Emigration and Wages: The EU Enlargement Experiment

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Abstract

While there is a vast literature on the impact of immigration on wages in the receiving countries, little is known about the wage effects of emigration in the source countries. This paper sheds light on the short-run impact of emigration on the wage level and wage distribution in the source countries. The large emigration wave from Central and Eastern Europe following EU enlargement in 2004 serves as an example for the analysis. Using microdata from Lithuania for the calibration of a structural model I show that emigration significantly changes the wage distribution. Following EU enlargement, emigration caused an increase in the real wages of young workers by around 6%, while it led to a decrease in the wages of old workers by around 1.2%.

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1 Introduction

The enlargement of the European Union (EU) in 2004 was followed by large migration movements from Central and Eastern Europe (CEE) to Western Europe. Between 2004 and 2007, between 5% and 9% of the workforce of Latvia, Lithuania, Poland and Slovakia 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 and presents two main findings. First, among those workers who stay in their home country, young workers gain from emigration while old workers lose. Second, the gain for young workers exceeds the losses for old workers. This distributional impact of emigration on wages is driven by two opposing 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 the wages of these workers. This was the case with young workers who stayed behind. Moreover, old and young workers are complements, so that the emigration of young workers lowers the labor demand for old workers and leads to a decrease in their wages.

Because of its exogenous change in the institutional framework, EU enlargement is a quasi-natural experiment. Prior to 2004 workers in CEE were facing high wage differentials compared to their peers in Western Europe. Workers in Poland and Lithuania, for example, earned on average 40% of the average wages in the UK.[2] These wage differentials gave workers a large incentive to emigrate, but emigration only occured in small numbers, as until 2004 Western European countries restricted the access to their labor markets for non-EU nationals. In 2004, with the accession of 10 new member states (NMS), workers from these countries received the right to emigrate and take up work in Ireland, the UK and Sweden. 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] A large share of them stayed for more than one year. Evidence from the Irish Central Statistics Office (2009) suggests that around 60% of migrants from the NMS stayed for at least two years after having received a work permit. Given the magnitude and the speed of post-enlargement emigration, this labor supply shock should have an impact on the level and distribution of wages in the source countries. Looking at figure 2, we can see that from 2002 to 2006 real wages changed significantly for all groups of workers. The wage changes were the highest for workers with a lower secondary education and lowest for workers with a third-level degree. The aim of this paper is to determine which share of

[1] See figure 1.
[2] Own calculations from Eurostat.
[3] Sources: Ireland: Central Statistics Office. UK: UK Home Office. Sweden: Wadensjö (2007).

these overall wage changes can be attributed to emigration.

The analysis is based on a factor demand model, which follows Katz & Murphy (1992), Borjas (2003) and Ottaviano & Peri (2006, 2008). The workforce consists of skill groups defined by the observable characteristics *education* and *work experience*. The model generates a labor demand framework that accounts for differences in substitutability between these skill groups. Using Lithuanian microdata, I estimate the structural parameters that characterize the labor market. To overcome simultaneity bias of labor supply and demand, birth cohort size and the number of emigrants from Poland serve as instrumental variables for labor supply. Based on these estimates I calibrate the model and simulate the post-2004 emigration wave on the Lithuanian labor market, which yields a separate wage effect for every skill group. 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. The wages of workers with 10 years or less of work experience increased by 6% to 8%, while the wages of workers with 30 and more years of work experience decreased by around 1.2%. The wages of workers with a work experience between 11 and 30 years were not affected by emigration. Compared to purely empirical studies, this structural approach has the advantage that it allows to disentangle the changes in wages caused by migration from all other factors that have an influence on wages. Hence, the typical problems of reduced form approaches, such as endogeneity and omitted variable bias, can be avoided. This is especially important in the case of EU enlargement, where accession countries saw increased trade flows and inflows of FDI and EU structural funds.

Lithuania is an excellent example to show the impact of emigration on the wages of stayers. As we can see in figure 1, following EU enlargement the country saw about 9% of its workforce emigrate to the UK and Ireland. This is a significant labor supply shock, which is comparable to the situations in Poland, Latvia and Slovakia after EU enlargement.

This paper relates to the literature on the wage effects of migration, as well as to the literature on the economic consequences of European integration. The migration literature focuses in large parts on the side of the receiving countries,[4] whereas the literature on the wage effects of emigration remains scarce. The existing studies focus mostly on the wage level. Docquier *et al.* (2011) analyze jointly the wage effect of immigration and emigration in a simulation-based approach for a sample of developed countries. They find that in the long run emigration decreased the wages of stayers. Mishra (2007) analyzes

[4] See Kerr & Kerr (2011) for a survey on the wage effect of immigration in general and Barrett *et al.* (2006) and Blanchflower & Shadforth (2009)for an analysis of the effect of the post-EU enlargement immigration on the labour markets in Ireland and the UK.

the long-run impact of emigration on the wages in Mexico and concludes that emigration to the US increased the average wage level in Mexico from 1970 to 2000. Elsner (2010) finds a similar effect of emigration on the overall wage level in the source country. Looking at the case of Lithuania after EU enlargement 2004, he finds that emigration increased the average wages of stayers in the short run. Compared to these studies, this current paper contributes to the literature on the wage effects of emigration as it shows that emigration does not only have a *short-run* effect on the wage level, but also on the wage distribution.

With respect to the literature on the economic impacts of EU enlargement, Batista (2007) analyzes jointly the impact of emigration and FDI on wages in Portugal after the country joined the EU in 1986. She finds that the long-run impact of emigration was small compared to the impact of FDI inflows. For the context of the EU enlargement 2004 and the migration wave that followed, Barrell *et al.* (2010) use a DSGE model to analyze the macroeconomic effects of the post-2004 migration wave. They conclude that migration decreases GDP and unemployment in the long run. Hazans & Philips (2009) and Fihel *et al.* (2006) document the migrant flows from the NMS to Western Europe, and the developments of the labor markets in the NMS. They show that after EU accession wages increased and unemployment decreased. In this paper, I show that there exists in fact a causal relationship between emigration and wages. Moreover, I quantify the magnitude of the wage changes for different groups of workers.

The remainder of the paper is structured as follows: sections 2 to 5 describe the structural model, the estimation of the structural parameters and the simulation of the post-2004 emigration wave. In section 6 I conduct a sensitivity analysis. Section 7 concludes.

2 Structural Model

The structural model presented in this section explains how a change in labor supply affects the wages of workers who differ in their observable skills. To model this heterogeneity in skills, the workforce is divided into 12 skill groups, which are defined by education and work experience. Each skill group constitutes a separate labor market, but all labor markets are interrelated. Workers with the same observable characteristics compete in the same labor market and are assumed to be 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, 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 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 fundamentally different skills.

Following the works of Katz & Murphy (1992), Borjas (2003) and Ottaviano & Peri (2008), the economy is modelled the economy as 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 is set up in a way that allows for an econometric identification of the labor demand curves. The model consists of three building blocks that are nested in an aggregate production function. First, capital and labor are combined to produce an aggregate output. As I am interested in the short-run effect of emigration on wages, I assume throughout the study that capital does not adjust to changes in labor supply. Neoclassical growth models such as Solow (1956) would predict that capital adjustment dampens the wage changes caused by an emigration shock, as the capital stock decreases in the long run until the capital-labor ratio is the same as in the initial steady state. However, in the time span of 5 years it is unlikely that firms get rid of their capital, it can be assumed as fixed. The second building block is a CES aggregate of three education groups, which reflects the fact that workers with a different education are imperfect substitutes in the labor market. The third building block follows the same logic. Workers within the same education group may differ in their human capital, especially when they have different levels of work experience, which makes them imperfect substitutes as well. To account for differences in work experience, each education group is represented by a CES aggregate of four experience groups.

2.1 Nested CES Production Function

The notation in this section closely follows Borjas (2003) and Ottaviano & Peri (2008). 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, 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} 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} 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 relative productivity between education groups.

Each education group 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 division of an eduction group into experience groups (j) I use intervals of 10 years of work experience, which gives a total of four experience groups: 0-10 years, 11-20 years, 21-30 years and more than 30 years of work experience. The choice of the intervals depends on the characteristics of the dataset.[5] On the one hand, shorter intervals, e.g. 2 years or 5 years, allow for a more differentiated picture of the labor market. On the other hand, with a given number of observations, the calculated average wages and labor inputs becomes less precise, as the calculations of average values per skill group are based on fewer observations. Aydemir & Borjas (2011) show that this *attenuation bias* can have a significant impact on the estimates of the structural parameters. The choice of 10-year intervals is a compromise that avoids attenuation bias and yet allows for a differentiated picture of the labor supply and wage changes.

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 $\sum_j \gamma_{ijt} = 1$. Econometric identification of σ_{EXP} requires the assumption that the relative productivity of each skill group ij is constant over time, i.e. $\gamma_{ijt} = \gamma_{ij}$. In a short-run analysis it is

[5] Most of the literature, e.g. Borjas (2003), Brücker & Jahn (2011), D'Amuri *et al.* (2010), Katz & Murphy (1992), Manacorda *et al.* (2006), Ottaviano & Peri (2006, 2008), uses 5-year experience groups.

not plausible that the relative productivity of one age group changes fundamentally, so that this restriction is justified. Additional assumptions required for identification are as follows. Total factor productivity A_t, the income share of labor α, as well as the relative productivities of education groups θ_{it} and experience groups γ_{ij} do not depend on labor supply.

Figure 3 illustrates the nested structure of the CES production function. From this picture we can see the assumptions the model makes with respect to the elasticities of substitution between any two education and experience groups, σ_{ED} and σ_{EXP}. These may seem restrictive at first glance, but they are necessary to bring together theory and empirics. Ideally, we would like to estimate a separate relative labor demand curve, i.e. a separate σ_{EXP} for every skill group, but the econometric identification of the structural parameters 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 a small number of observations that is typically available from aggregate labor market data. The nested CES structure collapses the number of structural parameters that need to be estimated to two elasticities of substitution. Given these elasticities and the variation in the number of emigrants across skill groups, we can nevertheless obtain a differentiated pictures of the impact of emigration on the wages of each skill group.

Moreover, I assume that the slope of the labor demand curves is time-invariant, i.e. σ_{ED} and σ_{EXP} are constant over time. This assumption is in line with the ceteris paribus interpretation of this analysis: the estimated values for σ_{ED} and σ_{EXP} characterize the labor market before the emigration shock. Emigration alters the labor supply and demand and changes the wages *all other things equal* but it does not change the overall characteristics of the labor market, i.e. the substitutability between groups of workers.

2.2 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, obtained from a partial differentiation of equations (1)-(3),

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

Equation (4) describes the firms' labor demand for skill group ijt. The log of this equation gives a labor demand curve that is log-linear in L_{ijt},

$$\log w_{ijt} = \log \alpha A_t + (1-\alpha)\log K_t + (\alpha - 1 + \frac{1}{\sigma_{ED}})\log L_t + \log \theta_{it} + (\frac{1}{\sigma_{EXP}} - \frac{1}{\sigma_{ED}})\log L_{it} + \log \gamma_{ij} - \frac{1}{\sigma_{EXP}}\log L_{ijt}, \tag{5}$$

where $\frac{1}{\sigma_{EXP}}$ is the slope coefficient of the demand curve, while all other terms on the RHS of equation (5) are intercepts that vary along the dimensions indicated by the indices, i.e. time, education and experience. As $\sigma_{EXP} > 0$ the labor demand curves are downward-sloping. Any change in one of the factors on the right-hand side of equation (5) alters the marginal product, which leads to a change in the real wage *ceteris paribus*. The wage of group ij depends on its own labor supply, but also on the labor supply of all other groups of workers through higher nests of the CES production function. Therefore, it is not only the absolute scarcity of group ij that determines its wage, but also the relative scarcity of this group compared to all other skill groups in the labor market.

From equation (5), it is possible to generate an estimating equation for σ_{EXP}, controlling for all other factors that affect w_{ijt}. For the case of Lithuania, 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 may all 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 (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 consistently estimated from the equation

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

3 Data and Descriptive Statistics

The empirical analysis requires two datasets: one for the estimation of the structural parameters that characterize the Lithuanian labor market in section 4 and one for the quantification of the number of emigrants per skill group, which I will use in the simulations in section 5. 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 number of emigrants per skill group cannot be taken from an already existing dataset, as the statistical offices usually do not keep detailed records about emigrants. An obvious 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 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. Consequently, we can obtain the number of emigrants from the register data of those destination countries. As the numbers of migrants to Sweden were minor[6], I will neglect Sweden and only use census and work permit data from Ireland and the UK.

3.1 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 the variable *income from employment* is deflated using the harmonized consumer price index (HCPI).[7] Table 1a) displays the summary statistics for the HBS. Most workers have an upper secondary education. The average real wage increases 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 for men and women in the HBS in table 1a) with the averages from the average monthly wage for men and women working in the private sector from the Lithuanian live register in table 1d), the difference

6 See Wadensjö (2007).
7 See table 1d) for the HCPI.

between the two turns out to be minor, indicating 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 the wage determination in the public sector is usually not based on the market mechanism of supply and demand, but on seniority pay. Additionally, I drop the following observations: if the variable *disposable income* is negative[8], if the socioeconomic status is *pensioner* or *other*,and if workers are self-employed and/or own a farm, as all these are not part of the workforce.

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, 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 workers to apply for an international M.Sc programme, so it also includes workers with M.Sc or PhD degrees. 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. Workers with a degree *Bakalauras*, *Magistras* or higher are classified as third-level degree. Workers with some college, but a degree that requires less schooling than the two mentioned above are classified as having an upper secondary education.[9] This clustering is fairly broad, given that the Lithuanian education system offers a variety of educational tracks.[10] However, these broad categories are necessary to match the characteristics of the stayers with those of the emigrants. The HBS gives 12 education groups, while the data on the emigrants only distingiushes between 5. Furthermore, broad categories ensure that within each group there is a number of observations large enough to allow the calculation of reliable average wages and emigration numbers. Table 2 illustrates in detail the aggregation of the educational tracks into the three education groups.

The HBS does not give direct information about the actual work experience of an individual. Therefore, I calculate the work experience of individual i with the formula

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

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

10 See www.euroguidance.lt for a description of the Lithuanian education system.

$exp_i = age_i - education_i - 6$, 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 years. $education_i$ equals 10 years for lower secondary education, 12 for upper secondary education and 15 for third-level degree. 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 of this variable.

3.2 Irish Census

The Irish Census is conducted by the Irish Central Statistics Office (CSO) every 4-5 years and contains all people that 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 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 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 of the number of people who migrated from Lithuania to Ireland.

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. 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 younger than stayers and on average less educated, although the selection across education groups seems mild.

3.3 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 start working has to apply for a Personal Public Service (PPS) number in Ireland or a National Insurance Number NINo in the UK.[11] 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 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 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 of 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 of time and for that reason did not register can hardly be seen as emigrants in the sense that 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 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 is larger so that the calculated wage changes resulting from emigration are lower than the actual changes.

3.4 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 number of workers of the same skill group in Lithuania, L_{ij}. 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 in the population is the sum of the sampling weights p_{ijl}.

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

Thus, $L_{ij} = \sum_{l=1}^{L} p_{ijl}$.[12]

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 very detailed data on Lithuanian migrants coming to Ireland in 2002 and 2006, but only aggregate figures on the migrants coming to the UK. 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 NMS 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 NMS was similar in both countries.[13] 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.

For the baseline scenario the emigration rate from 2002 to 2006 is calculated as follows:

$$\Delta L_{ij} = L_{ij}^{IR,2006}\left(1 + \frac{NINO_{2006}}{PPS_{2006}}\right) - L_{ij}^{IR,2002}\left(1 + \frac{NINO_{2002}}{PPS_{2002}}\right) \tag{7}$$

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. $L_{ij}^{IR,2002}$ and $L_{ij}^{IR,2006}$ denote the number of Lithuanians in the Irish census in 2002 and 2006. The values are $\frac{NINO_{2002}}{PPS_{2002}} = 0.52$ and $\frac{NINO_{2006}}{PPS_{2006}} = 1.51$.

Table 3 summarizes the calculated emigration rates per skill group. Most emigrants are young, with a work experience of 10 years and less. Only very few older workers emigrated. The aggregate emigration rate, weighted by the size of the skill groups in the Lithuanian workforce is 5%.

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

[13] 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)).

4 Estimates of Structural Parameters

4.1 Identification and Estimation of σ_{EXP}

Using equation (6), I estimate σ_{EXP}, using the number of workers per skill group as a labor input L_{ijt}. [14]

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 labor supply shifter is needed that does not shift labor demand, i.e. an instrumental variable (IV). Given an appropriate instrument, we can consistently estimate $\frac{1}{\sigma_{EXP}}$ using a two-stage-least-squares (2SLS) estimator. For the estimation of $\frac{1}{\sigma_{EXP}}$ I propose two instruments, birth cohort size and emigration from Poland.

The first instrument, *birth cohort size*, 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. To be valid as an instrument, the size of a birth cohort must not be correlated with labor demand today, other than with 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 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 correlation that would violate the exclusion restriction of this instrument is an influence of the size of a birth cohort 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 my study 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.

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 4 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

[14] Ottaviano & Peri (2006, 2008) 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.

over time, which can potentially be exploited in the IV regressions. The data in this time series are annual, while the observations in my sample are skill groups that consist of 10 subsequent years, so that the question arises, which measure predicts most accurately the number of workers of a skill group today. 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. In this group 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. 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.[15] The F-Statistic of the median number of births is 16.085, which indicates a high correlation of the instrument with the endogenous regressor. The reason for the weak correlation of the first two instrument is their sensitivity to outliers in the number of births. As we can see in figure 4, the number of births was subject to high fluctuations and the sum and the average are very 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 and as such suitable as an instrument.

The second instrument, *emigration from Poland*, exploits the fact that Poland joined the European Union at the same time as Lithuania and experienced a similar emigration wave. The correlation between Polish and Lithuanian emigrants per skill group is 0.96, which means that Polish emigration and Lithuanian labor supply are highly correlated. The F-statistic is around 9, which is less than the commonly used threshold of 10, above which an instrument is seen as sufficiently correlated. 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.

The exclusion restriction for the instrument *emigration from Poland* is that Polish emigration should not be correlated with Lithuanian labor demand, over and above factors that are controlled for in the first stage. A common criticism of this restriction is that both countries should have the same business cycle, which leads to a correlation in the

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

labor demand of both countries. This correlation, however, is absorbed by the year fixed, which means that it would not violate the exclusion restriction. Moreover, given that the first instrument is exogenous, I run an IV regression using both instruments and test for overidentifying restrictions (OIR). If I had to reject the null hypothesis of OIR, this would mean that *emigration from Poland* is not a valid instrument. The F-statistic of the first stage with both instruments is 10.10, the p-value of the test for OIR is 0.838, so that we cannot reject the null hypothesis of OIR and the exclusion restriction of the second instrument is valid.

Table 4 reports the estimation results for σ_{EXP}. All regressions are weighted with sampling weights.[16] I report the OLS results for comparison but as described before, they are not reliable because of simultaneity bias. The IV estimates are consistently around -0.65, which implies a σ_{EXP} of around 1.5. The fact that the use of different instruments leads to the same estimates gives confidence in the accuracy of the results.

The results of the estimates for σ_{EXP} are lower than in studies that previously used a similar model for the United States and Germany. Borjas (2003) and Ottaviano & Peri (2008) estimate σ_{EXP} at 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 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. Consequently, the skills of young workers should be immediately applicable to the labor market, whereas older workers mey 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}. A recent paper by Brunello *et al.* (2011) backs this explanation. They find 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.

[16] 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.

4.2 Determination of σ_{ED}

The dataset used in this study consists of four survey rounds (2002, 2003, 2005, 2006) and in each year we can observe wages and labor inputs for three education groups. This results in 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),

$$\log \bar{w_{it}} = \delta_t + \delta_{it} - \frac{1}{\sigma_{ED}} \log \bar{L_{it}} + \varepsilon, \tag{8}$$

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). σ_{ED} can only be properly identified when the number of observations is sufficiently large. Otherwise, the model is too saturated and the coefficient $-\frac{1}{\sigma_{ED}}$ cannot be statistically distinguished from zero. To see this, let n be the number of education groups and t the number of years. Consequently, $n(t-1)+1$ parameters need to be estimated from nt observations, so that the number of observation exceeds the degrees of freedom by $n-1$, which is 2 in this case. The higher n, the more likely it is to obtain an economically meaningful estimate 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.

Given that I cannot increase the number of observations, I do not attempt to estimate σ_{ED}. Instead, I choose a value that seems economically reasonable for the simulations in the next section. At a later stage, I will analyze the sensitivity of the results by using different values for σ_{ED}. To choose σ_{ED}, I impose the restriction that $\sigma_{EXP} > \sigma_{ED}$ on the parameter. This inequality has a clear economic intuition. It says that it is on average more difficult to substitute two workers with different education than it is to substitute two workers who have the same education but different work experience.

5 Simulations

5.1 Simulation Equation

To obtain the wage change for each skill group, I derive the simulation equation from the theoretical model and calculate the labor supply shift, i.e. the number of emigrants for every skill group. These supply shifts, together with the labor demand curves estimated in section 4 lead to the new equilibrium wage. Consequently, the wage change is the difference between the equilibrium wage after and before the migration shock. To obtain the simulation equation I differentiate equation (5) and drop the time subscripts

$$
\begin{aligned}
\frac{\Delta w_{ij}}{w_{ij}} &= (1-\alpha)\frac{\Delta K}{K} - (1-\alpha)\frac{\Delta L}{L} + \frac{1}{\sigma_{ED}}\frac{\Delta L}{L} \\
&+ (\frac{1}{\sigma_{EXP}} - \frac{1}{\sigma_{ED}})\frac{\Delta L_i}{L_i} - \frac{1}{\sigma_{EXP}}\frac{\Delta L_{ij}}{L_{ij}}.
\end{aligned} \tag{9}
$$

Expressions L_t and L_{it} in equation (9) are labor aggregates and can as such be expressed in terms of L_{ijt}.[17] The Δs measure the change in a variable from 2002 to 2006.

5.2 Model Calibration and Simulation Results

For the calibration of equation (9) the parameters α, s_i, s_{ij}, σ_{ED} and σ_{EXP} need to be chosen. This set of parameters will determine the extent to which a change in labor supply affects real wages. I calculate α from the Lithuanian national accounts data and find that $\alpha = 0.8$. This value is higher than 0.7, which is commonly used for studies on industrialized countries, but given that Lithuania is more labor-abundant than for example the US, a value of 0.8 is plausible. The income shares s_i and s_{ij} are calculated from the sampling weights in the HBS using all men and women in the sample.[18] For the elasticities of substitution, σ_{EXP} and σ_{ED} I take the values from the estimations in section 4: $\sigma_{EXP} = 1.58$ and $\sigma_{ED} = 1.2$.

Figure 5 displays the simulated wage changes for the baseline scenario. A general pattern emerges: the wages of older workers decreased by between 1.2% and 1.6%, depending on their education. At the same time, the wages of young workers with 10 years of work experience or less increased by between 5.2% and 7.7%. Workers in the youngest group gained significantly more than older workers lost. Workers with a work experience between 10 and 30 years did not see significant wage changes from migration.

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, $\frac{1}{\sigma_{EXP}} \sim (\mu =$

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[17] 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 $\frac{\Delta L}{L} = \frac{1}{\alpha} \sum_i \sum_j s_{ij} \frac{\Delta L_{ij}}{L_{ij}}$. s_i denotes the income share of education group i and s_{ij} denotes the income share of skill group ij.

[18] See appendix A for a description of the calculation of s_{ij} and s_i.

$0.63, \sigma^2 = 0.03)$ and $\frac{1}{\sigma_{ED}} \sim (\mu = 0.83, \sigma^2 = 1)$.[19] The simulated standard errors reported in table 4 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 10% or less.

After noting that the predicted wage changes differ considerably between young and old workers, the question arises, which factors drive these results. As described in sections 2 and 5.1, the model accounts for substitutability and complementarity between different groups of workers and allows for a variety of channels, through which emigration affects the wages of stayers. 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 aggregate level of production, which again affects the wages of all other skill groups. The total wage effect can be decomposed into four effects. Table 5 displays the magnitude of each effect.

1. **Own-wage effect** $\left(-\frac{1}{\sigma_{EXP}} \frac{\Delta L_{ij}}{L_{ij}}\right)$. 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 is 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 $\sigma_{EXP} > \sigma_{ED}$. Intuitively, the positive sign follows the logic that workers with the same education are substitutes, even though not perfect ones. So if young workers emigrate, they can be replaced by older workers, which leads to an increase in the wages for older workers.

3. **Complementarity effect** $\frac{1}{\sigma_{ED}} \frac{\Delta L}{L}$. With the emigration of a considerable share of the workforce the composition of the workforce changes, which has a negative impact on the wages of all workers. This negative impact is due to the complementarities between workers of different education groups. A prominent example are professors and secretaries. If professors emigrate there is also less demand for secretaries and this negative demand effect is captured in the complementarity effect.

[19] Note that I take the inverse of the parameters, because these are the results of the IV regressions in section 4.1, for which standard errors are available. For $\frac{1}{\sigma_{ED}}$ I assume a variance of 1, which would mean that the coefficient of $\frac{1}{\sigma_{ED}}$ be insignificant at any reasonnable significance level.

4. **Aggregate Production Effect** $-(1-\alpha)\frac{\Delta L}{L}$. Emigration does not only change the composition of the workforce, it also leads to a decrease in aggregate production. However, the production effect is positive, as the output per worker increases when the number of workers decreases. This effect would disappear if we allowed for capital adjustment.

Taking all these effects together, we can draw the following conclusions: the post-EU-enlargement emigration wave led to an increase in the wages of young workers. They have become a more scarce resource, which caused their wages to increase. 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 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.

Although most of the wage changes predicted by the structural model 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 table 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 foreign investment, productivity growth, etc.

It is important to note at this point that this study does not aim to explain 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 he same as for a reduced-form approach. To assess the quality of the structural model, one has to compare the predicted wage changes from the structural model with the ones from a reduced-form regression. Elsner (2010) finds in a reduced-form approach that a percentage-point increase in the emigration rate increases the real wages of stayers on average by 0.66%. The upper graph in figure 6 compares the predicted wage changes from the structural model in this study to the reduced-form estimates in Elsner (2010). The predicted wage changes from the reduced-form are positive for each skill group, since the reduced form does not take into account the complementarity effects that arise from the fact that the majority of emigrants was young and that old and young workers are imperfect substitutes in aggregate production.

Once the complementarity effect and the aggregate production effect 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 6.

6 Sensitivity Analysis

The simulations in section 5 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, the structural parameters of the Lithuanian labor market are fundamentally different from the ones 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. Nevertheless, I re-run the simulations using parameter values from the literature. This exercise 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?

6.1 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 by Dustmann *et al.* (2009) and Barrett & Duffy (2008), from which it can be seen that the educational distribution of migrants from the NMS 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 5 with Irish data only. Column (2) in table 6 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, this means that the true wage effects from emigration will be at least as large as the ones based on simulations with Irish data only.

6.2 Calibration on Parameters from the Literature

In this section I calibrate the model on parameters that were obtained in the literature for the US and Germany. I use two studies on the effect of immigration on wages in the US, Borjas (2003) ($\sigma_{EXP} = 3.5$, $\sigma_{ED} = 1.3$) and Ottaviano & Peri (2008) ($\sigma_{EXP} = 7$, $\sigma_{ED} = 2$), as well as 2 studies on the wage effects of immigration in Germany, Brücker & Jahn (2011) ($\sigma_{EXP} = 30$, $\sigma_{ED} = 6.5$) and D'Amuri *et al.* (2010) ($\sigma_{EXP} = 3.3$, $\sigma_{ED} = 2.9$). Table 6 compares the baseline results with the results when the model is calibrated on parameters from the literature. As my parameter value for σ_{EXP} is lower than the one used in the literature, 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 the literature. However, for the ranges of parameter values $\sigma_{EXP} \in (3.3, 7)$ and $\sigma_{ED} \in (1.3, 2.9)$ the wage changes predicted by the model range between 2% and 4% for young workers and between 0% and 1% for workers with a work experience between 11 and 30 years. Even for the values estimated by Brücker & Jahn (2011), which are a multiple of the elasticities of substitution found in other studies, the model predicts wage increases between 1% and 1.3% for all groups of workers.

7 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 in the source countries. Lithuania is an excellent example to show the distributional impact of emigration, as migration was 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 of this paper are 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.

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A Income Shares by Skill Group

For the simulations in section 5, I calculate the income shares of each education-experience group, s_{ij}, as well as the one for each education group, s_i, from the sampling weights. Let the each skill group ij in the sample consist of N_{ij} workers, $n = \{1, ..., N_{ij}\}$. 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

$$s_{ij} = \alpha \left(\frac{W_{ij}}{W} \right). \tag{10}$$

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

$$s_i = \sum_j s_{ij}. \tag{11}$$

From the HBS 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 5 are the average of those four years.

B Emigration from Poland as an Instrument

In section 4.1 I use emigration from Poland by skill group as an instrument for Lithuanian labor supply. For the calculation of the number of emigrants I use the skill distribution from the Irish census and weight it with the number of work permits in Ireland and the UK measured by PPS and NINo numbers. As the census data are 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 1c), the skill distribution did not change significantly from 2002 to 2006, despite the fact that 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.

Let PPS_t and $NINO_t$ be the PPS and 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: $M_{ij2002} = x_{ij2002}\left(1 + \frac{NINO_{2002}}{PPS_{2002}}\right)$
- 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.[20] 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: $M_{ij2006} = x_{ij2006}\left(1 + \frac{NINO_{2006}}{PPS_{2006}}\right)$

[20] 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.

C Tables and Figures

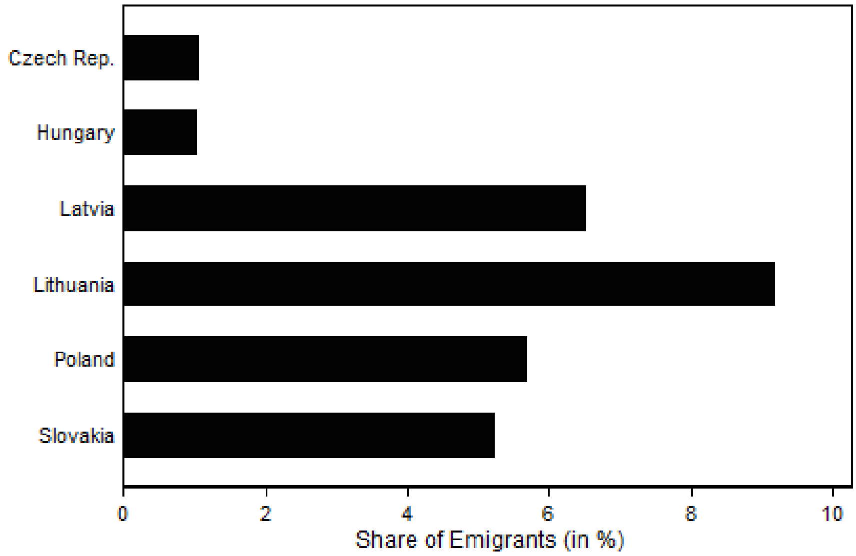


Figure 1 – Emigrant Shares in Central and Eastern Europe

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

Figure 2 – Actual wage changes by skill group.

Source: Lithuanian HBS.

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
			(10.2)	(10.1)	(10.2)	(10.1)
Experience			24.5	24.1	24.6	24.9
			(10.3)	(10.1)	(10.2)	(10.1)
Monthly Real Wage		All Workers	1084	1142	1339	1533
			(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

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

NINo Numbers	(UK)		1430	3140	10710	24200
PPS Numbers	(Ireland)		2709	2394	18680	16017

d) Aggregate Data, Lithuania

Monthly Real Wage		Men	1173	1227	1420	1676
		Women	998	1029	1167	1356
HCPI		2005=100	97.334	96.291	100	103.788
Immigration	to Lithuania	Lithuanians	809	1313	4705	5508
		Former Soviet U	2478	1915	874	1337
		Other	1823	1500	1210	900
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 3. 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.

Table 2 – 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.

Table 3 – Emigration Rates 2002-2006

		Education		
		Lower Sec	Upper Sec	Third-Level
Work Experience	0-10 Years	11%	16%	13%
	11-20 Years	5%	5%	3%
	21-30 Years	6%	2%	3%
	31+ Years	1%	1%	1%

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 3.4.

Table 4 – Regression results for σ_{EXP}

VARIABLES	OLS	IV (No of births)	IV (Emig PL)	IV (both)
log(Number of Workers)	-0.114	-0.631***	-0.665***	-0.644***
	[0.0719]	[0.1733]	[0.2414]	[0.1620]
Observations	48	48	48	48
R^2	0.9742	0.9416	0.9371	0.9398
First-stage coefficients of IV				
Number of birhts (in 1000)		-0.033		-0.022
Emigration from PL (in 1000)			-0.0056	-0.0026
F-Statistic		16.085	9.014	10.100
σ_{EXP}	**8.77**	**1.58**	**1.50**	**1.53**

Controls: $\delta_t, \delta_{it}, \delta_{ij}$
Robust standard errors in brackets
*** p<0.01, ** p<0.05, * p<0.1

Table 5 – Decomposition of the Wage Effect of Emigration

		.		Decomposition of Total Wage Change			
Education	Experience (Years)	**Total Wage Change**	Standard Error	(1) Own-wage	(2) Cross-wage	(3) Complementarity	(4) Production
Lower Secondary	0-10	**5.18**	1.15	7.24	1.16	-4.23	1.01
	11-20	**1.32**	0.59	3.37	1.16	-4.23	1.01
	21-30	**1.92**	0.59	3.97	1.16	-4.23	1.01
	31+	**-1.21**	0.97	0.84	1.16	-4.23	1.01
Upper Secondary	0-10	**7.68**	1.94	9.95	0.95	-4.23	1.01
	11-20	**0.71**	0.29	2.97	0.95	-4.23	1.01
	21-30	**-0.86**	0.53	1.40	0.95	-4.23	1.01
	31+	**-1.56**	0.70	0.70	0.95	-4.23	1.01
Third Level	0-10	**6.29**	1.42	8.35	1.15	-4.23	1.01
	11-20	**-0.02**	0.71	2.04	1.15	-4.23	1.01
	21-30	**-0.29**	0.76	1.77	1.15	-4.23	1.01
	31+	**-1.13**	0.93	0.93	1.15	-4.23	1.01

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.

Table 6 – Sensitivity Analysis

		(1) Baseline	(2) IE only	(3) Borjas (2003)	(4) Ottaviano & Peri (2008)	(5) Brücker & Jahn (2011)	(6) D'Amuri *et al* (2010)
	Country	Lithuania	Lithuania	US	US	Germany	Germany
	σ_{EXP}	1.58	1.58	3.5	7	30	3.3
	σ_{ED}	1.2	1.2	1.3	2	6.5	2.9
Education	**Experience**						
Lower Secondary	0-10	**5.18**	2.01	3.18	2.18	1.31	2.97
	11-20	**1.32**	0.50	1.43	1.31	1.11	1.12
	21-30	**1.92**	0.74	1.70	1.44	1.14	1.41
	31+	**-1.21**	-0.44	0.29	0.74	0.98	-0.08
Upper Secondary	0-10	**7.68**	2.89	3.88	2.41	1.33	4.23
	11-20	**0.71**	0.27	0.74	0.83	0.96	0.89
	21-30	**-0.86**	-0.32	0.03	0.48	0.88	0.13
	31+	**-1.56**	-0.59	-0.29	0.32	0.84	-0.20
Third Level	0-10	**6.29**	2.35	3.66	2.42	1.37	3.50
	11-20	**-0.02**	-0.03	0.82	0.99	0.10	0.48
	21-30	**-0.29**	-0.10	0.69	0.93	1.02	0.35
	31+	**-1.13**	-0.42	0.31	0.74	0.98	-0.05

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. (3)-(6) 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 and Germany.

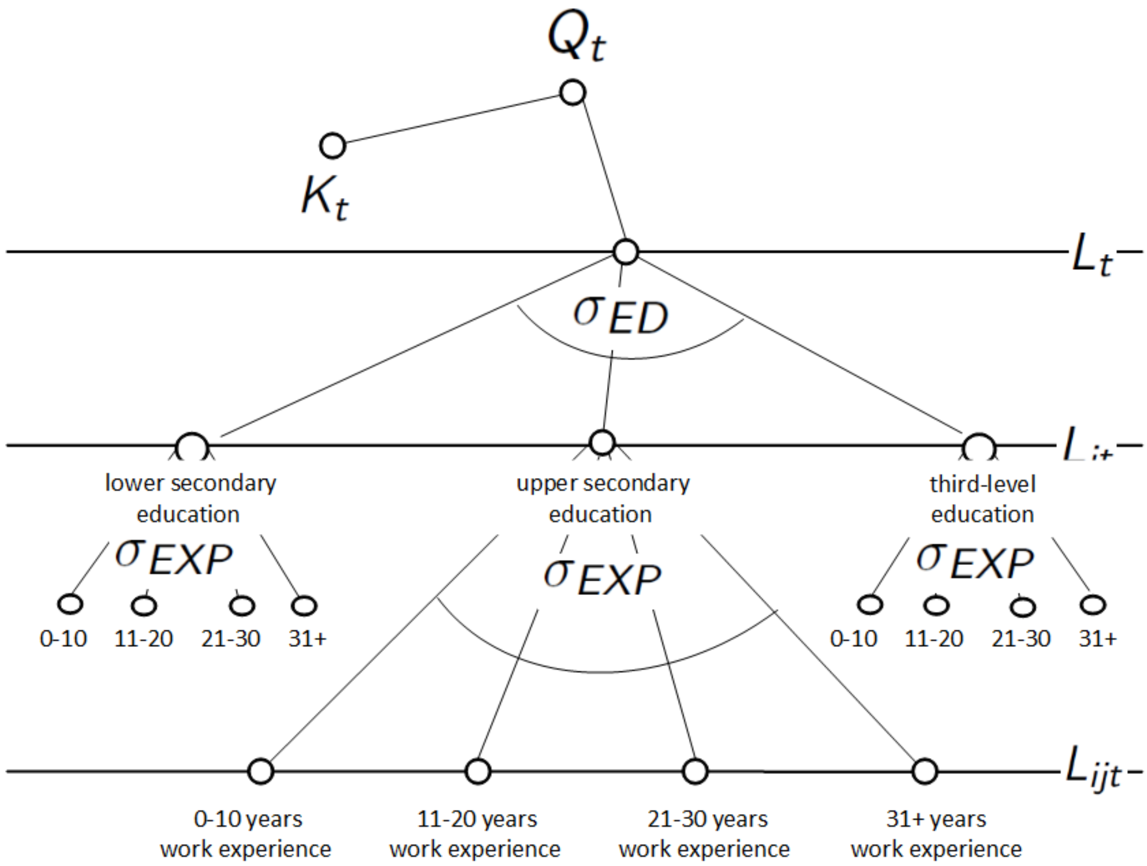
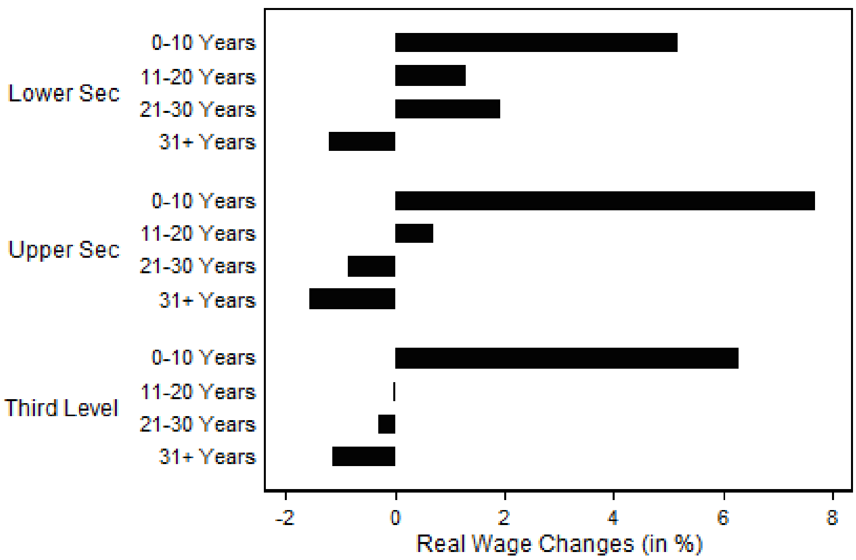


Figure 3 – Nested CES Production Function

Figure 4 – Number of Births per Year in Lithuania.

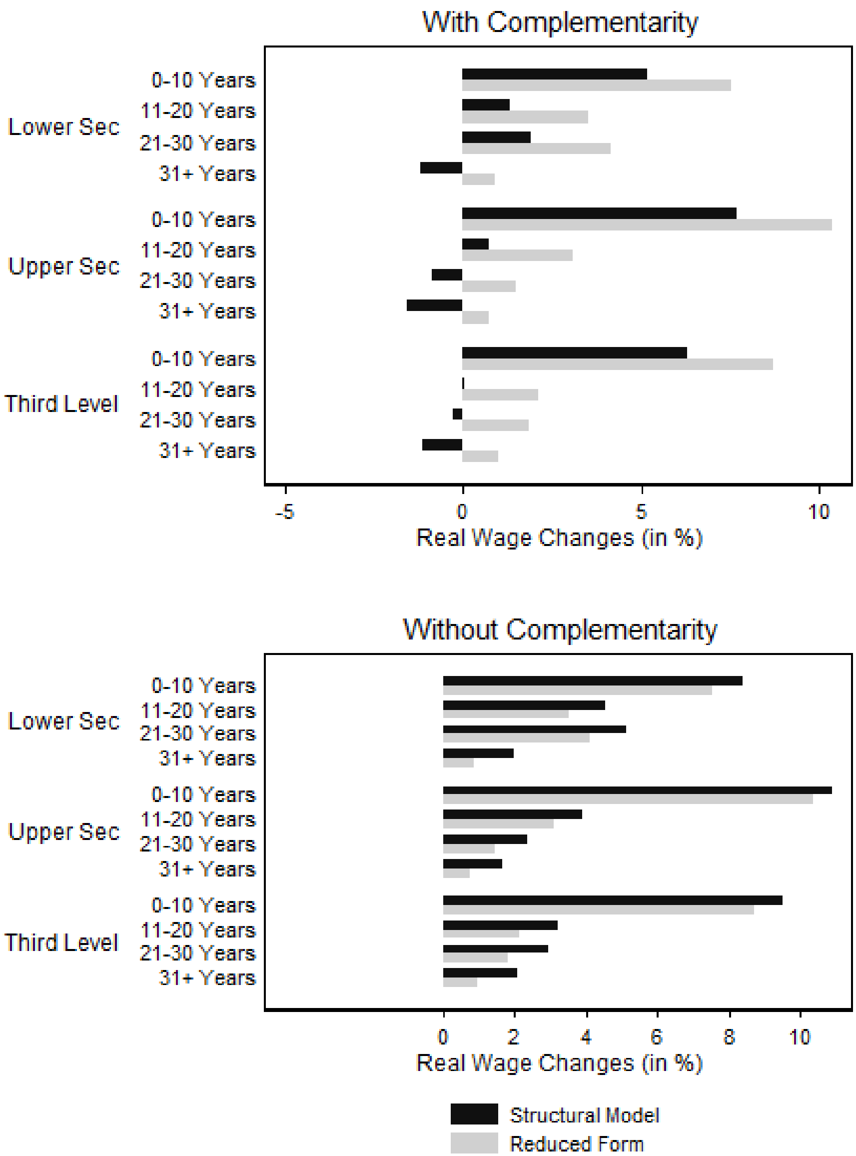
Note: Total number of people born per year in Lithuania. Source: Statistics Lithuania.

Figure 5 – Simulation Results Baseline Scenario



Note: Labels on the y-axis denote education and work experience. The graph displays the causal impact of emigration on wages, resulting from the simulation in section 5.1.

FIGURE 6 – 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.