo numbers could undercount the actual number of migrant workers coming to Ireland and the UK, as some workers might not have registered when they came to work for a short period in time or wanted to avoid having to pay income taxes. These cases should not be too important for the calculation of emigrant numbers, however. Workers who only migrated for a short period in time and did not register for that reason can hardly be seen as emigrants, because they were part of the Lithuanian workforce for the whole time. Assessing the number of workers who migrated for a longer period without registering is difficult, but it should be small given the high number of migrants who actually *did* register. In summary, even if the work permit data may slightly undercount the actual number of migrants, for the simulations this means that the actual labor supply shock might be larger so that the predicted wage changes resulting from emigration are lower than the actual ones.

4.4 Calculation of Emigration Rates

To simulate the effect of the migration of different skill groups on wages, the labor supply shock $\frac{\Delta L_{ij}}{L_{ij}}$ for each skill group has to be quantified. This fraction, which can be interpreted as the emigration rate, i.e. the percentage of workers in skill group ij who emigrated, consists of the change in labor supply in a given time span ΔL_{ij} and the

[15] For more information about PPS and NINo, see www.welfare.ie and www.direct.gov.uk

number of workers of the same skill group in Lithuania, L_{ij}.[16] L_{ij} can be directly computed from the HBS. Let the sample of a skill group ij contain $l = 1, ..., L$ workers. The number of workers in this skill group is the sum of the sampling weights p_{ijl}. Thus, $L_{ij} = \sum_{l=1}^{L} p_{ijl}$.[17]

The shift in labor supply ΔL_{ij} cannot be taken directly from the data, but needs to be computed from several Irish and UK data sources. This is due to the fact that I have detailed data on Lithuanian migrants living in Ireland from the Irish census, but only aggregate figures on the migrants coming to the UK.[18] To compute the labor supply shifts, I assume that the skill distribution of migrants coming to Ireland is the same as the distribution of those coming to the UK. This assumption can be justified by the fact that there was little visible sorting behavior of migrants from the New Member States between Ireland and the UK with respect to age and education. There may have been a sorting behavior with respect to occupations, for example immigrants in Ireland work more in the construction sector and immigrants in the UK in the service sector but this study focuses on more broadly defined skill groups, for which the distribution is similar.

Figure 5 shows the education and age distribution of all migrants from the New Member States in Ireland and the UK. The share of third-level educated workers was slightly higher in the UK, while the share of workers with an upper secondary education was higher in Ireland. In the youngest group, between 18 and 24 years of age, the UK saw relatively more immigrant workers than Ireland. Consequently, the assumption that the experience distribution are the same implies that the predicted wage changes for young workers can be slightly downward-biased, meaning that the actual wage changes caused

16 Note that the supply shifts only consist of emigrants, but leave out migrants who came to Lithuania. As this paper focuses on the impact of emigration and it is possible to isolate this effect in the simulations, I do not consider the potentially offsetting wage impact of immigration.

17 L_{ij} is the average value of L_{ijt} in the years $t = 2002, 2003, 2005, 2006$.

18 The UK labour force survey, the most accessible quarterly representative survey of the workforce in the UK, cannot be used to extract reliable data on the skill distribution of a particular country, as the number of observations per country is too small.

by emigration will be at least as high as those predicted by the model.

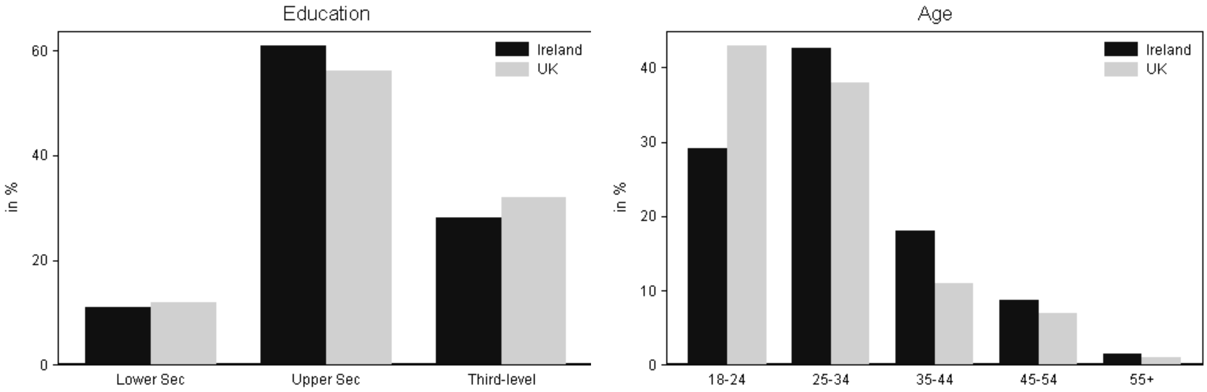

Figure 5 – Education and Age Distribution of Immigrants from the New Member States in the UK and Ireland

Source: Educational distribution as reported in Barrett & Duffy (2008)) for Ireland and Dustmann *et al.* (2010) for the UK. Age distribution: own calculations from the Irish census (Lithuanian migrants only) for Ireland. UK distribution of all A8 immigrants from Home Office, UK Border Agency (2009).

Using the information from the UK and Irish data sources, the number of emigrants per skill group ij is calculated as

$$\Delta L_{ij} = (IE_{ij,2006} - IE_{ij,2002}) \left(1 + \frac{\text{Work permits in the UK 2002-2006}}{\text{Work permits in Ireland 2002-2006}} \right). \tag{6}$$

$(IE_{ij,2006} - IE_{ij,2002})$ is the difference in the stock of Lithuanian immigrants in Ireland between 2002 and 2006 in skill group ij. The second expression in parentheses on the right-hand side of equation (6) augments the number of migrants to Ireland by a weighting factor that takes account of the number of workers who migrated from Lithuania to the UK. The 1 accounts for those who moved to Ireland and the fraction (Work permits in the UK 2002-2006)/(Work permits in Ireland 2002-2006) is the number of work permits given to Lithuanians in the UK between 2002 and 2006 as measured by the NINo numbers relative to the corresponding number in Ireland. Over the course of these 5 years 43% more Lithuanians received a work permit in the UK than in Ireland, so that the fraction is 1.43.

Table 2 – Emigration Rates 2002-2006

		Education		
		Lower Sec	Upper Sec	Third-Level
Work Experience	0-10 Years	10.7%	14.4%	12%
	11-20 Years	5%	4.3%	2.9%
	21-30 Years	5.8%	2.1%	2.6%
	31+ Years	1.3%	1%	1.4%

Note: The emigration rate per skill group denotes the share of workers in every skill group who emigrated between 2002 and 2006. The average emigration rate, weighted by the size of the skill group, is 5%. The emigration rates are calculated as the number of emigrants to Ireland and the UK divided by the average size of the skill group between 2002 and 2006. Sources: own calculations, as explained in Section 4.4.

Table 2 summarizes the calculated emigration rates per skill group and reveals the selection pattern of emigrants along the old-young dimension. Most emigrants are young, with a work experience of 10 years and less. Only very few older workers emigrated. Across education groups the emigration rates were balanced, so that the country did not suffer from a *brain drain*. The aggregate emigration rate, weighted by the size of the skill groups in the Lithuanian workforce is 5%.

5 Estimation of Structural Parameters

5.1 Identification and Estimation of σ_{EXP}

Using equation (5), I estimate σ_{EXP} with the number of workers per skill group as a labor input L_{ijt}.[19] An estimation of the demand curve with OLS does not yield consistent estimates as the results suffer from simultaneity bias. The equation is a demand curve, but the observations in the data are equilibrium points in the (w_{ijt}, L_{ijt}) space, which were determined by an interplay of supply and demand factors. To disentangle the labor demand and supply curves and identify the slope of the demand curve, an exogenous

[19] Ottaviano & Peri (2011) use the number of working hours from workers in this skill cell as a measure for labor input, which is more accurate than the number of workers. However, as the HBS does not include data on working hours, the number of workers serves as a proxy.

labor supply shifter is needed that does not shift labor demand, i.e. an instrumental variable (IV). Given an appropriate instrument, $\frac{1}{\sigma_{EXP}}$ can be consistently estimated with a two-stage-least-squares (2SLS) estimator.

Most of the literature, e.g. Borjas (2003), Aydemir & Borjas (2007), Ottaviano & Peri (2011), uses immigration as an instrument for labor supply. For the current study, the corresponding instrument would be emigration from Lithuania.[20] To be valid as an instrument, it has to be uncorrelated with labor demand over and above the correlation absorbed by the dummies and interaction terms in the estimating equation (5). However, in light of the scale of the emigration wave following EU enlargement, the emigration of workers of a specific skill group could also shift the demand for workers in this particular group.

Take as an example computer programmers, who most likely have a third-level degree and 0-10 years of work experience. The emigration of a large number of programmers may have a negative scale effect on the productivity of their firms, which lowers the demand for programmers that stay behind. Consequently, the emigration of workers in this skill group would be correlated with the group's labor demand, which makes emigration invalid as an instrument for labor supply.

To overcome the problem of identification in the presence of simultaneity bias, I propose a new instrument for labor supply, *birth cohort size*. This instrument follows the logic that the size of a birth cohort should be highly correlated with labor supply today. For example, if 50 years ago many people were born, we should observe many 50-year-olds in the workforce today. Obviously, the size of a birth cohort is not a perfect predictor for the labor supply today, because it does not take into account demographic factors like emigration, deaths or early retirement. However, as long as birth cohort size is *sufficiently correlated* with labor supply, it is suitable as an instrument.

[20] Immigration into Lithuania would be clearly invalid as an instrument, as it is very likely to be correlated with labor demand in Lithuania.

To be valid as an instrument, the size of a birth cohort must not be correlated with labor demand today, over and above the deterministic factors that are already controlled for in the first stage. In other words, the size of a birth cohort 50 years ago may well be correlated with contemporaneous demand shifters such as physical capital or total factor productivity but these correlations are absorbed in the first stage with the time dummies δ_t. The only possible violation of the exclusion restriction would be an impact of the birth cohort size on the stochastic part of the estimating equation, the error term ε_{ijt}. However, it is implausible that the size of a birth cohort, which was determined many years ago, leads to a stochastic shift in labor demand today. Note that the youngest cohort in the dataset is 18 years of age, the oldest 64. It appears unlikely that the number of people born at least 18 years ago leads to a stochastic shift of the labor demand curve today. This clear exogeneity of the birth cohort size makes it more suitable as an instrument than emigration.

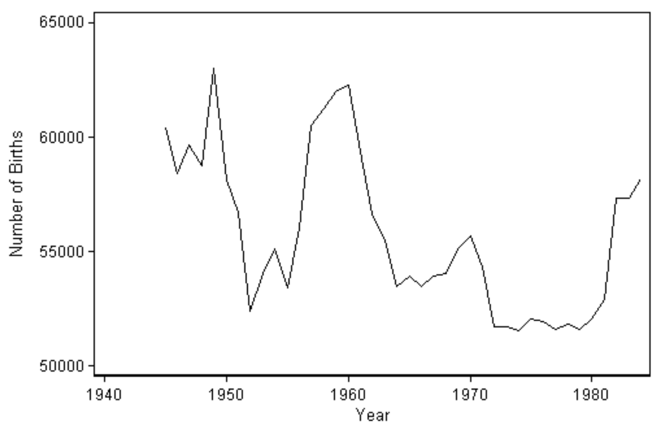

FIGURE 6 – NUMBER OF BIRTHS PER YEAR IN LITHUANIA.

Note: Total number of people born per year in Lithuania. *Source:* Statistics Lithuania.

The Lithuanian Statistical Office provides data on the total number of births per year from 1928 to 2010, excluding the years of the Second World war (1939-1945). Figure 6 shows the number of births per year from 1945 to 1984, the years in which most workers in the sample were born. As we can see there is a large variation in the number of births over time, which can potentially be exploited in the IV regressions. The data in this time series are annual, while the observations in the sample are skill groups that consist of 10 subsequent age cohorts, so that the question arises, which measure predicts the number of workers of a skill group today most accurately. There are three candidates: 1) the total number of births, 2) the average number of births and 3) the median number of births per skill group. Take as an example the skill group *upper secondary education, 0-10 years of work experience* in the HBS of 2002. This skill group consists of 11 birth cohorts, born between 1974 and 1984. The total number of births is the sum over all the people born between 1974 and 1984, the average number of births is the average in this time span and the median number of births is the corresponding median. Taking the average, the sum or the median of the number of births ensures sufficient variation in the calculated size of the birth cohort, since the time spans of the birth years of any two skill groups is different and so is the size of their birth cohort. As an example, consider workers with a work experience of 0-10 years in the HBS of 2002. Their birth years differ depending on their education. Workers with 0-10 years of work experience and a lower secondary education were born between 1976 and 1986, whereas those with a third-level degree were born five years earlier, between 1971 and 1981. Consequently, despite the same level of work experience, the cohort sizes of these two groups differ.

The choice of the instrument depends on its statistical power, i.e. on the correlation of the instrument with the endogenous regressor. As it turns out in the first-stage regressions, the total number and the average number of births are only weakly correlated with labor supply, so that they cannot be used as instruments.[21] The F-Statistic of the median number of births is 16.085, which is a sufficiently high correlation of the instrument with the endogenous regressor. The reason for the weak correlation of the first two instruments is their sensitivity to outliers in the number of births. As we can see in Figure 6, the number of births was subject to high fluctuations and the sum and

[21] The F-Statistics are 0.358 for the average number of births and 0.212 for the total number of births.

Table 3 – Regression results for σ_{EXP}

Dependent variable: log real wage

	(1)	(2)	(3)	(4)	(5)
Method:	OLS	IV	IV	IV	IV
Experience cells	10-year	10-year	10-year	20-year	5-year
log(Nr of Workers)	-0.114	-0.631***	-0.680**	-0.569***	-0.287
	[0.0719]	[0.1733]	[0.2927]	[0.161]	[0.604]
Observations	48	48	48	24	96
R^2	0.9742	0.9416	0.9440	0.9790	0.9466
F-Statistic		16.085	3.196	7.914	0.456
σ_{EXP}	8.77	1.58	1.47	1.76	3.48
Controls:					
δ_t	yes	yes	yes	yes	yes
δ_{it}	yes	yes	yes	yes	yes
δ_{ij}	yes	yes	yes	yes	yes
δ_{jt}	no	no	yes	no	no

Note: Robust standard errors in brackets. Significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Controls: δ_t: year dummies, δ_{it}: interaction year*education, δ_{ij} interaction education*experience, δ_{jt}: interaction experience*time. σ_{EXP} is calculated as the negative inverse of the estimated coefficients.

average are sensitive to large changes in the number of births. These jumps dilute the ability of the instruments to predict the labor supply of a whole *10-year* skill group. The median is not sensitive to these jumps, so that it is a better predictor for labor supply.

Table 3 reports the estimation results for σ_{EXP}. All regressions are weighted with sampling weights.[22] I report the OLS results for comparison but as previously explained, they are not reliable because of simultaneity bias. The IV estimates lie consistently around -0.63, which implies a σ_{EXP} of 1.58.

The estimating equation (5) does not contain an interaction *time*experience*, which could bias the results if the relative productivity of an experience group changes over time. This could be an issue if there is a positive selection of emigrants within an experience

[22] A sampling weight is the inverse probability that an observation is included in the sample. The survey contains sampling weights at the individual level. The sampling weight for each skill group is the sum of all the sampling weights of this skill group.

group. If workers with better unobservable characteristics leave, the remaining workers are on average less productive. As column (3) in Table 3 shows, the point estimate does not differ substantially from the baseline. However, the instrument has less power due to the high degree of saturation.

To ensure that the results are not merely driven by the choice of the intervals of the experience groups, I undertake the same analysis for 20-year and 5-year experience groups. In the case of 20-year groups the dataset only consists of 2 experience groups in every survey year. The estimated coefficient is smaller in absolute value than in the benchmark model with 10-year groups, which means that old and young workers can be seen as closer substitutes with this specification. However, the difference in absolute values of these coefficients is not substantial. In either of the two cases the labor demand curve is steeper than the one found in studies on the US or Germany. In the case of 5-year experience groups the instruments have considerably less power than in the case of 20 or 10-year groups. A reason for the weakness of the instrument can be the high degree of noise in the data, caused by a small number of observations per skill group.

The estimates for σ_{EXP} in the baseline scenario are lower in magnitude than those found in studies that previously used a similar model for the United States, the UK and Germany. For the US, the estimates range between 3.5 found by Borjas (2003) to 5 in Card & Lemieux (2001) to 7 in Ottaviano & Peri (2011). All these studies use data on 5-year experience groups, men only, and different rounds of the US census and Current Population Survey. Manacorda *et al.* (2011) estimate a yet higher elasticity of around 10 for the UK, whereas the estimates for Germany in D'Amuri *et al.* (2010) are lower with 3.1. The fact that the elasticities for Lithuania are lower than any of those listed above means that workers with different work experience are less substitutable in Lithuania than they are in Germany, the UK or the United States. A smaller value is plausible for two reasons. First, the above-mentioned studies estimate a long-run elasticity between skill groups while I estimate a short-run elasticity. In the long run, workers of any age can adjust their skills to changes in the labor market, which is not possible in the short run. As a consequence, any two skill groups are closer substitutes in the long run than in the short run.

A second reason lies in the history of the country. As Lithuania was part of the Soviet Union until 1990, older workers received their education and gathered their first work experience in a centrally planned economy, whereas younger workers were educated and grew up in the environment of a market economy. Consequently, the skills of young workers should be immediately applicable to the labor market, whereas older workers may need some time for adjustment and re-training, which can lead to a low degree of substitutability between old and young workers. A recent paper by Brunello *et al.* (2011) backs this explanation. They show that in transition countries men who were educated under socialism have lower returns to education than men who were educated under a free market economy.

5.2 Identification and Estimation of σ_{ED}

As a next step I estimate the elasticity of substitution between education groups σ_{ED}.

The estimation equation for this parameter is derived in the same way as equation (5),

$$\log \bar{w_{it}} = \delta_t + \delta_{it} - \frac{1}{\sigma_{ED}} \log \bar{L_{it}} + \varepsilon, \tag{7}$$

in which δ_t is a vector of year dummies and δ_{it} is a vector of interactions between education and year dummies. $\bar{w_{it}}$ is the average real wage paid to education group i at time t. $\bar{L_{it}}$ is a labor input calculated from the composite in equation (3).[23]

In theory, σ_{ED} can be identified from equation (7). However, due to the small number

[23] The γ_{ij} are calculated from the coefficients of the δ_{ij} in equation (3) with $ij = 11$ as the base

of observations, it is not possible to identify σ_{ED} without imposing further restrictions. Otherwise, the model would be too saturated and the coefficient for $-1/\sigma_{ED}$ cannot be statistically distinguished from zero. The dataset consists of four survey rounds (2002, 2003, 2005, 2006) with three education groups in each round, which results in a total of 12 observations, on which the estimations of σ_{ED} can be based.

To overcome this small sample problem I propose two solutions. First, to obtain a value for σ_{ED} or at least its order of magnitude, I estimate equation (7) with OLS, imposing restrictions on the dummies and interaction terms. Second, in Appendix B I re-run the simulations of the wage effect using the very small and very large values for σ_{ED}. Given that the large part of the wage effect is driven by the old-young dimension of the emigration wave and not by the selection of emigrants across education groups, the choice σ_{ED} has a relatively small impact on the results.

Table 4 – OLS Results for σ_{ED}

Dependent variable: log real wage

	(1)	(2)	(3)	(4)
log $\bar{L}_{it}$	-0.85***	-0.85***	-0.85***	-0.155
	[0.018]	[0.010]	[0.011]	[0.145]
Time trend	no	yes	no	no
Year dummies	no	no	yes	no
Educ-specific time trend	no	no	no	yes
Observations	12	12	12	12
Adj. R^2	0.9954	0.9985	0.9981	0.9999
σ_{ED}	1.18	1.18	1.18	8.69

Note: Robust standard errors in brackets. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table 4 shows the results of the OLS regressions. Surprisingly, in the first 3 specifications, the coefficients are highly significant. Only when δ_{ij} is approximated by linear time trends, the model is fully saturated and the coefficient becomes insignificant. The point

category, so that $\delta_{11} = 0$. Then, $\gamma_{ij} = \exp(\delta_{ij}) / \left(1 + \sum_i \sum_j \exp(\delta_{ij})\right)$.

estimates of columns (1)-(3) suggest an elasticity σ_{ED} of 1.18. I will use this parameter for the baseline simulations. Previous literature came to similar results for σ_{ED} for US data. Krusell *et al.* (2000), as well as Ciccone & Peri (2005) estimate a σ_{ED} of 1.5, Borjas (2003) 1.3 and Card & Lemieux (2001) 2.25. Compared to these results, the σ_{ED} in this study is a short-run elasticity, which explains why it is slightly smaller.

6 Simulation of the Wage Effects

6.1 Simulation Equation

In this section, I simulate the emigration shock that occured after EU enlargement in this labor market and calculate the new equilibrium wage for each skill group. The calculated wage change is the difference between the equilibrium wages after and before the migration shock. The results of this simulation have a *ceteris paribus* interpretation. The fundamental structure of the labor market is held constant, so that the simulations yield the change in wages in absence of other adjustment channels. To obtain the simulation equation I differentiate equation (4)[24] and drop the time subscripts

$$\begin{aligned}\frac{\Delta w_{ij}}{w_{ij}} &= (1-\alpha)\frac{\Delta K}{K} - (1-\alpha)\frac{\Delta L}{L} + \frac{1}{\sigma_{ED}}\frac{\Delta L}{L} \\ &+ (\frac{1}{\sigma_{EXP}} - \frac{1}{\sigma_{ED}})\frac{\Delta L_i}{L_i} - \frac{1}{\sigma_{EXP}}\frac{\Delta L_{ij}}{L_{ij}}.\end{aligned} \tag{8}$$

Expressions L_t and L_{it} in equation (8) are labor aggregates and can as such be expressed in terms of L_{ijt}.[25] The Δs measure the change in a variable from 2002 to 2006.

[24] A_t, α, θ_{it} and γ_{ij} are held constant.

[25] Note that $\frac{\Delta L_i}{L_i} = \sum_j \left(\frac{\gamma_{ij} L_{ij}^{\frac{\sigma_{EXP}-1}{\sigma_{EXP}}}}{\sum_j \gamma_{ij} L_{ij}^{\frac{\sigma_{EXP}-1}{\sigma_{EXP}}}} \right) \frac{\Delta L_{ij}}{L_{ij}} = \frac{1}{s_{it}} \sum_j s_{ijt} \frac{\Delta L_{ijt}}{L_{ijt}}$ and $\frac{\Delta L}{L} = \frac{1}{\alpha} \sum_i \sum_j s_{ij} \frac{\Delta L_{ij}}{L_{ij}}$.

6.2 Model Calibration and Simulation Results

The magnitude of the impact of the calculated wage changes depends on the parameters α, σ_{ED} and σ_{EXP}. Lithuanian national accounts data reveal that the income share of labor $\alpha = 0.8$ For the elasticities of substitution I take the values from the point estimates in Section 5, $\sigma_{EXP} = 1.58$ and $\sigma_{ED} = 1.18$.

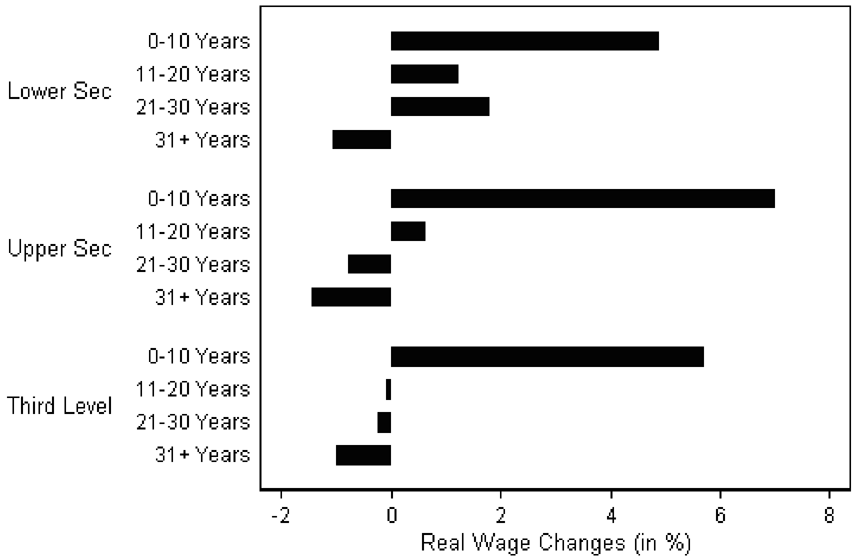

Figure 7 – The Impact of Emigration on Wages

Note: Labels on the y-axis denote education and work experience. The graph displays the simulation results for the baseline scenario, as described in Section 6.1.

Figure 7 displays the simulated wage changes for the baseline scenario. A general pattern emerges: emigration caused an increase in the wages of young workers, while the wages of old workers decreased. Young workers gained between 4.9% and 7% from emigration. For workers with a work experience between 10 and 30 years the model predicts wage changes close to zero. Old workers with more than 30 years of work experience lost around 1% from emigration.

s_i denotes the income share of education group i and s_{ij} denotes the income share of skill group ij. s_i and s_{ij} are calculated from the sampling weights in the HBS using the information on all men and women in the sample.

These results suggest that emigration had a significant impact on the wage distribution between old and young workers. Because of the emigration wave after 2004, the youngest cohort became significantly smaller and this change in the composition of the workforce changed the wage structure. As previously shown in Figure 3, the wage premium for older workers was reversed into a wage penalty between 2002 and 2006. Emigration cannot entirely account for these changes in the wage premium but the results give evidence that it played a significant role.

To account for the uncertainty in the estimates of the structural parameters I calculate the standard errors of the wage changes using Monte-Carlo simulations. The values of σ_{EXP} and σ_{ED} are drawn independently from a normal distribution, $\frac{1}{\sigma_{EXP}} \sim N(0.63, 0.03)$ and $\frac{1}{\sigma_{ED}} \sim N(0.85, 0.01)$.[26] The simulated standard errors reported in Table 3 are the average standard errors of 10000 replications. Comparing the calculated wage changes to the simulated standard errors, we can see that most wage changes are statistically significant at a significance level of 5% or lower. These simulated standard errors only take into account the uncertainty that arises from the estimation of the structural parameters. The additional uncertainty given by the assumptions about the number of migrants to the UK and the calculation of the labor aggregates are adressed in the robustness checks in Section B.

Although most of the predicted wage changes are statistically significant, only the wage changes for young workers are of economic significance. This can be seen when we compare the simulated wage changes caused by migration with the total wages changes for Lithuanian workers between 2002 and 2006 in Figure 2. The wages of all groups increased by between 20% and 80%, so that emigration can explain between 10% and 30% of the wage changes of young workers, but the wage changes of workers with a work experience higher than 10 years are driven solely by other factors, such as domestic and

[26] Note that I take the inverse of the parameters, because these are the results of the IV regressions in Section 5.1.

Table 5 – Decomposition of the Wage Effect of Emigration

Education	Experience (Years)	Total Wage Change	Standard Error	Decomposition of Total Wage Change (1) Own-wage	(2) Cross-wage	(3) Scale	(4) Production
Lower Secondary	0-10	**4.89**	0.93	6.76	1.15	-3.96	0.93
	11-20	**1.23**	0.08	3.10	1.15	-3.96	0.93
	21-30	**1.82**	0.08	3.69	1.15	-3.96	0.93
	31+	**-1.07**	0.72	0.80	1.15	-3.96	0.93
Upper Secondary	0-10	**7.02**	1.76	9.11	0.93	-3.96	0.93
	11-20	**0.64**	0.00	2.74	0.93	-3.96	0.93
	21-30	**-0.78**	0.40	1.31	0.93	-3.96	0.93
	31+	**-1.43**	0.58	0.66	0.93	-3.96	0.93
Third Level	0-10	**5.72**	1.19	7.62	1.13	-3.96	0.93
	11-20	**-0.07**	0.42	1.83	1.13	-3.96	0.93
	21-30	**-0.23**	0.46	1.66	1.13	-3.96	0.93
	31+	**-1.01**	0.68	0.88	1.13	-3.96	0.93

Note: All changes in %. Standard errors are determined by Monte Carlo simulations with 10000 replications for the parameters σ_{ED} and σ_{EXP}. The total wage change can be decomposed in four effects: 1) own-wage effect, 2) cross-wage effect within an education group, 3) cross-wage effect across education groups (complementarity effect), 4) aggregate production effect.

foreign investment or productivity growth.

After noting that the predicted wage changes differ considerably between young and old workers, the question arises which factors drive these results *within the model.* Due to the nested structure of the production function, there is a variety of channels through which a labor supply shock can affect wages. The total wage effect in equation (8) can be decomposed into four effects, which are shown in Table 5. The first effect is referred to in the literature as the partial effect of migration on wages. The effects 2, 3 and 4 are general equilibrium effects that reflect the re-adjustment of the labor demand for different skill groups following changes in labor supply.

1. **Own-wage effect** $\left(-\frac{1}{\sigma_{EXP}}\frac{\Delta L_{ij}}{L_{ij}}\right)$. This effect is a direct consequence of the supply shift. If workers of skill group L_{ij} emigrate, the stayers of this group become a more scarce resource, which leads to an increase in their wages. As most emigrants were young, the own-wage effect is greatest for young workers.

2. **Cross-wage effect within an education group** $(\frac{1}{\sigma_{EXP}} - \frac{1}{\sigma_{ED}})\frac{\Delta L_i}{L_i}$. This wage change is caused by a change in the size and composition of the labor aggregate of the worker's education group. For example, the emigration of young workers with a lower secondary education increases the demand for older workers with a lower secondary education. Intuitively, the positive sign follows the logic that workers with the same education are substitutes. However, as they are not perfect substitutes, the cross-wage effect is smaller in absolute value than the own-wage effect.

3. **Scale effect** $\frac{1}{\sigma_{ED}}\frac{\Delta L}{L}$. The wage of each group of workers depends positively on the total number of workers weighted by productivity. A decrease in the total number of workers will therefore lead to a decrease in wages and this effect is the same for all workers.

4. **Aggregate Production Effect** $-(1-\alpha)\frac{\Delta L}{L}$. This effect is a direct consequence

of the functional form of the aggregate production function. In a Cobb-Douglas production function, a decrease in aggregate labor leads to an increase in output per worker, because output decreases by less than aggregate labor. If capital were to adjust fully, this effect would disappear and the predicted wage changes would be about 1% lower.

Taking all these effects together, we can draw the following conclusions: the post-EU-enlargement emigration wave led to a substantial increase in the wages of young workers, as they have become a more scarce resource. The wage increase, caused by the own-wage effect, outweighed the negative aggregate production effect. Older workers did not emigrate in large numbers but their wages were affected negatively by the scale effect and the aggregate production effect. Thinking about the own-wage effect as a supply effect and the other 3 effects as demand effects, we can conclude that for young workers the positive supply effect exceeded the negative demand effect, whereas for old workers the negative demand effect exceeded the supply effect. Even though the CES production function does in itself not account for complementarities between groups of workers, the old-young distribution of migrants and the scale effect lead to the same effect as if old and young workers were complements.

6.3 Comparison of the Structural Estimates with Reduced-Form Results

It is important to note at this point that this study does not aim at explaining the change in real wages in its entirety, but only the share of the wage changes that can be attributed to emigration. This interpretation, identifying a causal effect after controlling for all other explanatory variables, is the same as for a reduced-form approach. To assess the quality of model predictions, one has to compare the predicted wage changes from both approaches. The upper graph in Figure 8 compares the predicted wage changes from the structural

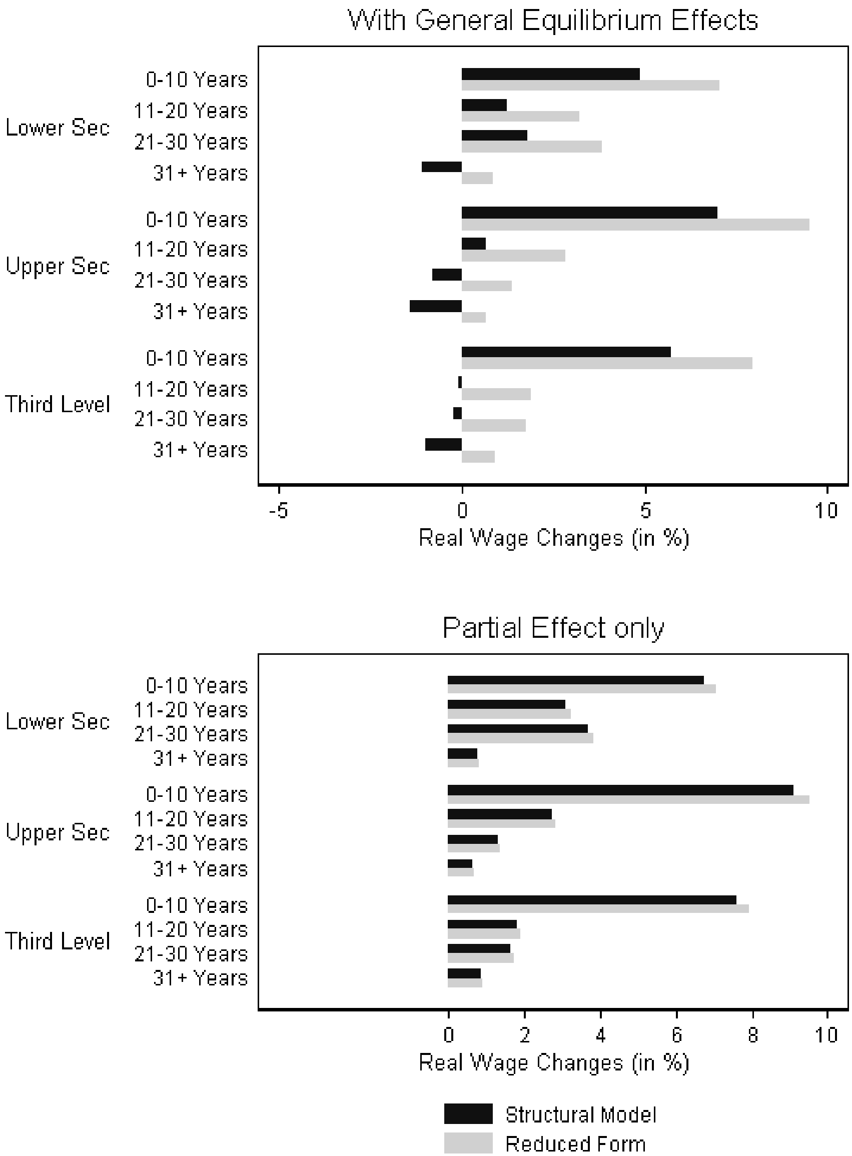

Figure 8 – Comparison: Structural Model vs. Reduced Form

Note: Labels on the y-axis denote education and work experience. The graphs display the causal impact of emigration on wages, as predicted by the structural model and the reduced form. In the upper figure the impacts on the highest nest of the CES production function, the complementarity effect and the production effect, are excluded from the structural estimates. In the lower figure, these effects are excluded.

model in this study to the estimates in Elsner (2010). The latter are positive for every skill group, since the reduced form does not take into account the complementarity effects. Once the general equilibrium effects are excluded from the structural estimates, it turns out that the predictions of both approaches are almost identical, as can be seen in the bottom graph of Figure 8.

This finding can have two interpretations. First, the reduced form identifies a partial effect and does not account for complementarities between groups of workers. In this case, the reduced form over-predicts the actual wage changes. Second, the general equilibrium effects at higher nests of the aggregate production function, i.e. the complementarity and the aggregate production effect, have no impact on wages, at least in the time span considered. In that case, the structural model under-predicts the actual wage changes.

A third possibility is that the general equilibrium effects show their effect at different times. The simulation of the structural model is a counterfactual exercise which only considers two states of the economy, before and after the shock. It is reasonable to think that the own-wage effect has a faster impact than the general equilibrium effects, which are the consequences of adjustment of the labor market through shifts in labor demand. In the 5-year period considered in this study these effects may not play a role in the wage determination yet, so that the wage changes predicted by the reduced form and the structural model without complementarity and aggregate production effect are more accurate. In the long run, going beyond the considered period in time, the general equilibrium effects may come into effect, which means that in the long run the predictions of the structural model are more adequate.

The structural model offers insights in the channels through which emigration affects the wages of stayers, but it does so at the cost of the reliance on a number of assumptions. The neoclassical demand framework presented in Section 3 is based on the assumption that labor markets clear and thus assumes away unemployment and wage rigidities. These factors could nevertheless play a role in the determination of wages, which would mean that the magnitude of the wage effects resulting from the simulations could be inaccurate. In fact, looking at Table 1d), we can see that the unemployment rate decreased substantially from 13.8% in 2002 to 5.6% in 2006, which means that labor markets became tighter over the considered period. Given the absence of information on the unemployment rate by skill group in the data, it is not possible to incorporate unemployment into the simulations. However, in the reduced-form approach Elsner (2010) controls for unemployment at the regional level and finds very similar results as in the structural model in this study. This indicates that unemployment does not alter the magnitude of the wage effect of emigration.

6.4 Discussion of the Results

In the structural model I am able to decompose the effect of emigration on wages and quantify the contribution of its subcomponents. However, there may be a number of reasons why emigration causes these wage changes in the real world that go beyond a story of a decrease in labor supply and subsequent adjustments in labor demand.

One explanation why young workers gain from the possibility of emigration is the increase in bargaining power. In 2004 workers in Central and Eastern Europe were granted the possibility to emigrate at a very small cost. For stayers this means that they should be able to negotiate higher wages under the threat of emigration. Before 2004 this threat was empty due to the high emigration costs. The gain in bargaining power was lower for older workers, since they have higher moving costs and their prospects of finding work in Ireland in the UK are considerably lower than for young workers. Moreover, because of the large number of young emigrants the labor market for young workers became tighter, which means that the same number of firms competes for fewer workers. If the labor markets for old and young workers are very different from each other, a positive wage effect should be visible among young workers but not among old workers. The finding in Section 5 that young and old workers are less substitutable in Lithuania than in the US or Germany confirms this hypothesis.

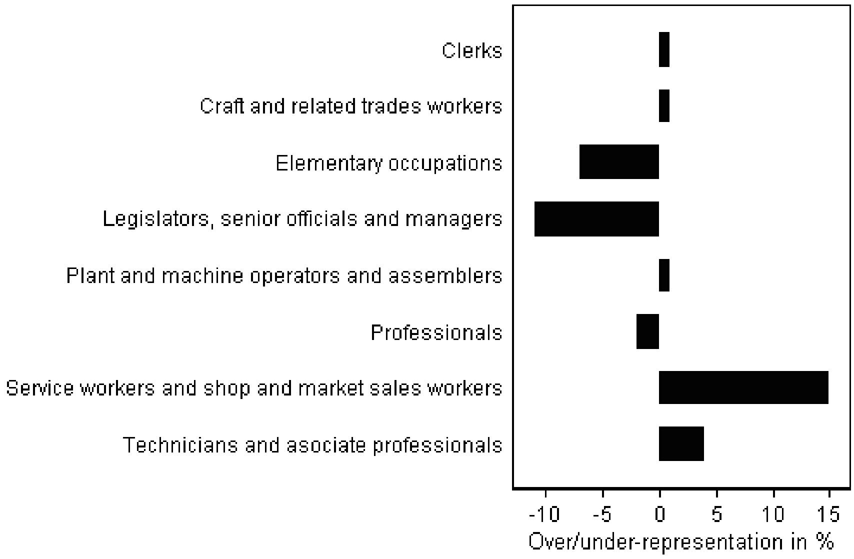

FIGURE 9 – OVER-/UNDER-EPRESENTATION OF WORKERS AGED 14-34 BY OCCUPATION

Note: The graph displays the degree of over- or under-representation of workers aged 34 and less compared to workers aged 35 and more. *Source:* 2002 Structure of Earnings Survey, conducted by Statistics Lithuania.

Another explanation could be the sectoral distribution of workers. If young workers tend to work in sectors with a high flexibility of work contracts and a high fluctuation of employees, they are more likely to switch to a better-paid job once emigration leads to labor shortages in the sector. This possibility should be more likely in the service sector, which in Lithuania only evolved in the last 15-20 years, and less likely in the manifacturing sector or in agriculture. If young workers are concentrated in the service sector, they should see higher wage increases. The same logic also applies to occupations. If young workers tend to choose occupations in which it is possible to switch easily to a better-paid job, the wages of young workers should increase. Figure 9 gives evidence for the concentration of young workers in certain groups of occupations. Workers aged 35 and less are over-represented in among service workers and technicians, while older workers are more concentrated among *legislators, senior officials and managers* and *elementary occupations*, which includes agriculure. These occupations tend to have a higher wage rigidity than occupations related to services, so that the sectoral and occupational composition within an age group could explain part of the wage changes for young workers.

7 Conclusion

Emigration in fact has an impact on the wages of stayers. However, this wage effect is not the same for all groups of workers. Focusing on the large emigration wave from Eastern to Western Europe after EU enlargement in 2004, I show that young workers gain from emigration, while old workers lose in the short run. Contrary to previous literature, I find no effect on the wage distribution between high- and low skilled workers. Hence, a *brain drain* from Eastern to Western Europe did not take place, but rather a general exodus of young workers of all education levels.

The case study of Lithuania is remarkable, because the country experienced a significant emigration shock in a short period in time, caused by a change in the legal framework. This quasi-natural experiment sheds light on the functioning of the labor markets in a transition country. The results may well carry over to countries that were exposed to a similar shock, for example Poland, Slovakia or Latvia. Furthermore, the findings of this paper can be of importance for countries like Croatia, Serbia, Montenegro or Turkey, which plan to join the European Union and have to evaluate the costs and benefits of doing so.

The magnitude of the effects found in this study is larger than in studies about the impact of immigration on labor markets. This difference is due to the fact that the structure of the labot market in the sending country is different. In the case of transition countries, old and young workers were educated under different economic systems and are therefore less substitutable. Furthermore, emigrants and stayers are different in their age structure. Emigrants were on average 13 years younger than stayers, which explains why the wage effect was concentrated among young workers.

The factor proportions approach used in this study comes with the caveat that it assumes away wage rigidities and unemployment, which can both have an impact on wages at the same time as migration. Comparisons with previous reduced-form results show that these factors do not dilute the impact of emigration on wages. The wage effect is indeed a result of a decrease in labor supply and the labor market adjustments it causes.

For future research, the large migration wave after EU enlargement offers several interesting directions. As more data becomes available, it will be interesting to analyze the causes and consequences of return migration. Anecdotal evidence from Ireland suggests that many migrant workers from the New Member States left the country when the economic crisis unfolded in 2008/09 and returned to their home countries. One relevant question would be to analyze the selection patterns of return migration, i.e. which groups of workers stay and which leave. Moreover, once they returned, it should be possible to investigate whether return migrants can earn a wage premium in their home countries.

Table 6 – Regression results for σ_{EXP} - Men only

Dependent variable: log real wage					
	(1)	(2)	(3)	(4)	(5)
Method:	OLS	IV	IV	IV	IV
Experience cells	10-year	10-year	10-year	20-year	5-year
log(Nr of Workers)	-0.070	-0.573**	-0.398*	-0.570***	0.198
	[0.078]	[0.241]	[0.200]	[0.192]	[0.919]
Observations	48	48	48	24	96
R^2	0.9727	0.9317	0.9626	0.9942	0.9326
F-Statistic		5.472	2.883	4.471	0.298
σ_{EXP}	14.29	1.74	2.51	1.75	-5.05
Controls:					
δ_t	yes	yes	yes	yes	yes
δ_{it}	yes	yes	yes	yes	yes
δ_{ij}	yes	yes	yes	yes	yes
δ_{jt}	no	no	yes	no	no

Note: Robust standard errors in brackets. Significance levels: *** p<0.01, ** p<0.05, * p<0.1. Controls: δ_t: year dummies, δ_{it}: interaction year*education, δ_{ij} interaction education*experience, δ_{jt}: interaction experience*time. σ_{EXP} is calculated as the negative inverse of the estimated coefficients.

A Estimation of σ_{EXP}: Data on Men only

The baseline estimation in Section 5.1 assigns the same level of work experience to men and women with the same age and education. This method can potentially lead to miscalculations for the work experience of women, who might have less actual work experience due to maternity leave. If this miscalculation was important, the results of the same regressions using data on men only would have to differ fundamentally from those with men and women. As we can see in Table 6, the results are different when using data on men only, but not fundamentally. For 10-year experience groups the estimated slope is slightly lower than in Table 3, 20-year it is the same. In all cases the instruments are weaker than in the specification with men and women, so that the results in Table 3 are more accurately estimated.

B Sensitivity Analysis

The simulations in Section 6 were based on a number of assumptions about the structural parameters and the number of emigrants per skill group. In this section I check the robustness of the simulation results to changes in these assumptions.

In addition, I re-run the simulations using parameter values from the literature. The structural parameters of the Lithuanian labor market are fundamentally different from those found in the literature for industrialized countries such as Germany and the US. This difference is not suprising, given that Lithuania is a transition country. The calibration of the model on parameters from the literature may answer another interesting question: suppose Lithuania had the labor market of Germany or the US, what would be the wage changes resulting from the emigration wave after 2004?

B.1 Variation in σ_{ED}

Due to the high level of aggregation and the resulting low number of observations in the data, the identification of σ_{ED} is subject to great uncertainty. However, as the selection of migrants took place along the old-young dimension, the results are robust to changes in σ_{ED}, even in cases when this parameter takes on extreme values. Columns (2) and (3) in Table 7 show the simulation results for $\sigma_{ED} = 1$ (Cobb-Douglas case) and for $\sigma_{ED} = \infty$, for which any two education groups are perfect substitutes. The predicted wage changes only vary mildly with the variation in σ_{ED}.

B.2 Irish data only

The calculation of the number of emigrants per skill group was based on the assumption that the distribution of Lithuanian migrants in Ireland is the same as in the UK. I based this assumption on previous studies, from which it can be seen that the educational distribution of migrants from the New Member States was approximately the same. However, there is some uncertainty about the joint education-experience distribution of Lithuanian migrants in Ireland. If, for example, relatively more younger workers went to the UK than to Ireland, the simulation results from the previous section would understate the impact of migration on real wages. Therefore, I re-run the simulations of Section 6 with Irish data only. Column (2) in Table 7 shows the simulated wage changes based on Irish data only. Compared to the baseline scenario, the magnitude of the wage effects is significantly lower, but the pattern prevails: young workers gain from emigration, while old workers lose. As the emigration rates taken from the Irish census data reflect a lower bound to emigration from Lithuania, the true wage effects from emigration will be at least as large as those based on simulations with Irish data only.

B.3 Calibration on Parameters from the Literature

In this section I calibrate the model on parameters that were obtained in the literature for the US, the UK and Germany.

Table 7 compares the baseline results with the results when the model is calibrated on parameters from the literature. As the labor demand curves in Lithuania are steeper, the first-order effects, i.e. the direct impact of a labor supply shift of a skill group on the wage of the same group, are greater with the parameter estimated for the Lithuanian labor market. On the other hand, the fact that σ_{ED} found here is smaller than the one in the literature means that the higher-order effects, i.e. the effects of the labor supply shifts of workers from one skill group on the wages of another skill group, are smaller in the Lithuanian case. Consequently, the negative wage effects I find for workers with more than 30 years of work experience disappear when calibrating the model on parameters from other studies. Despite the different magnitude in the wage changes, the main result of this study is robust to these parameter specifications.

TABLE 7 – SENSITIVITY ANALYSIS

		(1) Baseline	(2) high σ_{ED}	(3) low σ_{ED}	(4) IE only	(5) Card & Lemieux (2001)	(6) Borjas (2003)	(7) Manacorda et al. (2011)	(8) D'Amuri et al. (2010)
	Country	**Lithuania**	**Lithuania**	**Lithuania**	**Lithuania**	**US**	**US**	**UK**	**Germany**
	σ_{EXP}	1.58	1.58	1.58	1.58	5	3.5	10	3.3
	σ_{ED}	1.18	∞	1	1.18	2.25	1.3	5.8	2.9
Education	**Experience**								
Lower Secondary	0-10	**4.89**	4.29	5.00	2.01	2.31	3.00	1.59	2.78
	11-20	**1.23**	0.63	1.34	0.50	1.15	1.34	1.01	1.03
	21-30	**1.82**	1.21	1.93	0.75	1.34	1.61	1.10	1.31
	31+	**-1.07**	-1.67	-0.95	-0.44	0.43	0.31	0.65	-0.07
Upper Secondary	0-10	**7.02**	7.29	6.97	2.89	2.80	3.56	1.88	3.87
	11-20	**0.65**	0.92	0.60	0.26	0.79	0.68	0.88	0.82
	21-30	**-0.78**	-0.50	-0.83	-0.32	0.34	0.04	0.65	0.13
	31+	**-1.43**	-1.16	-1.48	-0.59	0.13	-0.26	0.55	-0.18
Third Level	0-10	**5.72**	5.22	5.81	2.35	2.55	3.32	1.71	3.19
	11-20	**-0.06**	-0.57	0.02	-0.03	0.72	0.71	0.80	0.42
	21-30	**-0.23**	-0.73	-0.14	-0.10	0.67	0.64	0.77	0.33
	31+	**-1.01**	-1.51	-0.92	-0.42	0.42	0.29	0.65	-0.03

Note: Column (1): baseline scenario. (2): same calibration as in baseline scenario, labor supply shock based on Irish data only. These are lower-bound estimates to the impact of emigration on wages. (5)-(8) same labor supply shock as in the baseline scenario, model calibrated on parameters found in the cited studies based on data from the United States, the UK and Germany.

C Tables and Figures

Table 8 – Aggregation of Education Groups in the Lithuanian HBS and the Irish Census.

This study	HBS 2002	HBS 2003-2006	Irish Census
lower secondary education duration: 10 years leaving age: 16	under primary (1) primary (2) basic (3)	vocational school after basic (7) vocational school after primary (8) basic school (9) primary school (10) literacy skills, but no education (11) illiterate(12)	primary school and less, lower secondary school,
upper secondary education duration: 12 years leaving age: 18	secondary (4)	professional college and college (2) specialized secondary school (3) secondary school (4) vocational school (after secondary) (5) vocational school (after basic) (6)	upper secondary education, third-level (but no B.Sc equivalent)
third-level degree duration: 15 years leaving age: 21	third-level (5) highest (6)	university (1)	third-level (B.Sc equivalent) and higher

Note: If applicable, variable code of the original dataset in parentheses.

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