The Distributional Impact of Emigration: The Case of EU Enlargement

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Abstract

This paper addresses the question whether emigration changes the wage distribution in the source country. In a theoretical model of a labor market I show that some groups of stayers gain, while others lose from emigration. This outcome depends on the degree of subsitutability between different groups of workers, as well as on skill distribution of emigrants. Using microdata on the Lithuanian labor market, I simulate the post-2004 emigration wave based on the theoretical model and calculate the resulting changes in wages for different groups of workers. I find that the wages of young workers increased by 2% to 6%, which is due to the fact that most emigrants were young. At the same time the model predicts that the wages of older workers decrease by 0.6% to 2% because their labor demand is negatively affected by the emigration of young workers. These results are important for future EU candidates in order to assess the costs and benefits of EU accession.

Keywords: Migration, EU Enlargement, European Integration, Wage Distribution
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1 Introduction

The enlargement of the European Union in 2004 was followed by large migration movements from Central and Eastern Europe to Western Europe. 5.2% of all Slovakian, 5.7% of all Polish, 6.5% of all Latvian and 9.2% of all Lithuanian workers received a work permit in Ireland and the UK.[1] This paper studies the impacts of this migration wave on the wage distribution of the source countries. I find that among those workers who stay in their home country, young workers gain from migration while old workers lose. The gains for the young workers are driven by a supply shift, whereas the losses for old workers are the result of a decrease in labor demand caused by the complementarity of old and young workers. Most emigrants were young, so that young workers who stay in their country become a more scarce resource, which leads to an increase in their wages. As old and young workers are complements in the production process, the emigration of young workers lowers the labor demand for old workers, which decreases their wages. These findings give evidence of the welfare impacts of migration and can inform the debate about costs and benefits of EU enlargement in potential EU candidates such as Croatia, Macedonia, Serbia or Turkey.

Because of the sudden change in economic conditions, the EU enlargement is a quasi-natural experiment. The accession of the new member states changed the economic opportunities of all workers in these countries from one day to another. Compared to their peers in Western Europe, workers in Central Europe were facing high wage differentials. These wage differentials gave workers a large incentive to emigrate, but emigration only occured in small numbers, as until 2004 Western European countries had strict laws on immigration of non-EU nationals in place. In 2004, with the accession of 10 new member states, workers from these countries got the right to emigrate and take up work in Ireland, the UK and Sweden.[2] Around 1.2m workers took this opportunity and received a work permit in Ireland (416,000), the UK (770,000) and Sweden (19,000).[3] Even though not all of these workers emigrated permanently, we can see from these numbers the decrease in the workforce in Central Europe after EU enlargement was significant. Given the magnitude and the speed of post-enlargement migration, I conjecture that this

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[1] Own calculations based on work permit data from Ireland (*PPS* numbers) and the UK (*NINo*). See figure 3.

[2] The 10 new member states were 8 former centrally planned economies in Central Europe, Czech Republic, Estonia, Hungary Latvia, Lithuania, Poland, Slovakia and Slovenia, as well as Malta and Cyprus. Except Ireland, the UK and Sweden all other old member states of the EU opted for a transitional period of up to seven years, in which they completely or partially restricted the access to their labor markets for workers from the new member states.

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

migration wave had an impact on the distribution of wages in the source countries.

To analyze the changes in wages resulting from migration, I use a stylized theoretical model of the labor market that accounts for differences in substitutability between groups of workers who differ in their observable characteristics *education* and *work experience.* The model is based on a nested CES production function, in which each of the skill groups enters as a separate labor input. From the model I obtain a labor demand framework, which allows me to estimate the elasticities of substitution between skill groups. To calculate the wage changes for each skill group I calibrate the model on the estimated parameters and simulate the post-2004 emigration wave. This approach follows Katz & Murphy (1992), Borjas (2003) and Ottaviano & Peri (2006, 2008). In my analysis Lithuania serves as an example for an EU accession country, as it was the country that lost the highest share of its workforce among the accession countries after 2004.

Based on Lithuanian Household Budget Survey data, I estimate the structural parameters of the model, which gives me the intercept and slope of the labor demand curve for each skill group. As wages are the equilibrium outcome of supply and demand factors, the identification of the demand curve requires an instrument for labor supply. Post-2004 migration from Lithuania seems to be an obvious choice, since the supply shift occured due to an exogenous change in the institutional framework of European labor markets. However, due to the magnitude of the emigration wave, Lithuanian emigration could also shift labor demand, which would lead to biased estimates. To overcome this problem, I instrument Lithuanian labor supply with emigration from Poland. After 2004 Poland experienced a similar emigration wave as Lithuania, with the skill distributions of Polish and Lithuanian workers being highly correlated. On the other hand, migration from Poland does not shift Lithuanian labor demand, which allows the identification of the demand curve.

To assess the magnitude of the migration movements for each skill group I use work permit data from Ireland and the UK. Since the access to labor markets in all other old EU member states remained restricted,[4] Irish and British immigration data provide a measure of the total number of emigrants for each skill group. Based on the estimated labor demand curve and the calculated labor supply shifts I calculate the wage changes for each skill group. For workers with 10 years or less of work experience who stay in Lithuania, migration caused a wage increase by 2% to 6%, whereas workers with more

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[4] Sweden was an exception here. The country opened its labor market to nationals from the new member states, but the number of migrants who went to Sweden is negligible compared to the numbers that went to Ireland and the UK.

than 30 years of work experience saw their wages decrease by 0.6% to 2%.

The remainder of the paper is structured as follows: Section 2 outlines the structural model. In section 3 I describe the data and estimate the structural parameters. In section 4 I simulate the impact of the post-2004 migration wave on the wages of different skill groups in the source country. Section 5 concludes.

2   Structural Model

The structural model explains, how a change in labor supply affects the wages of workers who differ in their observable skills. To model this heterogeneity in skills, I divide the workforce up into skill groups, which are defined by education and work experience. Each skill group constitutes a separate labor market and all labor markets are interrelated. Workers with the same observable characteristics compete in the same labor market and are perfect substitutes. Emigration of workers of a particular skill group shifts the labor supply and, given the demand curve, increases the wages of the stayers in this skill group. However, due to the interdependency of the labor markets for distinct skill groups, a change in the labor supply of one skill group affects the wages of all skill groups through changes in labor demand. The extent of these demand shifts depend on the degree of substitutability between skill groups. The wage changes are greater for workers with similar skills and smaller for those with very different skills. Following the works of Katz & Murphy (1992), Borjas (2003) and Ottaviano & Peri (2008), I model the labor market of this economy as a nested CES production function, in which each skill group enters as a distinct labor input. Under the assumption of firms maximizing profits, the model generates a factor demand equation for each skill group that can be econometrically identified.

2.1   Model Outline

Aggregate production in the economy is described by the Cobb-Douglas production function

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

The aggregate output Q_t is produced using physical capital K_t, labor L_t and total factor productivity A_t with a constant-returns-to-scale technology. $\alpha \in (0,1)$ is the share of

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labor in aggregate income, which is constant over time. The price of the aggregate output is normalized to $P_t = 1$. The labor force L_t consists of three different education groups L_{it}: 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

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

which accounts for the fact that workers who differ in their education i are not perfect substitutes and differ in their productivity. σ_{ED} describes 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 productivity between education groups.

Given that human capital formation of workers does not finish with an educational degree, workers of the same education group who differ in their work experience are not perfect substitutes and as such do not compete in the same labor market. To account for this difference in work experience, I model each education group L_{it} as a CES composite, which consists of several work experience groups L_{ijt}:

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

For the clustering of an education group into experience groups I use two intervals defining the size of the experience groups: 10 years and 5 years. In the case of 10-year experience groups, each education group consists of four experience groups: 0-10 years, 11-20 years, 21-30 years and more than 30 years of work experience. When considering 5-year experience groups, the clustering is finer: 0-4 years, 5-9 years, 10-14 years, etc up to 40 years of work experience. 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 $\sum_j \gamma_{ijt} = 1$. I assume that the relative productivity of each skill group ij is constant over time, i.e. $\gamma_{ijt} = \gamma_{ij}$, which ensures identification of σ_{EXP} and all γ_{ij}. This assumption would be questionable in the long run, as for example technological progress could benefit one experience group more than another. However, since this study is a short-run anal-

ysis and I consider the time span of five years from 2002 to 2006, changes in the relative productivity of an experience group over time should be negligible, which justifies the assumption. Furthermore, I assume that workers within an education group are closer substitutes than workers who differ in their education. Hence, I place the restriction $\sigma_{EXP} > \sigma_{ED}$ on the elasticities of substitution. Intuitively, this restriction means that it is easier to replace worker A with x years of work experience and a third-level education with worker B of the same education group and y years of work experience than it is to replace worker A with worker C who has a lower secondary education.

Labor markets are perfectly competitive and clear in every period. Profit-maximizing firms pay in labor market equilibrium each skill group L_{ijt} a real wage w_{ijt} equal to the group's marginal product

$$w_{ijt} = \frac{\partial Q_t}{\partial L_{ijt}}. \tag{4}$$

Equation 4 describes the firms' labor demand for skill group ijt. Taking logs from equation 4 gives a labor demand curve that is linear in $\log L_{ijt}$,

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\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_{ij} - \frac{1}{\sigma_{EXP}} \log L_{ijt}.
\end{aligned}
\tag{5}
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Any change in one of the factors on the right-hand side of equation (5) alters the marginal product, which leads ceteris paribus to a change in the real wage. Therefore, emigration of workers of the same skill group ij leads to an increase in the wage paid to this skill group. If workers with the same education, but a different work experience emigrate, i.e. L_{it} decreases, then the wage of skill group ij increases as long as the restriction $\sigma_{EXP} > \sigma_{ED}$ holds. If workers from a different education group emigrate so that L_t decreases, the wage of group ij decreases. This effect is due to the complementarity of workers with different education levels in the production process.

From equation (5), we can generate an equation that allows us to estimate σ_{EXP}, while controlling for all other factors that affect w_{ijt}. In the context of EU enlargement, this possibility of controlling for other factors is important, as EU enlargement was accompanied by increased FDI inflows, a deeper trade integration and the inflow of EU structural funds, which can all have an impact on labor demand in the source country. Controlling for such factors is possible because the variation in all terms on the right-hand side

of equation (5) 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 but not across skill groups, 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_{ij} are identified by an interaction of education group and experience group dummies δ_{ij}. σ_{EXP} can then be estimated from the equation

$$\log w_{ijt} = \delta_t + \delta_{it} + \delta_{ij} - \frac{1}{\sigma_{EXP}} \log L_{ijt}. \tag{6}$$

2.2 Discussion of the Model Assumptions

With the nested CES production function I impose a structure on the labor market, which is needed to make the model empirically tractable and allows me to obtain consisten estimates for the structural parameters.

Figure 1 illustrates the nested structure of the CES production function. From this picture we can see the restrictions the model makes with respect to the elasticities of substitution σ_{ED} and σ_{EXP}. Note that in the model σ_{ED} has the same value for any two education groups. This means for example that workers with lower secondary education and those with upper secondary education have the same degree of substitutability as workers with lower secondary education and those with third-level education. In reality, one would expect σ_{ED} to be smaller when the difference in years of education between two education groups is higher. Hence, it is easier to substitute a worker with a third-level degree with a worker with upper secondary education than it is to substitute the same worker with someone who only has a lower secondary education. A similar simplification applies to σ_{EXP}. First, σ_{EXP} is the same in each education group. Second, σ_{EXP} has the same value for all experience groups. This means that among workers with the same education the substitution of worker A with five years of work experience for worker B with 10 years is as easy as the substitution of worker A for worker C whose work experience is 40 years. These assumptions and simplifications are required for identification of the structural parameters of the model. We would obtain a more realistic picture of the labor market if we could estimate an elasticity of substitution between each skill group. In the case of 10-year experience groups this would mean that we have to estimate the elasticities of substitution between 12 skill groups, which amounts to 132 parameters. At the same time we only have 48 observations, which makes it impossible to identify such

an amount of coefficients.[5] Even though those assumptions might seem restrictive, σ_{EXP} and σ_{ED} can be interpreted as average elasticities of substitution between any two skill groups. Given that the labor supply shock after EU enlargement differed in size for each skill group, the model still allows for a differentiated picture of the effect of emigration on wages.

3   Estimation of Structural Parameters

As a next step, I bring the model from section 2 to the data and estimate the structural parameters σ_{EXP} and σ_{ED}. Using data from the Lithuanian Household Budget Survey, I estimate the parameter σ_{EXP}, which is the elasticity of substitution between experience groups and the negative inverse of the slope of the labor demand curve for each experience group. As OLS suffers from simultaneity bias, I use a 2-stage-least-squares estimator (2SLS) with emigration as an instrument for labor supply shifts.

The values for the elasticity of substitution between education groups, σ_{ED}, cannot be estimated due to data limitations. However, given the restriction $\sigma_{EXP} > \sigma_{ED}$ it is possible to determine a range of sensible values for the simulation exercise.

3.1   Data

The empirical analysis requires two datasets: one for the estimation of the structural parameters of the Lithuanian labor market in section 3 and one for the quantification of the number of emigrants by skill group, which I will use in the simulations in section 4 and as an instrument in the empirical part in section 3. For the estimation of the structural parameters of the labor market, I use the Lithuanian Household Budget Survey of the years 2002, 2003, 2005 and 2006. The relevant variables for the study are real wages and labor supply.

The number of emigrants per skill group cannot be taken from an already existing dataset, as the statistical offices usually do not keep reliable records about emigrants. An obvious reason for this lack of suitable data is that in most European countries there is no legal

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[5]   Ottaviano & Peri (2008) model the education aggregate as two CES nests. They divide the workforce into high-skilled and low-skilled workers, and each of those groups is divided into two education groups. This allows to determine two different elasticities of substitution between education groups, which is more realistic than having only one value. Due to the limitations of my dataset, it is not possible for me to choose a similar modelling approach.

obligation for migrants to de-register, once they emigrated. The consideration of the case of Lithuanian emigration after EU enlargement in 2004 has the advantage that within the EU Lithuanians were only allowed to migrate to the UK, Ireland and Sweden, while all other EU-15 countries closed their borders for a transitional period up to 2011. As a consequence, we can obtain the number of emigrants from the register data of those destination countries. As the migration movements to Sweden were small[6], I will neglect Sweden and only use data from Ireland and the UK. The construction of the dataset on emigration numbers works as follows: I take the skill distribution from the Irish census and weight it with data from the Irish and British data on work permits, measured by PPS numbers and NINo numbers. As this method only yields approximate values, I run two simulations: a lower bound that is based on Irish data only and one based the Irish census weighted with UK data. I explain the three data sources in greater detail below. For a detailed description of the clustering by skill group see sectionA.

3.1.1 Lithuanian Household Budget Survey

The Lithuanian Household Budget Survey is conducted annually by the Lithuanian Statistical Office with a sample of 7000-8000 households. The sample is representative at the individual level and includes all people aged 18 or older.

The income data is self-reported, which can be subject to a misreporting bias. Table 3j) compares the average monthly wage for men and women working in the private sector from the Lithuanian live register with the average wages from the HBS.[7] The difference between the two sources is small, which indicates that there is no misreporting bias in the data.

I restrict the sample to private sector workers aged 18-64 years. Additionally, I dropped the following observations if the variable *disposable income* is negative[8], if the socioeconomic status is *pensioner* or *other*, as they are not employees or otherwise part of the workforce and if workers are self-employed and or own a farm, as they are no employees.

3.1.2 Irish Census

The Irish Census is conducted by the Irish Central Statistics Office every 4-5 years and contains all people that are living in Ireland and that are present in the survey night. For this study, I use tabulations from the survey rounds in 2002 and 2006.The CSO provided

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[6]   See Wadensjö (2007).

[7]   The variable is *income from employment*, which is the monthly wage.

[8]   This is the case in 2002 with 67 people working in the agricultural sector.

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

The census does not capture all migrants who came to Ireland for work, but only those who are present in the survey night. People who came e.g. for a summer job or a time shorter than one year may not be included in the census. Therefore, the census data reflect a lower bound to the number of people who migrated from Lithuania to Ireland.

3.1.3 Work Permit Data: PPS and NINo numbers

Data on work permit defines an upper bound to migration from Lithuania to Ireland and the UK. Every worker who moves to Ireland or the UK has to apply for a PPS (Personal Public Service) number in Ireland or a NINo (National Insurance Number) in the UK.[9] These data capture all workers that emigrated from Lithuania to one of those two countries, regardless how long they stay in the host country. There is no obligation to de-register for workers, so that 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, as workers keep their PPS and NINo numbers, no matter how often they move back-and-forth between Lithuania and Ireland or the UK.

3.2 Identification and Estimation of σ_{EXP}

Using equation (6), I estimate σ_{EXP}. The estimation equation has the form

$$\log w_{ijt} = \delta_t + \delta_{it} + \delta_{ij} + \beta \log L_{ijt} + \varepsilon. \tag{7}$$

w_{ijt} is the average real wage of skill group ijt. δ_t is a vector of year dummies, δ_{it} is a vector of interaction terms between education and year dummies and δ_{ij} is an interaction term between education and experience group dummies. ε is an error term. L_{ijt} is the number of workers in skill group ijt in the workforce.[10] The coefficient of interest in this section is $\beta = -\frac{1}{\sigma_{EXP}}$, the slope of the labor demand curve.

An estimation of β with OLS does not yield consistent estimates, as the results suffer from simultaneity bias. The model equation (5) I wish to identify is a demand curve,

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

[10] Ottaviano & Peri (2006, 2008) use the number of working hours from workers in this skill cell as a measure for the labor input. This measure is more accurate than the number of workers. However, as the Household Budget Survey does not include data on working hours, I use the number of workers as a proxy.

which would mean that β should be negative. However, the outcomes we observe in the (w_{ijt}, L_{ijt}) space are equilibrium points on the labor market, which were determined by an interplay of supply and demand factors. If we want to disentangle the labor demand and supply curves and identify the slope parameter of the demand curve, we need an exogenous labor supply shifter that does not shift labor demand.[11] Given an appropriate instrument, we can consistently estimate β using 2SLS.

As in the works of Borjas (2003), D'Amuri *et al.* (2010) and Ottaviano & Peri (2008), I consider emigration as a supply shock. This is justified in the case of Lithuanian EU accession. As we can see in figure 2, the migration wave set in in 2004, when Lithuania joined the EU. Migration from Lithuania was not driven by a change in wage differentials, but was clearly caused by a law change. Before 2004, the labor markets of EU countries were closed for Lithuanians, while in 2004 the UK, Ireland and Sweden opened up their labor markets for East European workers.

I use emigration from Lithuania as a labor supply shifter to identify the slope of the labor demand curve.[12] To be suitable as an instrument, emigration has to be exogenous to labor supply, which means it should influence wages only through labor supply but not through labor demand, after controlling for *time*, an interaction (*time * education* and an interaction of *education * experience*. These controls absorb any demand shifts that are the same for all skill groups at any point in time, as well as demand shifts that are education-specific. The only potential systematic shift of demand that is not captured in this specification is a shift across experience groups over time. If migration does not only shift the supply curve but also the demand curve, the estimates of β could be biased. Such a scenario is possible, since the emigration of young workers could raise or lower the labor demand for old workers.

The direction of this bias is not straightforward. To see this, consider the simplified model as in Borjas (2003), $\log w = \alpha + \beta \log L + \varepsilon$, in which the log of the real wage w is regressed on a constant α, the log of labor supply L and an error term ε and the labor supply L is instrumented

$$\text{plim}\,\hat{\beta} = \beta + \frac{\text{cov}(\log M, u)}{\text{cov}(\log M, \log L)} \tag{8}$$

where $\frac{\text{cov}(\log M, u)}{\text{cov}(\log M, \log L)}$ characterizes the bias. If M and u are uncorrelated, the bias is zero and $\hat{\beta}$ is a consistent estimator for β. Emigration and labor supply are negatively corre-

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[11] i.e. an instrument that is excluded from the labor demand equation. See Hamilton (1994, ch.9) or Greene (2008, ch.13) for an explanation of the identification of simultaneous equation models.

[12] I explain the calculation of emigration rates in appendix C.1.

lated, as the more people migrate, the lower the labor supply, so that the denominator is negative, $\mathrm{cov}(\log M, \log L) < 0$. The sign of the numerator can be either positive or negative, which means that the direction of the bias is unkown. Suppose the economy is hit by a positive demand shock, then it is less attractive for workers to emigrate, so that $\mathrm{cov}(\log M, u) < 0$. In this case I would over-estimate β and σ_{EXP}. Because the estimated elasticity of substitution would be greater than the true parameter, the resulting wage changes would be smaller than the true values.

On the other hand, if workers emigrate and send money to their home country, this could result in a positive demand shock, so that $\mathrm{cov}(\log M, u) > 0$, which means that I would under-estimate β and σ_{EXP}, which would lead to an over-estimation of the wage changes. To eliminate this bias, I propose an instrument that derives from the fact that Lithuania was not the only country that joined the EU in 2004: Polish emigration. As we can see from figure 4, the emigration of Poles (denoted M_{PL}) to Ireland and the UK by skill group is strongly correlated with the emigration of Lithuanians, so that $\mathrm{cov}(M_{PL}, M_{LIT}) > 0$ and hence $\mathrm{cov}(M_{PL}, L) < 0$.[13] After controlling for time and an interaction of time and education dummies, I assume that emigration from Poland is not correlated with Lithuanian labor demand, so that the 2SLS estimator is consistent, i.e. $\mathrm{plim}\,\hat{\beta} = \beta$.

Table 4 reports the results for the estimation of σ_{EXP}. All regressions are weighted with sampling weights.[14] The upper panel uses intervals of 10 years of work experience for the calculation of skill groups, whereas the bottom panel reports the result for 5-year cells. In all cases except for women and 10-year experience cells, the OLS estimates are statistically insignificant. This means that we cannot reject the hypothesis that workers from different age groups are perfect substitutes. This result seems implausible, but as explained above, OLS does not produce consistent estimates. When we look at the IV estimates, we can see that for both genders together, as well as for men only, the coefficients are statistically significant. The point estimates for σ_{EXP} range between 1.2 and 2.0, depending on the specification and the instrument used. Equally important as statistical significance is the question of weak instruments. Looking at the specification *men only*, it occurs that the instrument is too weak to allow reliable inference. Even in the specification that considers men and women together, the F-Statistics of the in-

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[13]   The correlation coefficient is 0.9667. One point on the scatter represents one skill group. I only displayed the scatter for men and women and 10 year cells, but the correlations are of similar magnitude for each gender separately and for 5- and 10-year cells.

[14]   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. As STATA requires the weights to be integers, the weights are rounded to the nearest integer.

strument are below the commonly used threshold of 10. However, as Stock *et al.* (2002) show, estimates with one instrument for one exclusion restriction allow reliable inference at an F-statistic of 8.96 or higher. This would mean that the estimates for both genders together and for women with 10-year cells are reliable, whereas the instruments are too weak too allow reliable inference for 5-year cells.

Comparing the results for the two instruments, we can see that the estimates obtained using Polish emigration as an instrument are lower in absolute value than the estimates derived from Lithuanian emigration. Given that in the case of Polish migration the estimator is consistent and does not suffer from the bias as shown in equation (8), this difference in the estimates indicates that the Lithuanian migration used as an instrument leads to an under-estimation of σ_{EXP}. This in turn means that we over-estimate the wage changes. Therefore, the estimates obtained from the 2SLS estimator using Polish emigration are preferable to the ones using Lithuanian emigration.

The results of the estimates for σ_{EXP} are lower than in studies that previously used a similar model. Borjas (2003) and Ottaviano & Peri (2008) find a σ_{EXP} of 3.5 for the US taking 5-year experience groups, men only. D'Amuri *et al.* (2010) find an elasticity of 3.1 for Germany. The fact that the elasticities are lower for Lithuania means that workers who differ in their work experience groups are less substitutable in Lithuania than they are in Germany or the United States. This is plausible when we look at 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 planned economy, whereas younger workers were educated and grew up in the environment of a market economy. As such, the skills of young workers should be immediately applicable in the labor market, whereas older workers might need some time for adjustment and re-training. this can lead to a low degree of substitutability between old and young workers, which is reflected in the low values of σ_{EXP}.

3.3 Determination of σ_{ED}

The dataset used in this study consists of four years (2002, 2003, 2005, 2006) and in each year we can observe wages and labor inputs for three education groups. This makes a total of 12 observations, on which the estimations of σ_{ED} can be based. The estimation equation for this parameter is derived in the same way as equation (6),

$$\log \bar{w}_{it} = \delta_t + \delta_{it} - \frac{1}{\sigma_{ED}} \log \bar{L}_{it} + \varepsilon, \tag{9}$$

where 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). In equation (9), σ_{ED} can only be properly identified when the number of observations is large. Otherwise, the model is too saturated and the coefficient $-\frac{1}{\sigma_{ED}}$ cannot be statistically significant from zero. To see this, let n be the number of education groups and t the number of years. We would then have $n(t-1)+1$ parameters to estimate from nt observations, so that the number of observation exceeds the degrees of freedom by $n-1$. The higher n, the more likely it is to obtain a statistically significant coefficient for $-\frac{1}{\sigma_{ED}}$. However, as n is the number of education groups, there is a natural limit to n, as the number of educational tracks in a country is limited and typically small.

Borjas (2003) and Ottaviano & Peri (2008) approximate δ_{it} with education time trends. They have 24 observations, as they have four education groups and consider six years. Their point estimates are in line with the restriction that workers of the same education group are closer substitutes than workers with different education, i.e. $\sigma_{EXP} > \sigma_{ED}$. However, the standard errors of the estimates for σ_{ED} are high.

Given that I only have 12 observations, I do not attempt to estimate σ_{ED} from the available data. For the simulations to follow, I use the restriction $\sigma_{EXP} > \sigma_{ED}$ and choose a value lower than σ_{EXP}.

4 Simulations

In this section, I calculate the effect of migration on changes in real wages by calibrating the model from section 2 on the structural parameters obtained in section 3 and simulating the post-EU-enlargement migration shock on the Lithuanian labor market. As the model accounts for different degrees of substitutability and complementarity between groups of workers, we are able to obtain a differentiated picture of the wage changes for different groups of workers as a consequence of the migration wave, with some groups that gain much more from migration than others.

4.1 Simulation Equation

To derive an equation that allows me to simulate the migration shock in the structural model, I differentiate equation (5) and assume that A_t, θ_{it} and γ_{ij} do not depend on labor supply:

$$
\begin{aligned}
\frac{\Delta w_{ijt}}{w_{ijt}} &= (1-\alpha)\frac{\Delta K_t}{K_t} + (\alpha - 1 + \frac{1}{\sigma_{ED}})\frac{\Delta L_t}{L_t} \\
&+ (\frac{1}{\sigma_{EXP}} - \frac{1}{\sigma_{ED}})\frac{\Delta L_{it}}{L_{it}} - \frac{1}{\sigma_{EXP}}\frac{\Delta L_{ijt}}{L_{ijt}}
\end{aligned}
\tag{10}
$$

Expressions L_t and L_{it} in equation (10) are labor aggregates and can as such be expressed in terms of L_{ijt}. From this, and dropping the time subscripts, I obtain the simulation equation

$$
\begin{aligned}
\frac{\Delta w_{ij}}{w_{ij}} &= (1-\alpha)\frac{\Delta K}{K} + \left(\alpha - 1 + \frac{1}{\sigma_{ED}}\right)\frac{1}{\alpha}\sum_i\sum_j s_{ij}\frac{\Delta L_{ij}}{L_{ij}} \\
&+ \left(\frac{1}{\sigma_{EXP}} - \frac{1}{\sigma_{ED}}\right)\frac{1}{s_i}\sum_j s_{ij}\frac{\Delta L_{ij}}{L_{ij}} - \frac{1}{\sigma_{EXP}}\frac{\Delta L_{ij}}{L_{ij}}.
\end{aligned}
\tag{11}
$$

The Δ measure the change in a variable from 2002 to 2006. I explain the derivation of equation (11) in appendix D. α is the income share of labor, s_i denotes the income share of education group i and s_{ij} denotes the income share of skill group ij.

Equation 11 shows that that wage of a skill group does not only depend on the group's own labor supply, but on a number of factors. A change in the labor supply of *any* skill group will affect the wage of skill group ij. The size of this effect depends on the degree substitutability between group ij and another group $i'j'$, as well as on the relative share in income of both groups. This can be seen from the wage elasticities, i.e. the reaction of the wage of group ij on a change in labor supply of some group $i'j'$. For the sake of simplicity, I assume here that capital adjustment is zero ($\Delta K = 0$). Then,

$$
\varepsilon_{ij,ij} = \frac{\Delta w_{ij}}{w_{ij}}\frac{L_{ij}}{\Delta L_{ij}} = \left(\alpha - 1 + \frac{1}{\sigma_{ED}}\right)\frac{s_{ij}}{\alpha} + \left(\frac{1}{\sigma_{EXP}} - \frac{1}{\sigma_{ED}}\right)\frac{s_{ij}}{s_i} - \frac{1}{\sigma_{EXP}}.
\tag{12}
$$

is the own-wage elasticity. In my case, $\varepsilon_{ij,ij}$ is the change in the wage of group ij, when workers from this group emigrate, which encompasses one direct and three indirect

channels. The indirect effects result from changes in labor aggregates in higher nests of the aggregate production function. Emigration of workers in skill group ij also decreases the number of workers in education group i and the entire labor force L, which leads to a decrease in production Q_t. These effects are represented in equation (12) as follows: $-\frac{1}{\sigma_{EXP}}$ is the direct reaction of the wage of group ij to a change in its labor supply. If we want to think of it graphically, this means that in the case of emigration we move upwards on the labor demand curve. The change in education group i and its effect on the wage of group ij is represented by $\left(\frac{1}{\sigma_{EXP}} - \frac{1}{\sigma_{ED}}\right)\frac{s_{ij}}{s_i}$. Finally, $\left(\alpha - 1 + \frac{1}{\sigma_{ED}}\right)\frac{s_{ij}}{\alpha}$ contains two effects, the reaction of wages to a change in aggregate labor and the reaction to a change in production.[15]

If workers from a different experience group $j' \neq j$ but the same education group i emigrate, this has an effect on the wages of group ij through three channels: the education group, aggregate labor and production. This can be seen from the elasticity,

$$\varepsilon_{ij',ij} = \frac{\Delta w_{ij}}{w_{ij}}\frac{L_{ij'}}{\Delta L_{ij'}} = \left(\alpha - 1 + \frac{1}{\sigma_{ED}}\right)\frac{s_{ij'}}{\alpha} + \left(\frac{1}{\sigma_{EXP}} - \frac{1}{\sigma_{ED}}\right)\frac{s_{ij'}}{s_i}. \tag{13}$$

If workers from a different education group $i' \neq i$ emigrate, the wage of group ij is only affected by a change in aggregate labor and aggregate production. The respective elasticity is

$$\varepsilon_{i'j,ij} = \frac{\Delta w_{ij}}{w_{ij}}\frac{L_{i'j}}{\Delta L_{i'j}} = \left(\alpha - 1 + \frac{1}{\sigma_{ED}}\right)\frac{s_{i'j}}{\alpha}. \tag{14}$$

The interpretation of equations (13) and (14) is analogous to equation (12). Table 5 reports the own-wage and cross-wage elasticities for each skill group for the parameter values $\sigma_{EXP} = 1.4$ and $\sigma_{ED} = 1.1$. The own-wage elasticities have the expected sign. The emigration of workers of the same skill group is a negative labor supply shock, which increases the wages of workers of the same skill group. The cross-wage elasticities reflect changes in the composition of the workforce caused by migration. The emigration of 1% of group ij affects the labor demand of all the other groups by $\varepsilon_{i'j,ij}$ percent. As we can see, the own wage effect is greater than the cross-wage effects.

---

[15] To be precise, $\frac{s_{ij}}{\alpha}\alpha = s_{ij}$ is the effect of a change in production and $\left(\frac{1}{\sigma_{ED}} - 1\right)$ is the effect of a change in aggregate labor.

4.2 Calculation of Emigration Rates

To simulate the effect of the migration of different skill groups on wages using equation (11), I have to quantify the exogenous labor supply shock for each skill group $\frac{\Delta L_{ij}}{L_{ij}}$. This fraction, which can be interpreted as the emigration rate, consists of the change in labor supply in a given time span ΔL_{ij} and the number of workers of the same skill group in Lithuania, L_{ij}. L_{ij} can be directly computed from the Lithuanian Household Budget Survey. Let the sample of a skill group ij contain $i = 1, ..., N$ workers. Then, I obtain the number of workers of this skill group in the population by adding the sampling weights p_{ijl}. Thus, $L_{ij} = \sum_{i=1}^{N} p_{ijl}$.[16]

The shift in labor supply ΔL_{ij} cannot be taken directly from the data, but needs to be computed under a number of assumptions. This is due to the fact that I have very detailed data on Lithuanian migrants coming to Ireland in 2002 and 2006, but on the migrants coming to the UK I only have raw figures. To compute the labor supply shifts, I use the skill distribution from the Irish census and assume that the number of migrants coming to the UK is proportional to the one of those coming to Ireland. This assumption is justified, as there was little visible sorting behavior of migrants from the new EU member states between Ireland and the UK. Comparing the studies of Barrett & Duffy (2008) on migration to Ireland and Dustmann *et al.* (2009) on the UK, we can see that the educational distribution of migrants from the new member states was similar in both countries.[17] 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 in this study I am interested in more broadly defined skill groups, for which the distribution is similar.

As the calculations of emigration rates can include uncertainty about the exact values for ΔL_{ij}, I calculate two different specifications $k = 1, 2$ for the emigrant numbers ΔL_{ijk}, with $k = 1$ based on very conservative assumptions and $k = 2$ on more optimistic ones. The first specification reflects a lower bound to migration, as it only uses data from the Irish census, which is the number of migrants we know for sure.[18] The lower bound is

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[16]   Since L_{ij} comes without time subscript, I take the average value of L_{ijt} the years $t = 2002, 2003, 2005, 2006$.

[17]   Ireland: lower secondary education 11.1%, upper secondary education 61% and third-level degree 28.2% (see Barrett & Duffy (2008)). The corresponding values for the UK are 11.9%, 56.1% and 32% (see Dustmann *et al.* (2009)).

[18]   I am aware of the fact that some of those migrants may have emigrated out of unemployment, so that even specification 1 is not exactly a lower bound. On the other hand, this specification only uses Irish census data and leaves out the high number of migrants who went from Lithuania to the

$$\Delta L_{ij1} = L_{ij}^{IR,2006} - L_{ij}^{IR,2002} \tag{15}$$

The second specification assumes that the number of Lithuanian migrants coming to Ireland is proportional to the number of those coming to the UK.

$$\Delta L_{ij2} = L_{ij}^{IR,2006} \left(1 + \frac{NINO_{2006}}{PPS_{2006}} \right) - L_{ij}^{IR,2002} \left(1 + \frac{NINO_{2002}}{PPS_{2002}} \right) \tag{16}$$

In this equation, $\frac{NINO_{2006}}{PPS_{2006}}$ and $\frac{NINO_{2002}}{PPS_{2002}}$ are weighting factors based on the numbers of work permits, which are a proxy for the total number of Lithuanian migrants coming to Ireland (PPS) and the UK (NINO) in a given year. For example, if in a given year the number of Lithuanians going to the UK was twice the number of those going to Ireland, the weighing factor would be $\frac{NINO_t}{PPS_t} = 2$. Table 6 reports the calculated emigration numbers by skill group for both specifications.

4.3 Model Calibration and Simulation Results

For the calibration of equation (11), I need to chose the parameters α, s_i, $s_i j$, σ_{ED} and σ_{EXP}. These parameters will determine the extent to which a change in labor supply affects real wages. α is the share of labor in GDP, which I can calculate from the Lithuanian national accounts data provided by the Statistics Office. In the case of Lithuania, $\alpha = 0.8$. I calculate the income shares s_i and s_{ij} from the sampling weights in Household Budget Survey,[19] using all men and women in the sample. See appendix B for a description of the calculation of s_{ij} and s_i.

I take the elasticities of substitution, σ_{EXP} and σ_{ED}, from the estimations in section 3 (specification *men and women together*). Since the estimations naturally include uncertainty about the results, I choose two different sets of values for σ_{EXP} and σ_{ED} for the simulations with 5-year and with 10-year experience cells: a pair of low values and a pair of high values. The low values of σ_{EXP} and σ_{ED} will produce higher wage changes, as the own-wage elasticity will be high when the degree of substitutability between workers is low. With the lower values of σ_{EXP} and σ_{ED} it is exactly the other way round. Wage changes will be lower, as the own-wage elasticity is lower when the degree of substitutability is high and one group of workers can easily be replaced by another. Table 4

UK (see table 3f). Due to the conservative nature of this assumption I believe that missing a few cases of people migrating out of unemployment does not change the overall picture.

[19]   see appendix 3.1.1 for a description of the data cleaning.

reports the point estimates for σ_{EXP}, as well as the 90% confidence bands. Based on the restriction $\sigma_{EXP} > \sigma_{ED}$, I choose σ_{ED} to be 0.3 less than the σ_{EXP} counterpart. Table 1 summarizes the choice of substitution elasticities for the computation of wages changes.

Table 1: Calibration values for σ_{ED} and σ_{EXP}

	5-year exper cells		10-year exper cells	
	low	high	low	high
σ_{EXP}	1.35	1.82	1.30	1.50
σ_{ED}	1.05	1.50	1.00	1.20

The low values reflect the lower bound of the 90%-confidence intervals given in table 4, the high values the upper bound.

Table 7 displays the results of the simulations with 10-year experience groups. Given that the choice of σ_{ED} is arbitrary, I run the simulations with different values for σ_{ED} to see, whether the results are robust to the choice of this parameter. The reference parameters from table 1 are displayed in bold letters. As we can see, the extent to which the results vary with σ_{ED} is small. This follows from the fact that σ_{ED} only enters the CES production function in a higher nest. As a consequence, it only affects the magnitude of the demand shifts that result from emigration. However, the demand shifts also depend on the share of labor in aggregate income and the income share of each education group, so that a change in σ_{ED} does not lead to a large change in the size of the wage effects.

From the simulations general pattern emerges: older workers lost from migration, whereas young workers gained and workers in the youngest group gained significantly more than older workers lost. In specification 1 I only use the data on migrants from Lithuania to Ireland. Even in absence of migration to the UK, the wage increases for workers with 10 years and less of work experience caused by emigration amount to 2-3%. For workers with a work experience between 11 and 30 years the effect is close to zero and it tends to be slightly negative for workers with an experience of more than 30 years.

When we include the number of migrants who went to the UK in specification 2, we can see that the effects on the real wages are in general much higher than in specification 1. Again, the youngest experience group saw the highest real wage increases, whereas the oldest group lost the most. The wage changes for workers with work experience between 10 and 30 years depend on their education: workers with lower-secondary education gained, whereas workers with an education higher than lower-secondary experienced wage changes close to zero.

For 5-year experience groups, the a similar pattern emerges, as we can see in table 9.

19

Regardless of the specification and education, workers with a work experience of less than 10 years gained, whereas the older workers lost from migration. For workers with an education between 10 and 35 years, the effect depends on their education. Workers with lower-secondary education gain if their work experience lies between 10 and 30 years, and the change is close to zero for those with a work experience of 30-34 years. The wage changes for the youngest group of workers are significantly higher than the wage changes of any other group, which might arise doubts about the reliability of the data on migration. Since the simulations are based on the migration rate $\frac{\Delta L_{ij}}{L_{ij}}$, the high wage increses for the group of workers with 0-4 years of work experience can be driven by high emigration rates for this group. A high emigration rate can not only be the result of a high number of people emigrating, i.e. ΔL_{ij}, but also of a low number of workers in the workforce in Lithuania, i.e. L_{ij}. One reason for this high rate could be that young workers emigrated right after graduation and did not migrate out of the workforce. Moreover, when the number of skill cells increases, the number of observations per skill cell decreases. As a consequence, the calculations of migration numbers are based on a low number of observations per skill group and are as such less reliable than the calculations based on broader skill groups, as pointed out by Aydemir (2010). In light of these problems, I consider the results based on 10-year experience cells in table 7 as more reliable.

One caveat applies to the interpretation of the results in this section: the interpretation is ceteris paribus, i.e. all other factors equal. The results only reflect the contribution of migration to the changes in wages, but they do not represent the total change in wages in the given time span. Other forces, for example capital adjustment, can attenuate or amplify the wage effects of migration. In terms of the commonly used terminology for the interpretation of empirical work, the results read as follows: change in wage caused by migration after controlling for all other factors.

After noting that the wage changes differ considerably between young and old workers, the question arises, what drives these results. As described in sections 2 and 4.1, the model accounts for substitutability and complementarity between different groups of workers. The change in the labor supply of one skill group does not only affect the wage of this skill group, but it also affects the composition of the labor force and the level of production and as such the wages of all other skill groups. Since the migrants were mostly young, the own-wage effect for young workers was much higher than for old workers. As a consequence, for older workers the negative composition and production effect exceeds the own-wage effect, so that emigration causes their wages to decrease. To illustrate the driving forces of the wage changes, I report the decomposition wage effects for 10-year

experience groups[20] in table 10. The total wage change by skill group consists of three effects, which are represented in equation (11). Effect 1, $\left(-\frac{1}{\sigma_{EXP}}\frac{\Delta L_{ij}}{L_{ij}}\right)$ is the own-wage effect, i.e. the change in wages caused by emigration of workers belonging to the same skill group. Because workers of the same skill group are perfect substitutes, this effect is positive for all skill groups. The magnitude of the own-wage effect depends on the size of the emigration rate. The own-wage effect decreases with age, because the migration rate decreases with age.

Effect 2 in table 10, $\left(\left(\frac{1}{\sigma_{EXP}}-\frac{1}{\sigma_{ED}}\right)\frac{1}{s_i}\sum_j s_{ij}\frac{\Delta L_{ij}}{L_{ij}}\right)$, represents the wage change caused by a change in the size and composition of the labor aggregate of the worker's education group. If workers from skill group ij emigrate, this has an impact on all other experience groups $j' \neq j$ within education group i. The effect is positive due to the restriction that workers with the same education are closer substitutes than workers who differ in their education, i.e. $\sigma_{EXP} > \sigma_{ED}$. Intuitively, the positive sign follows the logic that workers with the same education are substitutes, even though not perfect ones.

Effect 3, $\left(\left(\alpha-1+\frac{1}{\sigma_{ED}}\right)\frac{1}{\alpha}\sum_i\sum_j s_{ij}\frac{\Delta L_{ij}}{L_{ij}}\right)$, is negative and the same for all workers and represents the changes in the composition, as well as the decline in output caused by migration. For older workers, this effect is greater than effects 1 and 2 taken together, which results in negative wage changes.

5 Conclusion

This study answers the question, which groups of workers gain and which lose from emigration. I show for the case of EU enlargement that emigration leads to a significant increase in the real wages of young workers and to slight decreases for older workers. To show the distributional consequences of the emigration wave that followed EU enlargement, I set up a stylized model of a labor market, estimate its structural parameters, calibrate it on the Lithuanian economy and simulate the post-2004 emigration wave to determine the changes in wages for different groups of workers. The results give evidence for the distributional and welfare impacts of migration flows. They can be important 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.

However, migration is only one aspect of European integration. Other factors, such as

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[20]   as reported in table 7.

trade, capital flows or EU structural funds also play an important role for the labor markets in Central and Eastern Europe. To assess all the factors at the same time, a dynamic macro model would be required that captures the dynamics and interdependencies of the factors and that disentangles short-run effects from long-run developments. Because EU enlargement only occured very recently, the required data for the calibration of such a model is not yet available, so that this type of analysis will be left for future research.

Acknowledgements

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A Data

Large parts of this section are similar to Elsner (2010).

A.1 Education Groups

Throughout the study, I cluster the workforce into three education groups: lower secondary education, upper secondary education and third-level degree. For each worker, the highest obtained degree counts for her classification into one of the education groups. Lower education includes all workers that have less than a high school degree that would allow them to go to college. Upper secondary school are all workers with a high school degree that allows them to go to college and workers who obtained a degree that is less than the equivalent of a B.Sc degree, i.e. they cannot apply for an international M.Sc with this degree. Third-level degrees are all degrees that are at least equivalent to a B.Sc and would allow the workers to apply for an international M.Sc programme, so it also includes workers with M.Sc or PhD degrees. This clustering is fairly broad, given that the Lithuanian education system offers a variety of educational tracks.[21] However, these broad categories are necessary to match the Lithuanian HBS of different years with the Irish census and to ensure that within each group there is a number of observations large enough to be able to calculate average wages and emigration numbers. The Irish census has five education categories, the Lithuanian HBS has 5 categories different from the Irish census in 2002 and 12 categories from 2003 onwards. Table 2 illustrates the aggregation of the educational tracks into three education groups.

Table 2: Aggregation of education groups in the Lithuanian HBS and the Irish census. If applicable, variable code of the original dataset in parentheses.

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)

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

A.2 Experience Groups

Within each education group, I cluster the workforce in experience groups. The number of experience groups depends on the length of the chosen interval: 5 years or 10 years of work experience. In a workforce clustered in 5-year cells, each education group consists of 9 experience groups: 0-4 years, 5-9, 10-14, 15-19, 20-24,..., 40+ years. With 10-year cells, the clustering is 0-10 years, 11-20, 21-30 and 30+ years. A shorter interval length has the advantage of a finer clustering of the workforce, but the calculation of average wages is based on a smaller sample. On the other hand, a small number of experience groups with longer intervals (i.e. 10-year cells) has the advantage of more accurate average wages, but it only allows for a less differentiated picture of wage changes for different skill groups. As Aydemir & Borjas (2010) point out, the attenuation bias caused by inaccurate calculation of average wages as a consequence of a small number of observation per skill group can be severe. Therefore, I prefer 10-year experience groups with a smaller number of clusters and a higher number of workers per skill group. However, in the empirical part of the study in section 3, I use 5-year as well as 10-year cells.

From the Household Budget Survey, I do not have information about the actual work experience of an individual. I calculate the work experience of individual i from the formula $exp_i = age_i - education_i - 6$, where $education_i$ 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. $education_i$ equals 10 years for lower secondary education, 12 for upper secondary and 15 for third-level degree.[22]

For the sake of convenience, I use the term *work experience* throughout the study, although *potential work experience* or *exposure to the labor market* would admittedly give a more accurate description.

B   Income Shares by Skill Group

For the simulations in section 4, I calculate the income shares of each education-experience group, $s_i j$, as well as the one for each education group, s_i, from the sampling weights. Let the each skill group ij consist of $n = \{1, ..., N_{ij}\}$. The N_{ij} are allowed to differ from group to group. The sampling weight of observation n is p_{ijn} and her real wage is w_{ijn}. The wage bill accruing to skill group ij is $W_{ij} = \sum_n p_{ijn} w_{ijn}$. Adding up the wage bills of all skill groups gives the total wage bill of the population $W = \sum_i \sum_j W_{ij}$. The share of skill group ij in GDP given by

$$s_{ij} = \alpha \left(\frac{W_{ij}}{W} \right). \tag{17}$$

$\frac{W_{ij}}{W}$ is group ij's share in total labor income. As total labor income is α times GDP, we

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[22]   For example, a 60-year old worker with a third-level degree would have $60 - 15 - 6 = 39$ years of work experience.

have to multiply $\frac{W_{ij}}{W}$ with α.

To obtain the income share of education group i, I add up the income shares of all groups s_{ij},

$$s_i = \sum_j s_{ij}. \tag{18}$$

From the Household Budget Survey I calculate values of s_{ij} and s_i for every year in 2002, 2003, 2005 and 2006. The values of s_i and s_{ij} that enter the simulations in section 4 are the average of those four years.

C   Calculation of Emigration Rates - Details

I use the number of emigrants as an instrument for the identification of σ_{EXP} in section 3.2 and the emigration rate (i.e. the percentage of a skill group that emigrated) for the calculation of wage changes in section 4.

C.1   Emigration numbers: instrument for labor supply

For the calculation of emigration numbers used as an instrument in section 3.2, I use the skill distribution from the Irish census and weight this distribution with the number of work permits in Ireland and the UK. As the census data is only available for 2002 and 2006, I make the assumption that the skill distribution of emigrants before EU accession was the same for 2003 and 2002. Following the same logic, I assume that the skill distribution of emigrants after EU accession was the same over time, so that the distribution in 2005 is the same as in 2006. As we can see from table 1e), the skill distribution did not change significantly from 2002 to 2006, despite the number of immigrants was more than ten times higher in 2006. Furthermore, I assume that the skill distribution of migrants who went to Ireland is the same as of those who went to the UK. This allows me to use the work permit data from the UK as weights in the calculation of migration numbers. This might seem like a strong assumption, but comparing the studies of Barrett & Duffy (2008) on Ireland and Dustmann *et al.* (2009) on the UK, we can see that the skill distribution of post-EU-enlargement migrants in both countries is very similar.[23]

I calculate the emigration numbers for Lithuania and Poland the same way. Let PPS_t and $NINO_t$ be the Irish PPS and British NINo numbers granted in year $t = \{2002, 2003, 2005, 2006\}$ and let x_{ijt} be the number of workers of skill group ij at time t in the Irish census. Then, the number of migrants M_{ijt} for the four years under consideration are:

- 2002: $M_{ij2002} = x_{ij2002}\left(1 + \frac{NINO_{2002}}{PPS_{2002}}\right)$

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[23]   Distribution in Ireland (see Barrett & Duffy (2008)): lower secondary education 11.1%, upper secondary education 61% and third-level degree 28.2%. The corresponding values for the UK are 11.9%, 56.1% and 32% (see Dustmann *et al.* (2009)).

- 2003: $M_{ij2003} = x_{ij2002} \left(\frac{PPS_{2003}}{PPS_{2002}} + \frac{NINO_{2003}}{PPS_{2002}} \right)$, where $\frac{PPS_{2003}}{PPS_{2002}}$ accounts for the difference in the number of migrants to Ireland between 2002 and 2003 and $\frac{NINO_{2003}}{PPS_{2002}}$ is a weight accounting for the difference in migrants coming to Ireland and the UK.[24] The calculation for the other years follows the same logic.

- 2005: $M_{ij2005} = x_{ij2006} \left(\frac{PPS_{2005}}{PPS_{2006}} + \frac{NINO_{2005}}{PPS_{2006}} \right)$

- 2006: $M_{ij2006} = x_{ij2006} \left(1 + \frac{NINO_{2006}}{PPS_{2006}} \right)$

C.2 Emigration numbers: Simulations

In the basic simulations in section 4, I use two different specifications $k = 1, 2$ for the calculation of the emigrant numbers ΔL_{ijk}, with $k = 1$ based on very conservative assumptions and $k = 2$ on more optimistic ones. The first specification reflects a lower bound to migration, as it only uses data from the Irish census, which is the number of migrants we know for sure.

$$\Delta L_{ij1} = L_{ij}^{IR,2006} - L_{ij}^{IR,2002} \tag{19}$$

D Technical Appendix

D.1 Derivation of Equation (5)

The derivative in equation (4) can be represented as

$$
\begin{aligned}
w_{ijt} &= \frac{\partial Q_t}{\partial L_t} \times \frac{\partial L_t}{\partial L_{it}} \times \frac{\partial L_{it}}{\partial L_{ijt}} \\
&= \left(\alpha A_t L_t^{\alpha-1} K_t^{1-\alpha} \right) \left(L_t^{\frac{1}{\sigma_{ED}}} \cdot \theta_{it} \cdot L_{it}^{-\frac{1}{\sigma_{ED}}} \right) \left(L_{it}^{\frac{1}{\sigma_{EXP}}} \cdot \gamma_{ij} \cdot L_{ijt}^{-\frac{1}{\sigma_{EXP}}} \right) \quad (20)
\end{aligned}
$$

$$\tag{21}$$

Taking the logs of equation (20), we get equation (5)

D.2 Derivation of the Simulation Equation (11)

Note that $\frac{\Delta L_t}{L_t}$ and $\frac{\Delta L_{it}}{L_{it}}$ can be rewritten in terms of $\frac{\Delta L_{ijt}}{L_{ijt}}$:

---

[24] The expression $\frac{NINO_{2003}}{PPS_{2002}}$ is derived from $\frac{NINO_{2003}}{PPS_{2003}} \times \frac{PPS_{2003}}{PPS_{2002}}$, where PPS_{2003} cancels out. $\frac{NINO_{2003}}{PPS_{2003}}$ is the number of migrants to the UK relative to the number of migrants to Ireland and $\frac{PPS_{2003}}{PPS_{2002}}$ is the number of migrants to Ireland in 2003 relative to the same number in 2002.

$$\begin{aligned}
\frac{\Delta L_{it}}{L_{it}} &= \frac{\sum_j \gamma_{ij} L_{ijt}^{\eta} \frac{\Delta L_{ijt}}{L_{ijt}}}{L_{it}^{\eta}} \\
&= \frac{\sum_j \gamma_{ij} L_{ijt}^{\eta} \frac{\Delta L_{ijt}}{L_{ijt}}}{\sum_j \gamma_{ij} L_{ijt}^{\eta}} \\
&= \sum_j \left(\frac{\gamma_{ij} L_{ijt}^{\eta}}{\sum_j \gamma_{ij} L_{ijt}^{\eta}} \right) \frac{\Delta L_{ijt}}{L_{ijt}} \qquad (22) \\
&= \frac{1}{s_{it}} \sum_j s_{ijt} \frac{\Delta L_{ijt}}{L_{ijt}},
\end{aligned}$$

where $\left(\frac{\gamma_{ij} L_{ijt}^{\eta}}{\sum_j \gamma_{ij} L_{ijt}^{\eta}} \right) = \frac{s_{ijt}}{s_{it}}$. The same logic applies to $\frac{\Delta L_t}{L_t}$:

$$\begin{aligned}
\frac{\Delta L_t}{L_t} &= \frac{\sum_i \theta_{it} L_{it}^{\rho} \frac{\Delta L_{it}}{L_{it}}}{L_t^{\rho}} \qquad (23) \\
&= \sum_i \left(\frac{\theta_{it} L_{it}^{\rho}}{\sum_i \theta_{it} L_{it}^{\rho}} \right) \frac{\Delta L_{it}}{L_{it}} \\
&= \frac{1}{s_{Lt}} \sum_i s_{it} \frac{\Delta L_{it}}{L_{it}},
\end{aligned}$$

where $\left(\frac{\theta_{it} L_{it}^{\rho}}{\sum_i \theta_{it} L_{it}^{\rho}} \right) = \frac{s_{ijt}}{\alpha}$. Plugging (22) into (23), we get

$$\begin{aligned}
\frac{\Delta L_t}{L_t} &= \sum_i \frac{s_{it}}{\alpha} \sum_j \frac{s_{ijt}}{s_{it}} \frac{\Delta L_{ijt}}{L_{ijt}} \qquad (24) \\
&= \frac{1}{\alpha} \sum_i \sum_j s_{ijt} \frac{\Delta L_{ijt}}{L_{ijt}}.
\end{aligned}$$

Plugging (22) and (24) into (10), we get the simulation equation (11).

E   Tables and Figures

Table 3: Descriptive Statistics

Year		2002	2003	2005	2006
a) Number of observations in the Lithuanian HBS, employees aged 18-64					
All workers		3950	4136	4042	3874
Men		2322	2411	2426	2314
Women		1628	1725	1616	1560
b) Number of observations in the Irish census, employees aged 18-64					
All workers		1904	-	-	21779
Men		987	-	-	12300
Women		917	-	-	9479
c) Mean private sector income from employment in Litas, deflated by the HCPI. Source: own calculations from the Lithuanian HBS					
All workers		1084	1142	1339	1533
Men		1139	1216	1405	1628
Women		906	905	1107	1249
d) Distribution of education in the Lithuanian HBS					
lower secondary		9%	10.6%	10.9%	9.9%
upper secondary		68.8%	69.0%	67.5%	67.5%
third-level		22.2%	20.4%	21.6%	22.6%
e) Distribution of education of Lithuanians in the Irish census					
lower secondary		16.7%	-	-	20.4%
upper secondary		63.4%	-	-	62.2%
third-level		19.9%	-	-	17.4%
f) Numbers of work permits (PPS and NINo). Sources: Irish Department of Social and Family Affairs UK Department for Work and Pensions.					
PPS		2709	2394	18680	16017
NINo		1430	3140	10710	24200
g) Lithuanian HCPI, 2005=100, source: Eurostat					
		97.334	96.291	100	103.788
h) Immigrants to Lithuania (by nationality), source: Statistics Lithuania					
Lithuanian		809	1313	4705	5508
Belarussian, Russian, Ukrainian		2478	1915	874	1337
Other		1823	1500	1210	900
Total		5110	4728	6789	7745
i) Unemployment rate in Lithuania, source: Statistics Lithuania					
		13.8%	12.4%	8.3%	5.6%
j) Average monthly gross wage, private sector workers, in LTL					
Statistics Lithuania	Men	1173	1227	1420	1676
	Women	998	1029	1167	1356
Lithuanian HBS (calculated average)	Men	1185	1252	1440	1688
	Women	940	988	1189	1303
k) real GDP growth, year-on-year, source: Statistics Lithuania					
		6.8%	10.2%	7.8%	7.8%

Table 4: Regression results for σ_{EXP}

OLS and IV results, 10-year cells

VARIABLES	Men and Women			Men only			Women only		
	(1) OLS	(2) IV (LIT)	(3) IV (PL)	(4) OLS	(5) IV (LIT)	(6) IV (PL)	(7) OLS	(8) IV (LIT)	(9) IV (PL)
log(Number of Workers)	-0.114	-0.766***	-0.665***	-0.070	-0.841***	-0.706***	-0.244**	-0.452*	-0.379*
	[0.0719]	[0.2414]	[0.1961]	[0.0783]	[0.3251]	[0.2653]	[0.1124]	[0.2427]	[0.2294]
Observations	48	48	48	48	48	48	48	48	48
Adjusted R^2	0.9533	0.8596	0.8863	0.9506	0.7769	0.8325	0.8920	0.8829	0.8882
F-Statistic		9.698	9.014		4.753	5.166		11.602	9.757
$\hat{\sigma}_{EXP}$ (point estimate)	**8.77**	**1.31**	**1.50**	**14.29**	**1.18**	**1.42**	**4.10**	**2.21**	**2.64**
$\bar{\hat{\sigma}}_{EXP}$ (upper 90% CI)	9.04	1.33	1.53	15.09	1.21	1.44	4.20	2.27	2.71
$\underline{\hat{\sigma}}_{EXP}$ (lower 90% CI)	8.51	1.29	1.48	13.57	1.17	1.39	4.01	2.16	2.56

OLS and IV results, 5-year cells

VARIABLES	Men and Women			Men only			Women only		
	(1) OLS	(2) IV (LIT)	(3) IV (PL)	(4) OLS	(5) IV (LIT)	(6) IV (PL)	(7) OLS	(8) IV (LIT)	(9) IV (PL)
log(Number of Workers)	-0.056	-0.737***	-0.555***	-0.055	-0.781*	-0.499**	-0.058	-0.464*	-0.320
	[0.0527]	[0.2375]	[0.1677]	[0.0477]	[0.4394]	[0.2356]	[0.0800]	[0.2717]	[0.2219]
Observations	108	108	108	108	108	108	107	107	107
Adjusted R^2	0.9230	0.7865	0.8498	0.9188	0.6963	0.8358	0.8420	0.7826	0.8173
F-Statistic		8.234	8.274		1.875	2.678		6.164	6.585
σ_{EXP} (point estimate)	**17.85**	**1.36**	**1.80**	**18.18**	**1.28**	**2.00**	**17.24**	**2.16**	**3.13**
$\bar{\hat{\sigma}}_{EXP}$ (upper 90% CI)	18.41	1.37	1.82	18.69	1.30	2.03	18.03	2.20	3.20
$\underline{\hat{\sigma}}_{EXP}$ (lower 90% CI)	17.34	1.34	1.78	17.70	1.26	1.97	16.52	2.16	3.06

Robust standard errors in brackets

*** p<0.01, ** p<0.05, * p<0.1

Table 5: Calculated wage elasticities (for $\sigma_{EXP} = 1.4$ and $\sigma_{ED} = 1.1$) and income shares.

Education	Work experience	Own-wage elasticity	Cross-wage elasticity within educ group	Cross-wage elasticity across educ groups
lower secondary	0-10	-0.696	-0.029	0.012
	11-20	-0.706	-0.040	0.017
	21-30	-0.681	-0.014	0.006
	31+	-0.701	-0.034	0.014
upper secondary	0-10	-0.631	0.036	0.060
	11-20	-0.589	0.078	0.129
	21-30	-0.581	0.086	0.143
	31+	-0.616	0.051	0.084
third-level	0-10	-0.667	0.001	0.049
	11-20	-0.667	0.000	0.047
	21-30	-0.667	0.000	0.046
	31+	-0.667	0.000	0.025

Table 6: Descriptive statistics: calculated emigration numbers (migrants to Ireland only and migrants to Ireland and the UK), size of the skill group in the workforce, income shares by education-experience group and by education group. The income shares add up to 0.8, which is the share of labor in aggregate income.

Education	Years of work experience	Emigrants IE only	Emigrants IE & UK	Nr of workers in Lithuania	Income share skill group ij	Income share skill group j
	0-10	619	1610	14085	1.56	
	11-20	400	1057	19836	2.14	6.31%
	21-30	187	490	7801	0.77	
	31+	101	259	19429	1.84	
	0-10	3108	8248	52468	7.60	
	11-20	1911	5047	107391	16.34	52.60%
	21-30	1011	2625	118403	18.01	
	31+	328	852	76533	10.66	
	0-10	1180	3143	23829	6.16	
	11-20	266	723	22395	5.90	21.08%
	21-30	226	582	20881	5.85	
	31+	75	191	13038	3.18	
Sum		9412	24827	496089	0.8	0.8

Table 7: Calculated wage changes in % ($\frac{\Delta w_{ij}}{w_{ij}}$) resulting from the post-2004 migration shock. 10-year experience groups.

Lower bound: $\sigma_{EXP} = 1.5$

Education	Years of Work Experience	$\sigma_{ED} = 1.0$		$\sigma_{ED} = 1.2$		$\sigma_{ED} = 1.3$		$\sigma_{ED} = 1.7$	
		IE only	IE & UK	IE only	IE & UK	IE only	IE & UK	IE only	IE & UK
lower	0-10	2.13	5.50	2.08	5.40	2.03	5.30	2.01	5.20
secondary	11-20	0.55	1.40	0.50	1.30	0.45	1.20	0.42	1.10
	21-30	0.80	2.10	0.75	1.90	0.70	1.80	0.68	1.80
	31+	-0.45	-1.20	-0.50	-1.40	-0.55	-1.50	-0.57	-1.50
upper	0-10	3.01	8.00	3.03	8.10	3.05	8.10	3.06	8.10
secondary	11-20	0.25	0.60	0.27	0.70	0.29	0.80	0.30	0.80
	21-30	-0.37	-1.00	-0.35	-0.90	-0.33	-0.90	-0.32	-0.90
	31+	-0.66	-1.70	-0.63	-1.70	-0.61	-1.60	-0.60	-1.60
third	0-10	2.49	6.70	2.45	6.50	2.40	6.40	2.39	6.40
level	11-20	-0.02	0.00	-0.06	-0.10	-0.10	-0.20	-0.12	-0.30
	21-30	-0.09	-0.30	-0.13	-0.40	-0.17	-0.50	-0.19	-0.60
	31+	-0.43	-1.20	-0.47	-1.30	-0.51	-1.40	-0.53	-1.40

Upper bound: $\sigma_{EXP} = 1.3$

Education	Years of Work Experience	$\sigma_{ED} = 1.0$		$\sigma_{ED} = 1.2$		$\sigma_{ED} = 1.3$		$\sigma_{ED} = 1.5$	
		IE only	IE & UK	IE only	IE & UK	IE only	IE & UK	IE only	IE & UK
lower	0-10	2.43	6.20	2.35	6.10	2.29	5.90	2.26	5.80
secondary	11-20	0.60	1.60	0.53	1.40	0.46	1.20	0.43	1.10
	21-30	0.89	2.30	0.82	2.10	0.75	1.90	0.72	1.90
	31+	-0.55	-1.50	-0.63	-1.70	-0.69	-1.90	-0.72	-1.90
upper	0-10	3.40	9.00	3.43	9.10	3.46	9.20	3.48	9.20
secondary	11-20	0.21	0.60	0.24	0.60	0.28	0.70	0.29	0.80
	21-30	-0.50	-1.40	-0.47	-1.30	-0.44	-1.20	-0.42	-1.10
	31+	-0.83	-2.20	-0.79	-2.10	-0.76	-2.00	-0.75	-2.00
third	0-10	2.83	7.60	2.77	7.40	2.72	7.30	2.69	7.20
level	11-20	-0.06	-0.10	-0.12	-0.20	-0.18	-0.40	-0.21	-0.50
	21-30	-0.14	-0.40	-0.20	-0.60	-0.26	-0.70	-0.29	-0.80
	31+	-0.53	-1.40	-0.59	-1.60	-0.65	-1.80	-0.68	-1.80

Table 8: Calculated wage changes in % ($\frac{\Delta w_{ij}}{w_{ij}}$) resulting from the post-2004 migration shock. 5-year experience groups.

Upper bound: $\sigma_{EXP} = 1.35$

Education	Years of Work Experience	$\sigma_{ED} = 0.8$		$\sigma_{ED} = 1.05$		$\sigma_{ED} = 1.2$		$\sigma_{ED} = 1.5$	
		IE only	IE & UK	IE only	IE & UK	IE only	IE & UK	IE only	IE & UK
lower secondary	0-4	6.33	16.10	6.24	15.90	6.21	15.80	6.33	16.10
	5-9	1.90	4.90	1.81	4.70	1.78	4.60	1.90	4.90
	10-14	0.76	2.00	0.67	1.70	0.64	1.70	0.76	2.00
	15-19	0.74	1.90	0.65	1.70	0.62	1.60	0.74	1.90
	20-24	0.98	2.40	0.89	2.20	0.86	2.10	0.98	2.40
	25-29	0.79	2.10	0.70	1.90	0.67	1.80	0.79	2.10
	30-34	0.17	0.30	0.08	0.10	0.04	0.00	0.17	0.30
	35-39	-0.48	-1.30	-0.57	-1.50	-0.60	-1.60	-0.48	-1.30
	40+	-0.70	-1.90	-0.79	-2.10	-0.82	-2.20	-0.70	-1.90
upper secondary	0-4	5.58	14.70	5.62	14.80	5.63	14.80	5.58	14.70
	5-9	2.87	7.70	2.91	7.80	2.92	7.80	2.87	7.70
	10-14	0.82	2.20	0.85	2.30	0.87	2.40	0.82	2.20
	15-19	0.07	0.20	0.11	0.20	0.12	0.30	0.07	0.20
	20-24	-0.40	-1.10	-0.36	-1.00	-0.35	-0.90	-0.40	-1.10
	25-29	-0.46	-1.20	-0.42	-1.10	-0.41	-1.10	-0.46	-1.20
	30-34	-0.64	-1.70	-0.60	-1.60	-0.58	-1.60	-0.64	-1.70
	35-39	-0.85	-2.30	-0.81	-2.20	-0.80	-2.10	-0.85	-2.30
	40+	-0.84	-2.20	-0.80	-2.10	-0.79	-2.10	-0.84	-2.20
third level	0-4	4.32	11.80	4.26	11.60	4.23	11.50	4.32	11.80
	5-9	2.22	5.90	2.16	5.70	2.13	5.60	2.22	5.90
	10-14	0.34	1.00	0.28	0.80	0.25	0.70	0.34	1.00
	15-19	-0.12	-0.30	-0.19	-0.40	-0.21	-0.50	-0.12	-0.30
	20-24	-0.09	-0.20	-0.15	-0.40	-0.18	-0.50	-0.09	-0.20
	25-29	-0.11	-0.30	-0.17	-0.50	-0.20	-0.60	-0.11	-0.30
	30-34	-0.36	-1.00	-0.43	-1.20	-0.45	-1.20	-0.36	-1.00
	35-39	-0.59	-1.60	-0.66	-1.70	-0.68	-1.80	-0.59	-1.60
	40+	-0.74	-2.00	-0.81	-2.10	-0.83	-2.20	-0.74	-2.00

Table 9: Calculated wage changes in % $\left(\frac{\Delta w_{ij}}{w_{ij}}\right)$ resulting from the post-2004 migration shock. 5-year experience groups.

Lower bound: $\sigma_{EXP} = 1.82$

Education	Years of Work Experience	$\sigma_{ED} = 1.0$ IE only	$\sigma_{ED} = 1.0$ IE & UK	$\sigma_{ED} = 1.2$ IE only	$\sigma_{ED} = 1.2$ IE & UK	$\sigma_{ED} = 1.5$ IE only	$\sigma_{ED} = 1.5$ IE & UK	$\sigma_{ED} = 2.0$ IE only	$\sigma_{ED} = 2.0$ IE & UK
lower secondary	0-4	4.81	12.20	**4.76**	**12.10**	4.72	12.00	4.67	11.90
	5-9	1.53	4.00	**1.48**	**3.80**	1.43	3.70	1.38	3.60
	10-14	0.68	1.80	**0.63**	**1.60**	0.59	1.50	0.54	1.40
	15-19	0.67	1.70	**0.62**	**1.60**	0.57	1.50	0.52	1.30
	20-24	0.85	2.10	**0.80**	**2.00**	0.75	1.90	0.70	1.80
	25-29	0.70	1.90	**0.66**	**1.80**	0.61	1.60	0.56	1.50
	30-34	0.24	0.60	**0.19**	**0.40**	0.14	0.30	0.10	0.20
	35-39	-0.24	-0.70	**-0.29**	**-0.80**	-0.34	-0.90	-0.38	-1.00
	40+	-0.40	-1.10	**-0.45**	**-1.20**	-0.50	-1.30	-0.55	-1.50
upper secondary	0-4	4.23	11.10	**4.25**	**11.20**	4.27	11.20	4.29	11.30
	5-9	2.22	5.90	**2.24**	**6.00**	2.26	6.00	2.28	6.10
	10-14	0.69	1.90	**0.71**	**1.90**	0.74	2.00	0.76	2.00
	15-19	0.14	0.30	**0.16**	**0.40**	0.18	0.50	0.20	0.50
	20-24	-0.21	-0.60	**-0.19**	**-0.50**	-0.17	-0.50	-0.15	-0.40
	25-29	-0.25	-0.70	**-0.23**	**-0.60**	-0.21	-0.60	-0.19	-0.50
	30-34	-0.38	-1.00	**-0.36**	**-1.00**	-0.34	-0.90	-0.32	-0.90
	35-39	-0.54	-1.40	**-0.52**	**-1.40**	-0.50	-1.30	-0.48	-1.30
	40+	-0.53	-1.40	**-0.51**	**-1.40**	-0.49	-1.30	-0.47	-1.30
third level	0-4	3.32	9.00	**3.28**	**8.90**	3.25	8.80	3.21	8.70
	5-9	1.76	4.60	**1.73**	**4.50**	1.69	4.40	1.65	4.30
	10-14	0.37	1.00	**0.33**	**0.90**	0.30	0.80	0.26	0.70
	15-19	0.02	0.10	**-0.01**	**0.00**	-0.05	-0.10	-0.09	-0.20
	20-24	0.05	0.10	**0.01**	**0.00**	-0.03	-0.10	-0.06	-0.20
	25-29	0.03	0.10	**0.00**	**0.00**	-0.04	-0.10	-0.07	-0.20
	30-34	-0.16	-0.40	**-0.19**	**-0.50**	-0.23	-0.60	-0.26	-0.70
	35-39	-0.33	-0.90	**-0.36**	**-1.00**	-0.40	-1.10	-0.43	-1.20
	40+	-0.44	-1.20	**-0.47**	**-1.30**	-0.51	-1.40	-0.54	-1.50

Table 10: Decomposition of the wage effect of emigration. Example: $\sigma_{EXP} = 1.3$, $\sigma_{ED} = 1.2$

|	Work Experience	Total Wage Change	Effect 1 Own-wage	Effect 2 Effect within educ group	Effect 3 Effect composition & production
lower	0-10	2.35	3.38	0.51	-1.54
secondary	11-20	0.53	1.55	0.51	-1.54
	21-30	0.82	1.84	0.51	-1.54
	31+	-0.63	0.40	0.51	-1.54
upper	0-10	3.43	4.56	0.41	-1.54
secondary	11-20	0.24	1.37	0.41	-1.54
	21-30	-0.47	0.66	0.41	-1.54
	31+	-0.79	0.33	0.41	-1.54
third	0-10	2.77	3.81	0.50	-1.54
level	11-20	-0.12	0.91	0.50	-1.54
	21-30	-0.20	0.83	0.50	-1.54
	31+	-0.59	0.44	0.50	-1.54

Figure 1: Nested CES production function
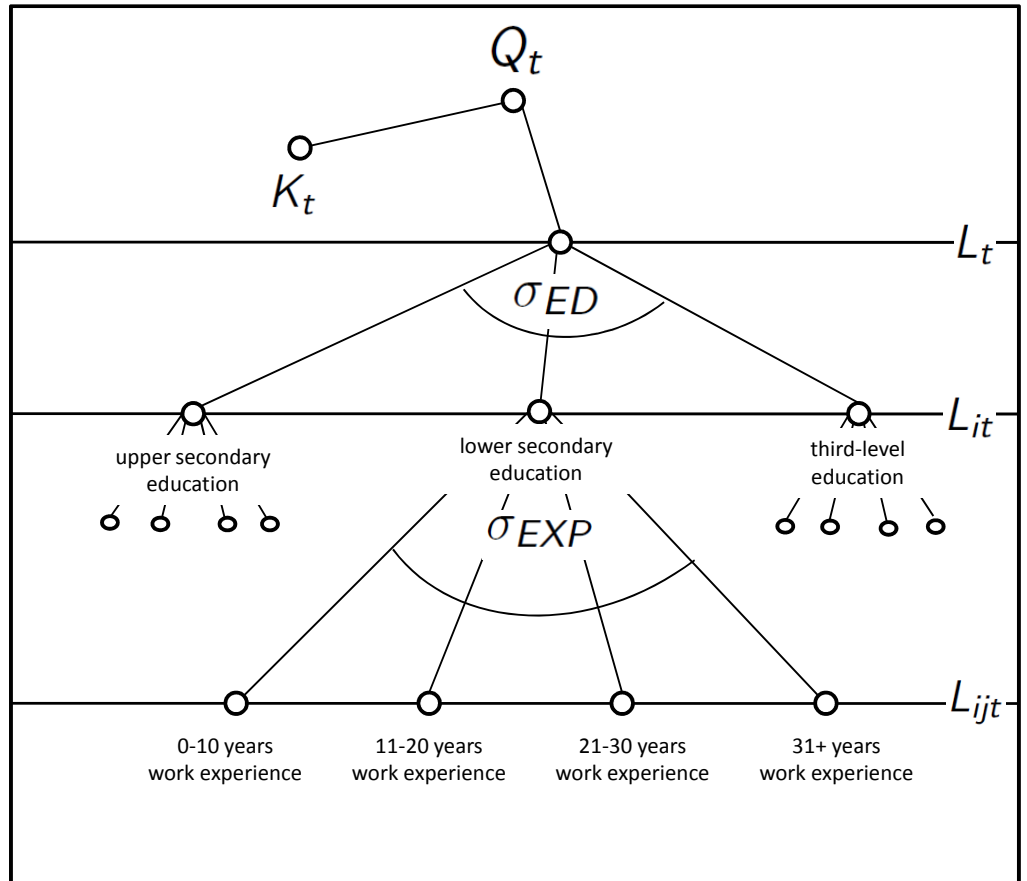
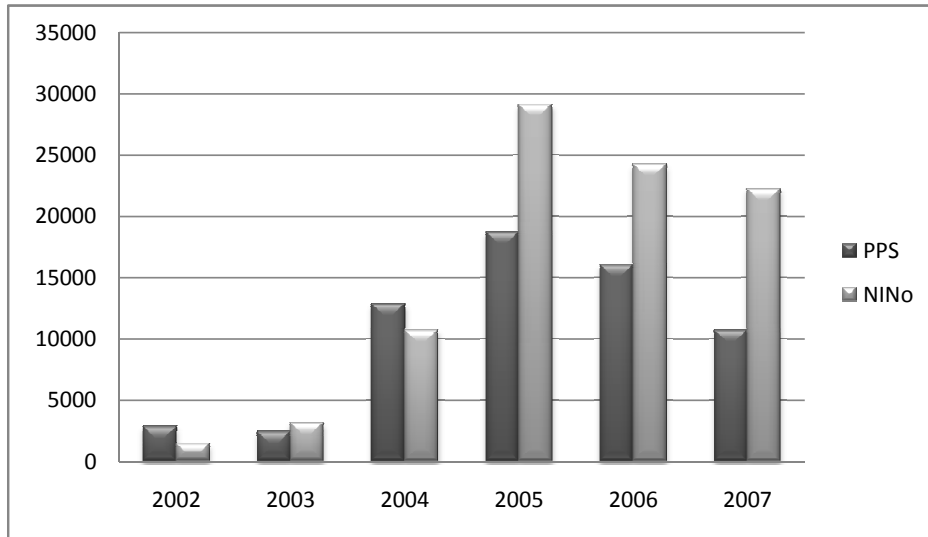Figure 2: Work Permits to Lithuanian nationals, in Ireland (PPS) and the UK (NINo), 2002-2007

Figure 3: Number of emigrants 2004-2007 relative to the total workforce in 2003. Number of emigrants calculated from the work permit numbers in Ireland (PPS) and the UK (NINo). Workforce from Eurostat.
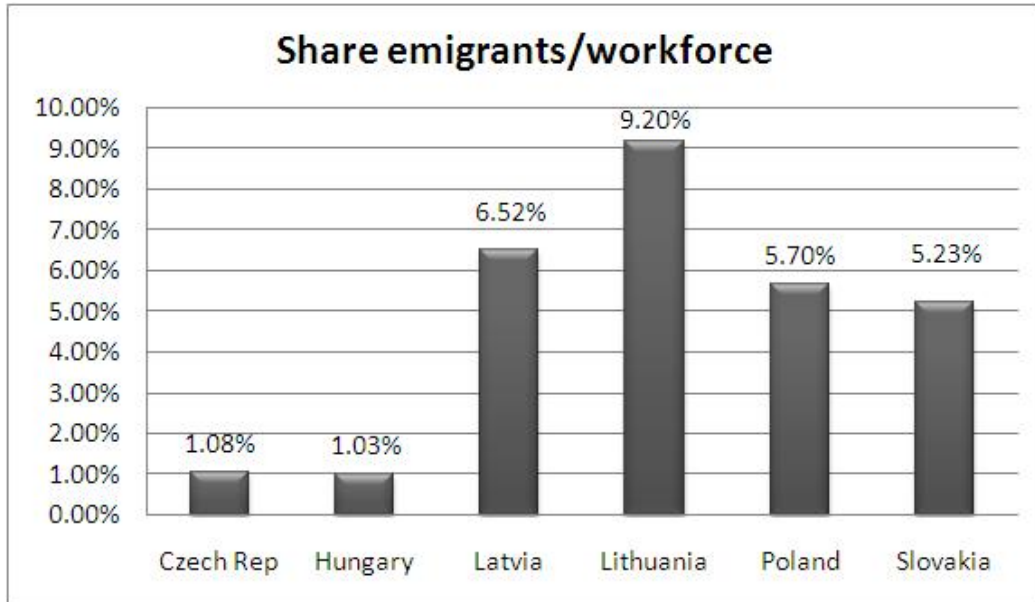

Figure 4: Correlation of emigration rates Poland - Lithuania