The Distributional Impact of Emigration: The Case of EU Enlargement

Benjamin Elsner*

January 31, 2011

Abstract

The enlargement of the European Union in 2004 caused a large migration wave from Central Europe to Ireland and the UK. This paper addresses the question whether such an emigration wave 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 from Lithuania, 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 around 6% while the wages of older workers decrease by around 2%. The wage increase for young workers is the result of the supply shift: most of the emigrants were young, so that young workers who stay behind become a more scarce resource on the labor market. At the same time, the emigration of young workers decreases the labor demand for older workers, which results in a decrease of their wages. These results are important for future EU candidates in order to assess the costs and benefits of EU accession.

Preliminary Draft. Please do not cite without permission of the author.

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

*Trinity College Dublin, Department of Economics and the Institute for International Integration Studies (IIIS). Email: elsnerb@tcd.ie.

1 Introduction

The enlargement of the European Union in 2004 was followed by large migration movements from Central and Eastern Europe to Western Europe. In the time from 2004 to 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. 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 aggregate 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 constitutes 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] These numbers reflect an upper bound to post-enlargement migration, as they also include workers who might have worked in the destination country for a short period in time and returned afterwards. However, a large share of the migrants stayed for more than one year. Evidence

[1] Own calculations based on work permit data from Ireland (*PPS* numbers) and the UK (*NINo).* See figure 10.

[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).

from the Irish Central Statistics Office (2009) suggests that around 60% of migrants from the New Member States stay for at least two years after having received a work permit, which means that the workforce of the New Member States has decreased significantly. Given the magnitude and the speed of post-enlargement migration, I conjecture that this migration wave had an impact on the distribution of wages in the source countries. Looking at figure 1, 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 these overall wage changes can be attributed to emigration.

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, since it was one of four countries that lost a substantial share of its workforce after 2004.

Compared to purely empirical studies, the structural approach has the advantage that it is possible to disentangle the changes in wages caused by migration from all other factors that have an influence on wages through labor demand, so that the typical problems of reduced form regressions, such as endogeneity and omitted variable bias can be overcome. 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.

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 should not be correlated 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, 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 of 6%, whereas workers with more than 30 years of work experience saw their wages decrease by around 2%.

This paper relates to the literature on the wage effects of migration, as well as to the literature on the economic consequences of economic integration, especially for the case of EU enlargement. The migration literature focuses in large parts on the side of the receiving countries.[4] while the literature on the wage effects of emigration remains scarce. One of the few studies about the impact of emigration on wages is by Mishra (2007), who finds that emigration to the US increased the wage level in Mexico in the long run, from 1970 to 2000. In a recent paper, Docquier *et al.* (2011) look at the long-run wage effects of both immgration and emigration in European countries. They find that immigration increases the wages of natives in the long run, while emigration slightly decreases the wages of natives. These three articles focus on the effect of migration on the wages of stayers in the long run. In that light, the small wage effects found in these studies are not surprising. An economy has multiple adjustment mechanisms to react to the change in labor supply caused by emigration, e.g. capital adjustment or immigration from other countries, so that long-run effects are typically smaller in absolute value than short-run effects. The contribution of my paper is that it analyzes the impact of emigration on wages in the short run. The knowledge of the extent of these effects can be beneficial for policymakers in countries that face a similar emigration shock, for example future EU candidates.

With respect to the literature on the economic impacts of EU enlargement, Batista (2007)

[4] See, for example, Borjas (2003) Butcher & Card (1990), Card (1990), Dustmann *et al.* (2008), Friedberg (2001), Manacorda *et al.* (2006), Ottaviano & Peri (2006, 2008) for the wage effect of immigration in general and Barrett *et al.* (2006), Barrett & Duffy (2008), Blanchflower & Shadforth (2009), Drinkwater *et al.* (2006), Dustmann *et al.* (2005), Lemos & Portes (2008), Wadensjö (2007) for an analysis of the effect of the post-EU enlargement immigration on the labour markets in Western Europe.

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. In 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, but they do not give information on wages. Hazans & Philips (2009) and Fihel *et al.* (2006) document the migrant flows from the New Member States to Western Europe, and the developments of the labor markets in the New Member States. They show that after EU accession wages increased and unemployment decreased, but without undertaking an econometric analysis that links these developments. These documentations are informative, but in my opinion only an econometric analysis is needed to disentangle the effect of migration from the effect of other factors on wages in the source country. A first step in this direction is a previous paper of mine, in which I show for the case of Lithuania that emigration led to an increase in wages in the source country and that this effect is stronger for men than for women.[5] In the current paper I am analyzing which skill groups actually gained and which lost from the post-enlargement migration.

The remainder of the paper is structured as follows: Section 2 outlines the structural model. In section 3 I describe the data and in section 4 I estimate the structural parameters. In section 5 I simulate the impact of the post-2004 migration wave on the wages of different skill groups in the source country. Robustness checks can be found in section 6, before section 7 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 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 for distinct skill groups, a change in the labor supply of one skill group affects the wages

[5] See Elsner (2010).

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 very different skills. Following the works of Katz & Murphy (1992), Borjas (2003) and Ottaviano & Peri (2008), I model the economy as a nested CES production function, in 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, while allowing for different degrees of substitutability between groups of workers. At the same the structural parameters, i.e. the slope of the labor demand curves, can be econometrically identified from a repeated cross section of data on real wages and labor inputs. Ideally, we would like to have a separate relative labor demand curve for each skill group, but the econometric identification of the required structural parameters would be impossible. With 12 skill groups the number of parameters to be estimated amounts to 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.

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 following an emigration shock the capital stock would decrease in the long run until the capital-labor ratio is the same as in the initial steady state. Consequently, capital adjustment would dampen the wage changes. However, given that I am considering a short time span of 5 years, capital adjustments should not play an important role.

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 these differences in work experience, each education group is represented by a CES aggregate of four experience groups.

2.1 Nested CES Production Function

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 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 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

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

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.

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 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. Most of the literature, e.g. Borjas (2003), Brücker & Jahn (2009), D'Amuri *et al.* (2010), Katz & Murphy (1992), Manacorda *et al.* (2006), Ottaviano & Peri (2006, 2008), uses 5-year experience groups. However, the choice of the interval length is arbitrary. Shorter intervals result in a higher number of skill groups, which allows for a more differentiated picture of the effect of emigration on wages. On the other hand, with more skill groups and a given number of observations in the data, the calculated average wages and labor inputs becomes less precise, because the calculations of average values are based on fewer observations. In a recent paper, Aydemir & Borjas (2011) show that this so-called *attenuation bias* can have a significant impact on the estimates of the structural parameters. To reduce this potential bias I chose 10-year intervals for the baseline scenario and the more commonly-used 5-year cells for a robustness check.

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 the econometric identification of σ_{EXP} and all γ_{ij}. This assumption would be questionable when looking at long-run effects, as for example technological progress could benefit one experience group more than another. However, since this study is a short-run analysis 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. Furthermore, I assume that workers within an education group are closer substitutes than workers who differ in their education, which is ensured by the restriction $\sigma_{EXP} > \sigma_{ED}$. Intuitively, this restriction means that it is on average 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.

An additional assumption required for identification is that 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. In the long run emigration can lead to education externalities and alter the productivity of certain skill groups, but within the time span of five years under consideration in this study it is not plausible that the human capital of a particular skill group or TFP changes because of emigration.

Figure 7 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}, but that are necessary to bring together theory and empirics. 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 11 years is as easy as the substitution of worker A for worker C whose work experience is 40 years. Even though those assumptions might seem restrictive at first glance, 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 great deal of variation in the effect of emigration on wages.

2.2 Labor Market Equilibrium

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 log-linear in L_{ijt},

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

$\frac{1}{\sigma_{EXP}}$ 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, 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 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

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

3 Data and Descriptive Statistics

The empirical analysis requires two datasets: one for the estimation of the structural parameters of 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 and as an instrument in the empirical part in section 4. 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 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 migration movements 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, and personal characteristics such as marital status, number of children, place of residence are available. The HBS does not contain information on the sector the respondents are working in.

The income data is self-reported, which can be subject to a misreporting bias. Table 2j) 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 minor, which indicates the absence of 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. The workforce 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.[9] However, these broad categories are necessary to match the Lithuanian HBS of different years with characteristics of emigrants that

---

6 See Wadensjö (2007).
7 The variable is *income from employment*, which is eqiuvalent to the monthly wage.
8 This is the case in 2002 with 67 people working in the agricultural sector.
9 See www.euroguidance.lt for a description of the Lithuanian education system.

are obtained from the Irish and UK data. Furthermore, broad categories ensure that within each group there is a number of observations large enough to be able to calculate reliable average wages and emigration numbers. The Irish census contains five education categories, the Lithuanian HBS has 5 categories different from the Irish census in 2002 and 12 categories from 2003 onwards. Table 1 illustrates in detail the aggregation of the educational tracks into the three education groups. From the HBS, I do not have information about the actual work experience of an individual. Therefore, 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 years. $education_i$ equals 10 years for lower secondary education, 12 for upper secondary 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 are living in Ireland and that are present in the survey night. 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 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.

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. Figure 9 shows the skill distribution of Lithuanian migrants. The education group with the highest number of migrants was upper secondary education. Within each education group, the number of migrants decreases with work experience.

3.3 Work Permit Data: PPS and NINo numbers

The numbers 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 has to apply for a PPS (Personal Public Service) number in Ireland or a NINo (National Insurance Number) in the UK.[10] 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 Lithuania and the UK. The PPS and NINo numbers can undercount the actual number of migrant workers coming to Ireland and the UK, as some workers might not have registered because they came to work for a short period in time or wanted to avoid having to pay income taxes. These cases should not be too important for the calculation of emigrant numbers. Workers who only migrated for a short period in time and did not register because of that can hardly be seen as emigrants in a sense that they were for the whole time part of the Lithuanian workforce. The number of workers who migrated for a longer period without registering is difficult to assess, but given the high number of migrants who did register, I conjecture that it is small. Even if the work permit data slightly undercounts the actual number of migrants, this would mean for the simulations that the actual labor supply shock would be larger so that the calculated wage changes resulting from emigration are lower than the actual changes.

4 Estimates of Structural Parameters

4.1 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.[11] The coefficient of interest in this

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

[11] 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,

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, but 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.[12] 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, which is plausible for the case of Lithuanian EU accession. As we can see in figure 8, 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. The incentives to migrate existed before and after 2004. 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.[13] 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 by migration M. The estimated coefficient for β using a 2SLS

as the Household Budget Survey does not include data on working hours, I use the number of workers as a proxy.

12 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.

13 See appendix C for a detailed explanation of the calculation of emigration rates.

estimator is

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

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 correlated, as the more people migrate, the lower the labor supply, so that the denominator is negative, $\text{cov}(\log M, \log L) < 0$. 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 $\text{cov}(\log M, u) < 0$. 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 $\text{cov}(\log M, u) > 0$, 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 11, the emigration of Poles (denoted M_{PL}) to Ireland and the UK by skill group is strongly correlated with the emigration of Lithuanians ($corr = 0.9667$), so that $\text{cov}(M_{PL}, M_{LIT}) > 0$ and hence $\text{cov}(M_{PL}, L) < 0$. 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. $\text{plim}\,\hat{\beta} = \beta$.

Table 3 reports the results for the estimation of σ_{EXP}. All regressions are weighted with sampling weights.[14] In all cases except for women, 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 in the presence of simultaneous equations. 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} for the specification of men and women together range between 1.3 and 1.5,

[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.

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 instrument 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. [15]

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 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}. A recent paper by Brunello *et al.* (2011) backs this explanation. They find that in transition countries men who were educated under communism have lower returns to education than men who were educated under a free market economy.

[15] As a robustness check I conducted the same analysis for 5-year cells. The point estimates for σ_{EXP} lie between 1.4 and 1.8 depending on the instrument. I do not report the output in the appendix, but it is available upon request.

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 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 sufficiently 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 $n-1$, which is 2 in my case. 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 baseline scenario in the simulations to follow in section 5, I choose a value for σ_{ED} that is in line with the restriction $\sigma_{EXP} > \sigma_{ED}$ and check the sensitivity of the results by varying the size of σ_{ED}.

5 Simulations

5.1 Simulation Equation

In this section I calculate the impact of the post-EU enlargement emigration wave on the real wages in Lithuania. To obtain the wage change for each skill group I first need to calculate the labor supply shift, i.e. the number of emigrants per skill group. These supply shifts, together with the labor demand curves estimated in section 4 allow me to calculate the new equilibrium wage. Consequently, the wage change is the difference between the equilibrium wage after and before the migration shock. Within the theoretical framework the simulation equation (10)describes the wage changes for each skill group. To obtain this equation I differentiate equation (5)

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

Expressions L_t and L_{it} in equation (10) are labor aggregates and can as such be expressed in terms of L_{ijt}.[16] 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. 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 $i'j'$. As I am interested

[16] Note that $\frac{\Delta L_{it}}{L_{it}} = \sum_j \left(\frac{\gamma_{ij} L_{ijt}^{\eta}}{\sum_j \gamma_{ij} L_{ijt}^{\eta}}\right)\frac{\Delta L_{ijt}}{L_{ijt}} = \frac{1}{s_{it}}\sum_j s_{ijt}\frac{\Delta L_{ijt}}{L_{ijt}}$

and $\frac{\Delta L_t}{L_t} = \sum_i \left(\frac{\theta_{it} L_{it}^{\rho}}{\sum_i \theta_{it} L_{it}^{\rho}}\right)\frac{\Delta L_{it}}{L_{it}} = \frac{1}{s_{Lt}}\sum_i s_{it}\frac{\Delta L_{it}}{L_{it}}$

in a short-run effect, I assume here that capital adjustment is zero ($\Delta K = 0$). Then,

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

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.[17]

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,

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

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

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

The interpretation of equations (13) and (14) is analogous to equation (12). Table 4 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

[17] 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.

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.

5.2 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 labor supply shock $\frac{\Delta L_{ij}}{L_{ij}}$ for each skill group. 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, $L_{ij} = \sum_{i=1}^{N} p_{ijl}$.[18]

The shift in labor supply ΔL_{ij} cannot be taken directly from the data, but needs to be computed under 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 from work permit data. 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.[19] 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.

For the baseline scenario I calculate the change in labor supply from 2002 to 2006 as

---

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

[19] 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)).

follows:

$$\Delta L_{ij} = L_{ij}^{IR,2006}\left(1+\frac{NINO_{2006}}{PPS_{2006}}\right) - L_{ij}^{IR,2002}\left(1+\frac{NINO_{2002}}{PPS_{2002}}\right) \quad (15)$$

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. The values are $\frac{NINO_{2002}}{PPS_{2002}} = 0.52$ and $\frac{NINO_{2006}}{PPS_{2006}} = 1.51$. Table 5 reports the calculated emigration numbers.

5.3 Model Calibration and Simulation Results

For the calibration of equation (11), I need to chose the parameters α, s_i, s_{ij}, 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 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 using all men and women in the sample.[20]

For the elasticities of substitution, σ_{EXP} and σ_{ED} I take the values from the estimations in section 4 (specification *men and women together*): $\sigma_{EXP} = 1.4$ and $\sigma_{ED} = 1.2$. In section 6 I check the sensitivity of the results to variations in the parameter values for σ_{EXP} and σ_{ED}. The lower these elasticities are, the larger will be the complementarity effects and the higher will be the wage changes.

Figure 2 displays the calculated wage changes for the baseline scenario. A general pattern emerges: the wages of older workers decreased by between 1.6% and 2%, depending on their education. At the same time did the wages of young workers with 10 years of work experience or less increase by between 5.9% and 8%. 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.

After noting that the 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 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

20 See appendix B for a description of the calculation of s_{ij} and s_i.

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 in table 6. 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 6, $\left(\left(\frac{1}{\sigma_{EXP}}-\frac{1}{\sigma_{ED}}\right)\frac{1}{s_i}\sum_j s_{ij}\frac{\Delta L_{ij}}{L_{ij}}\right)$, 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.

Effects 3 and 4 are combined in $\left(\left(\alpha-1+\frac{1}{\sigma_{ED}}\right)\frac{1}{\alpha}\sum_i\sum_j s_{ij}\frac{\Delta L_{ij}}{L_{ij}}\right)$ [21]. Effect 3 is the wage effect that results from changes in the composition of L. This effect is positive in our case, which indicates that the positive impact of less competition on the labor market across education groups is greater than the potential complementarity between workers with different education. Hence, workers who differ in their education are gross substitutes in this model.

The fourth effect reflects the impact of emigration on aggregate production. If workers leave the economy, aggregate production decreases, which in turn decreases the wages of all workers.

[21] $\frac{1}{\alpha}\left(\frac{1}{\sigma_{ED}}\right)\left(\sum_i\sum_j s_{ij}\frac{\Delta L_{ij}}{L_{ij}}\right)$ is the wage effect related to changes in the composition of the labor aggregate L. $\sum_i\sum_j s_{ij}\frac{\Delta L_{ij}}{L_{ij}}$ is the production effect

6 Robustness checks

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 and finally re-run the simulations using parameter values from the literature.

6.1 Irish data only

The calculation of the number of emigrants per skill group was based 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 New Member States was approximately the same. However, there is some uncertainty about the joint education-experience distribution of Lithuanian migrants in Ireland. If, for example, relatively more younger workers went to the UK than to Ireland, the simulation results from the previous section would understate the impact of migration on real wages. Therefore, I re-run the simulations of section 5 with Irish data only. Figure 3 compares the results from the simulations with Irish data to the baseline scenario. The magnitude of the wage effects is significantly lower when using Irish data only, but the sign prevails. 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 Variation of σ_{EXP} and σ_{ED}

The econometric estimation of the parameters σ_{EXP} and σ_{ED} in section 4 includes uncertainty. In the baseline scenario I used a parameter value for σ_{EXP} that lies between the point estimates obtained from the two IV regressions. Furthermore, I determined the value for σ_{ED} using the restriction $\sigma_{ED} < \sigma_{EXP}$. To make sure that the simulation results are robust to the choice of these parameters, I re-run the simulations with values higher and lower for each parameter compared to the baseline case of $\sigma_{EXP} = 1.4$ and $\sigma_{ED} = 1.2$. High values for these parameters mean that the corresponding skill groups are closer substitutes so that the relative labor demand curve is flatter, which translates into a lower wage effect in absolute value. With low values for σ_{EXP} and σ_{ED} it is the other way round. The results in figures 4 and 5 show the sensitivity of the results to changes

in each parameter by ± 0.2, which means an increase/decrease of 14% with respect to σ_{EXP} and 17% with respect to σ_{ED}. As we can see in both figuress, a change in the structural parameters does not significantly alter the simulation results. Moreover, the results are robust to the choice of instrument in section 4, as the estimated values for σ_{EXP} lie within the range of 1.4 ± 0.2 regardless of the instrument chosen.
Comparing figures 4 and 5, we can see that the results are more sensitive to changes in σ_{EXP} than to changes in σ_{ED}. σ_{EXP} is part of the own-wage effect, which is the first-order effect and dominates cross-wage effects for most skill groups (see table 6). The value of σ_{ED} influences the size of the higher-order effects, i.e. cross-wage effects, and has therefore a smaller impact on the wage changes than σ_{EXP}.

6.3 Calibration on Parameters from the Literature

As described in section 4.1, the estimated parameters σ_{EXP} and σ_{ED} are lower in value than the ones in the literature on the wage effects of immigration. Although the parameter values from the literature have been estimated for different countries and for 5-year intervals, it would be interesting to see how a calibration of the model with these parameters would change the results. Suppose I calibrate the model on the parameters for the German labor market and simulate the emigration shock Lithuania experienced after 2004, the interpretation would be: if the Lithuanian labor market had the same characteristics with respect to the substitutability between groups of workers, these would be the changes in wages. 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 (2009) ($\sigma_{EXP} = 30$, $\sigma_{ED} = 6.5$) 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 my σ_{ED} 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 my case. Consequently, the negative wage effects I found 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 (2009), 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 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. 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 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

I am particularly grateful to Gaia Narciso for all her support and encouragement. Furthermore, I would like to thank Catia Batista, Christian Danne, Julia Anna Matz, Carol Newman, Conor O'Toole, Pedro Vicente, Michael Wycherley and the participants at the 7th conference of the Irish Society of New Economists, the Geary Institute Behavioral Seminar, the Development Working Group at TCD and the department seminar at TCD for helpful suggestions. The help of the Irish Central Statistical Office and the Lithuanian Statistical Office in producing the data is gratefully acknowledged. This work is funded by the Strategic Innovation Fund (SIF) of the Irish Higher Education Authority (HEA). All errors are mine.

References

Aydemir, Abdurrahman, & Borjas, George J. 2011. Attenuation Bias in Measuring the Wage Impact of Immigration. *Journal of Labor Economics*, **29**(1).

Barrell, Ray, FitzGerald, John, & Riley, Rebecca. 2010. EU Enlargement and Migration: Assessing the Macroeconomic Impacts. *Journal of Common Market Studies*, **48**(2), 373–395.

Barrett, Alan, & Duffy, David. 2008. Are Ireland's Immigrants Integrating into its Labour Market? *International Migration Review*, **42**(3), 597–619.

Barrett, Alan, Bergin, Adele, & Duffy, David. 2006. The Labour Market Characteristics and Labour Market Impacts of Immigrants in Ireland. *The Economic and Social Review*, **37**, 1–26.

Batista, Catia. 2007. Joining the EU: Capital Flows, Migration and Wages. *University of Oxford, Department of Economics Discussion Paper Series*, **342**.

Blanchflower, David G., & Shadforth, Chris. 2009. Fear, Unemployment and Migration. *The Economic Journal*, **119**, 136–182.

Borjas, George J. 2003. The Labor Demand Curve IS Downward Sloping: Reexamining the Impact of Immigration on the Labor Market. *The Quarterly Journal of Economics*, **118**(4), 1335–1374.

Brücker, Herbert, & Jahn, Elke J. 2009. Migration and Wage Setting: Reassessing the Labor Market Effects of Migration. *Kiel Working Papers*, **1502**.

Brunello, Giorgio, Crivellaro, Elena, & Rocco, Lorenzo. 2011. Lost in Transition? The Returns to Education Acquired under Communism 15 Years after the Fall of the Berlin Wall. *IZA Discussion Paper*, **5409**.

Butcher, Kristin F., & Card, David. 1990. Immigration and Wages: Evidence from the 1980s. *AEA Papers and Proceedings*, **81**(2), 292–296.

Card, David. 1990. The Impact of the Mariel Boatlift on the Miami Labor Market. *Industrial and Labor Relations Review*, **43**(2), 245–257.

Central Statistics Office. 2009. *Foreign Nationals: PPSN Allocations, Employment and Social Welfare Activity, 2008.* Tech. rept. Central Statistics Office Ireland.

D'Amuri, Francesco, Ottaviano, Gianmarco I.P., & Peri, Giovanni. 2010. The Labor Market Impact of Immigration in Western Germany in the 1990s. *European Economic Review*, **54**, 550–570.

Docquier, Frédéric, Çağlar Özden, & Peri, Giovanni. 2011. The Wage Effects of Immigration and Emigration. *NBER Discussion Paper*, **16646**.

Drinkwater, Stephen, Eade, John, & Garapich, Michal. 2006. Poles Apart? EU Enlargement and the Labour Market Outcomes of Immigrants in the UK. *IZA Discussion Paper*, **2410**.

Dustmann, Christian, Fabbri, Francesca, & Preston, Ian. 2005. The Impact of Immigration on the British Labour Market. *The Economic Journal*, **115**, F324–F341.

Dustmann, Christian, Glitz, Albrecht, & Frattini, Tommaso. 2008. The Labor Market Impact of Immigration. *Oxford Review of Economic Policy*, **24**(3), 477–494.

Dustmann, Christian, Frattini, Tommaso, & Halls, Caroline. 2009. Assessing the Fiscal Cost and Benefits of A8 Migration to the UK. *CReAM Discussion Paper*, **18**.

Elsner, Benjamin. 2010. Does Emigration Benefit the Stayers? The EU Enlargement as a Natural Experiment. Evidence from Lithuania. *IIIS Discussion Paper*, **326**.

Fihel, Agnieszka, Kaczmarczyk, Pawel, & Okolski, Marek. 2006. Labour Mobility in the Enlarged European Union. *CMR Working Paper*, **14/72**.

Friedberg, Rachel M. 2001. The Impact of Mass Migration on the Israeli Labor Market. *The Quarterly Journal of Economics*, **116**(4), 1373–1408.

Greene, William H. 2008. *Econometric Analysis*. 6 edn. Pearson International Edition.

Hamilton, James D. 1994. *Time Series Analysis*. Princeton University Press.

Hazans, Mihails, & Philips, Kaia. 2009. The Post-Enlargement Migration Experience in the Baltic Labor Markets. *Chap. 10, pages 255–304 of:* Kahanec, Martin, & Zimmermann, Klaus F. (eds), *EU Labor Markets after Post-Enlargement Migration*. Springer-Verlag Berlin.

KATZ, LAWRENCE F., & MURPHY, KEVIN M. 1992. Changes in Relative Wages, 1963-1987. *The Quarterly Journal of Economics*, **107**(1), 35–78.

LEMOS, SARA, & PORTES, JONATHAN. 2008. New Labour? The Impact of Migration from the Central and Eastern European Countries on Unemployment and Wages in the UK. *IZA Discussion Paper*, **3756**.

MANACORDA, MARCO, MANNING, ALAN, & WADSWORTH, JONATHAN. 2006. The Impact of Immigration on the Structure of Male Wages: Theory and Evidence from Britain. *CEP Discussion Paper*, **754**.

MISHRA, PRACHI. 2007. Emigration and Wages in Source Countries: Evidence from Mexico. *Journal of Development Economics*, **82**, 180–199.

OTTAVIANO, GIANMARCO, & PERI, GIOVANNI. 2006. Rethinking the Effects of Immigration on Wages. *NBER Working Paper*, **12497**.

OTTAVIANO, GIANMARCO, & PERI, GIOVANNI. 2008. Immigration and National Wages: Clarifying the Theory and the Empirics. *NBER Working Paper*, **14188**.

SOLOW, ROBERT M. 1956. A Contribution to the Theory of Economic Growth. *The Quarterly Journal of Economics*, **70**(1), 65–94.

STOCK, JAMES H., WRIGHT, JONATHAN H., & YOGO, MOTOHIRO. 2002. A Survey of Weak Instruments and Weak Identification in Generalized Method of Moments. *Journal of Business & Economic Statistics*, **20**(4), 518–529.

WADENSJÖ, ESKIL. 2007. Migration to Sweden from the New EU Member States. *IZA Discussion Paper*, **3190**.

s_{ij},

A Data - Clustering of Education Groups

Table 1: 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)

B 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 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

$$s_{ij} = \alpha \left(\frac{W_{ij}}{W} \right). \tag{16}$$

$\frac{W_{ij}}{W}$ 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},

$$s_i = \sum_j s_{ij}. \tag{17}$$

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 5 are the average of those four years.

C Emigration Rates as an Instrument - Calculation

In section 4.1 I use the emigration rates by skill group as an instrument for Lithuanian labor supply. The emigration rate is the number of emigrants per skill group divided by the number of workers in Lithuania of the same skill group.

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 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 2e), 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.[22]

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: $M_{ij2002} = x_{ij2002}\left(1 + \frac{NINO_{2002}}{PPS_{2002}}\right)$
- 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.[23]

[22] 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)).

[23] 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.

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

Dividing the number of emigrants by the number of workers in the workforce for each skill group gives the emigration rate.

D Tables and Figures

Table 2: 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 3: Regression results for σ_{EXP}

OLS and IV results, 10-year cells

	Men and Women			Men only			Women only		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	OLS	IV (LIT)	IV (PL)	OLS	IV (LIT)	IV (PL)	OLS	IV (LIT)	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

Robust standard errors in brackets

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

Table 4: 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 5: 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 6: Decomposition of the wage effect of emigration for the baseline scenario.

	Work Experience	Total Wage Change	Effect 1 Own-wage effect	Effect 2 Effect within educ group	Effect 3 Effect across educ groups	Effect 4 Production
lower secondary	0-10	5.60	8.17	0.69	0.85	-4.06
	11-20	1.30	3.81	0.69	0.85	-4.06
	21-30	2.00	4.48	0.69	0.85	-4.06
	31+	-1.60	0.95	0.69	0.85	-4.06
upper secondary	0-10	8.60	11.23	0.56	0.85	-4.06
	11-20	0.70	3.36	0.56	0.85	-4.06
	21-30	-1.10	1.58	0.56	0.85	-4.06
	31+	-1.90	0.79	0.56	0.85	-4.06
third level	0-10	6.90	9.42	0.68	0.85	-4.06
	11-20	-0.20	2.31	0.68	0.85	-4.06
	21-30	-0.50	1.99	0.68	0.85	-4.06
	31+	-1.50	1.05	0.68	0.85	-4.06

Figure 1: Actual wage changes by skill group. Source: Lithuanian Household Budget Survey

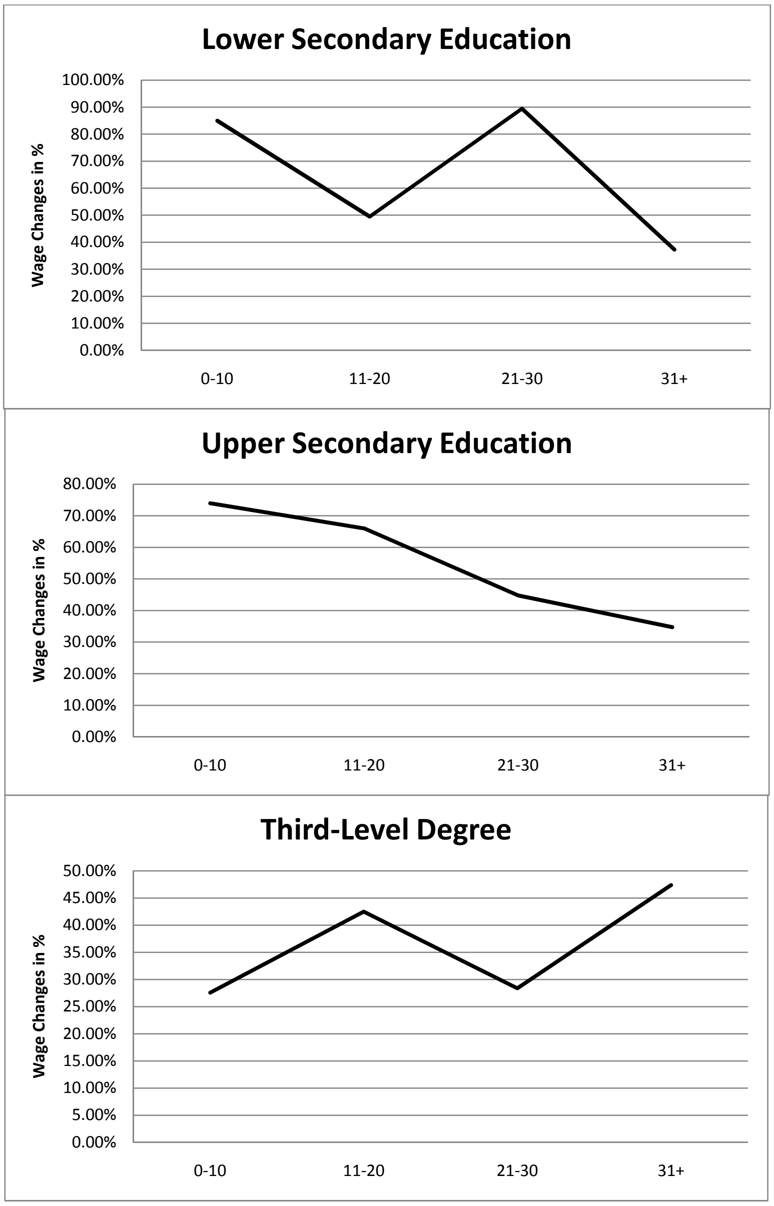

Figure 2: Simulation Results Baseline Scenario

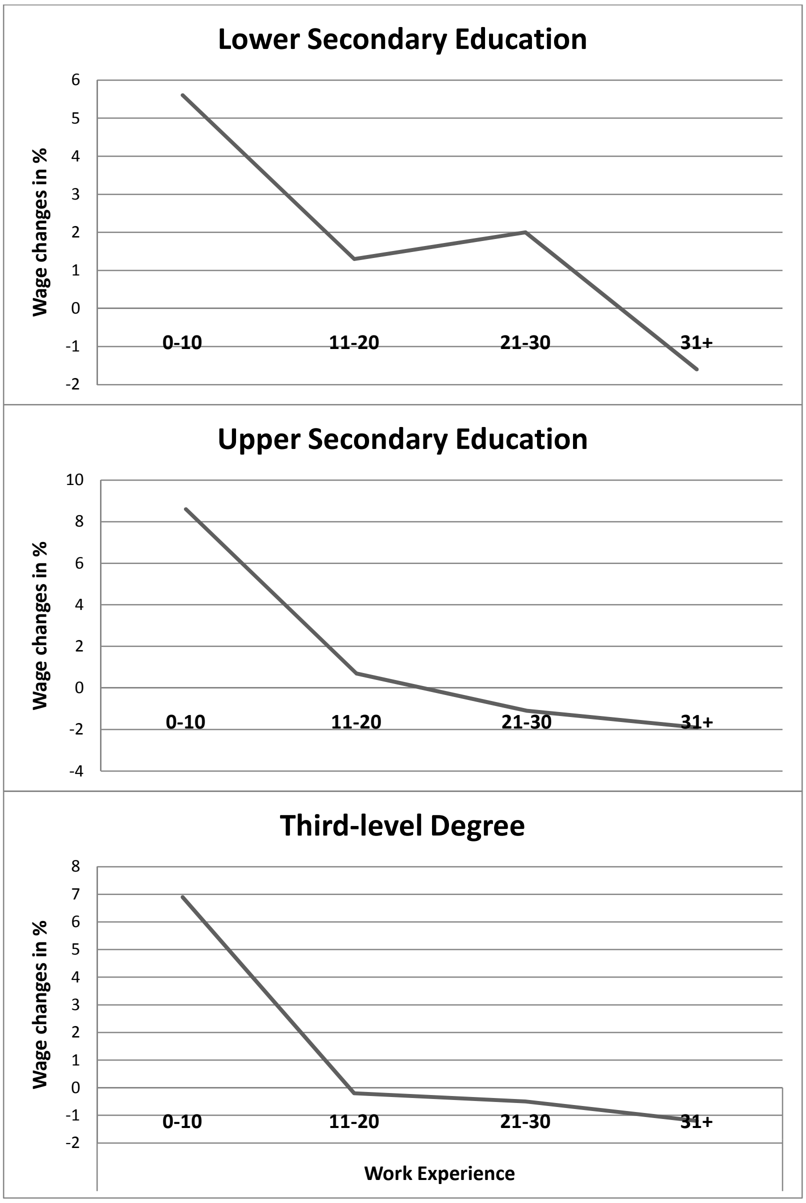

Figure 3: Simulation Results, Using Irish Data only

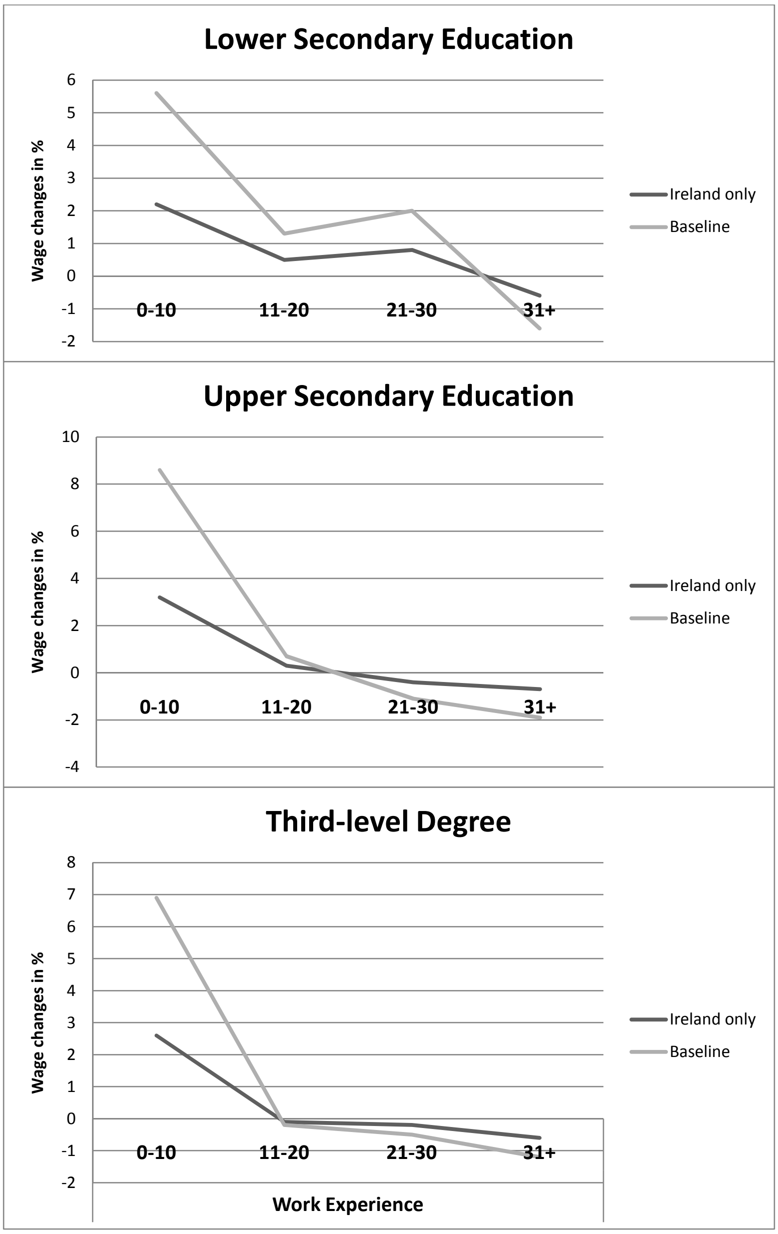

Figure 4: Simulation Results: variation of σ_{EXP}. High value $\sigma_{EXP}^{high} = 1.6$, low value $\sigma_{EXP}^{low} = 1.2$, $\sigma_{ED} = 1.2$.

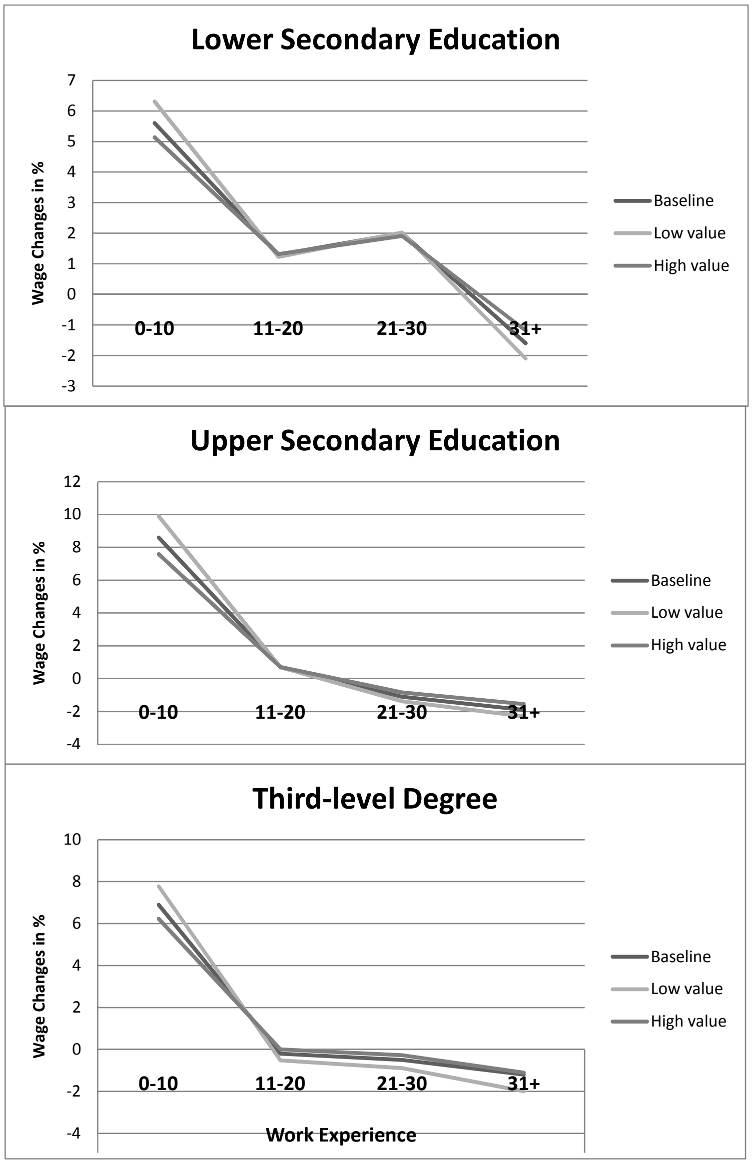

Figure 5: Simulation Results: variation of σ_{ED}. High value $\sigma_{ED}^{high} = 1.4$, low value $\sigma_{ED}^{low} = 1.2$, $\sigma_{EXP} = 1.4$.

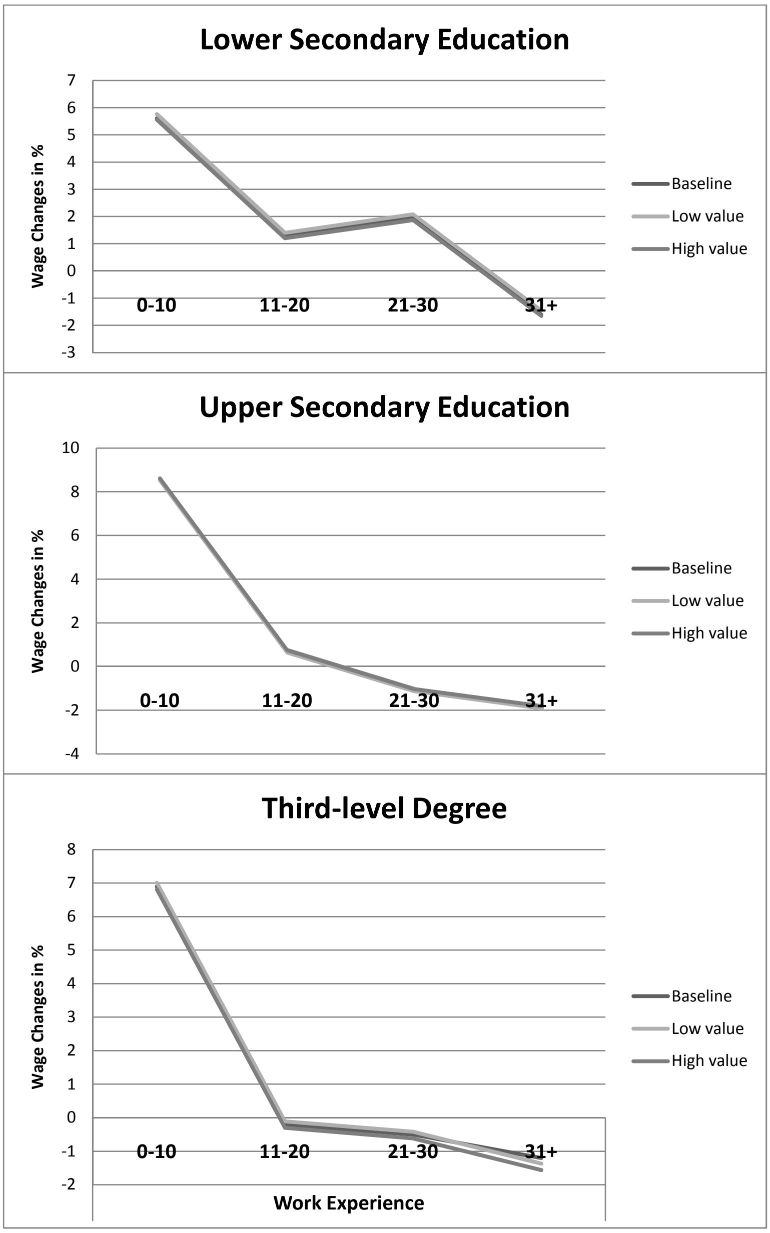

Figure 6: Simulation Results: calibration on the structural parameters from Borjas (2003), Ottaviano & Peri (2008), Brücker & Jahn (2009) and D'Amuri *et al.* (2010).

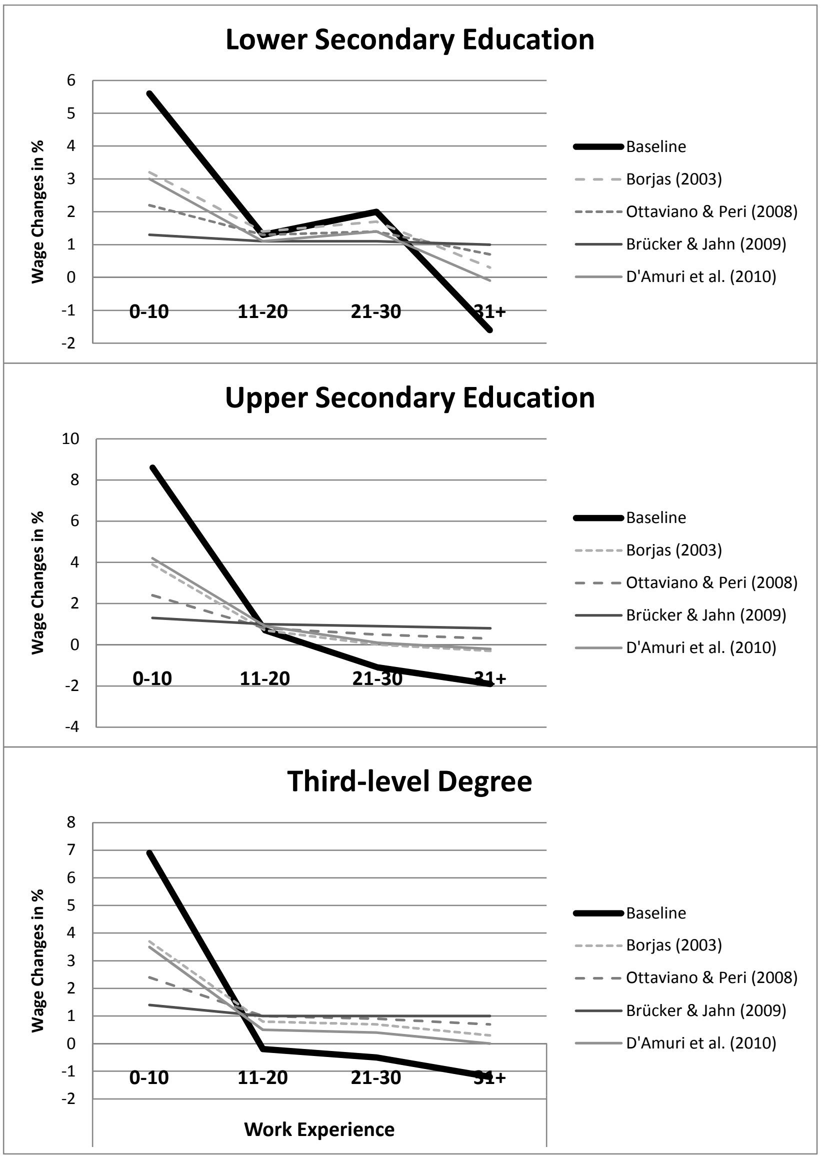

Figure 7: Nested CES production function

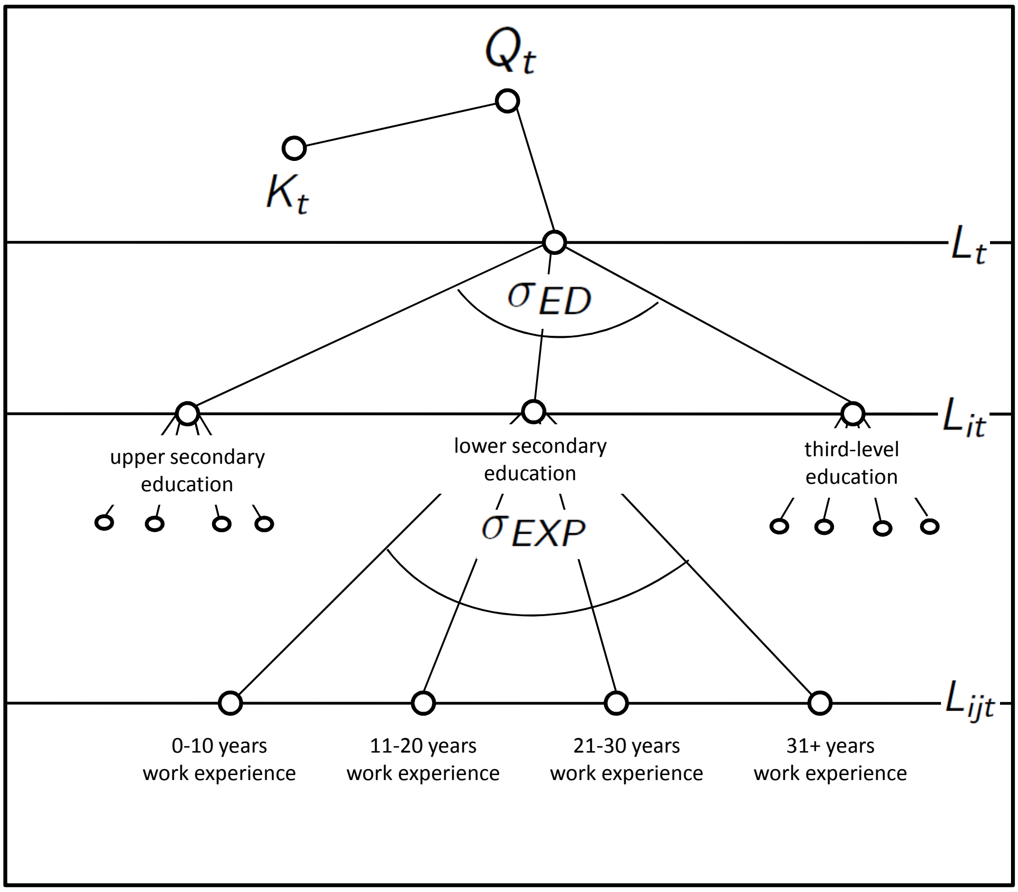

Figure 8: Work Permits to Lithuanian nationals, in Ireland (PPS) and the UK (NINo), 2002-2007

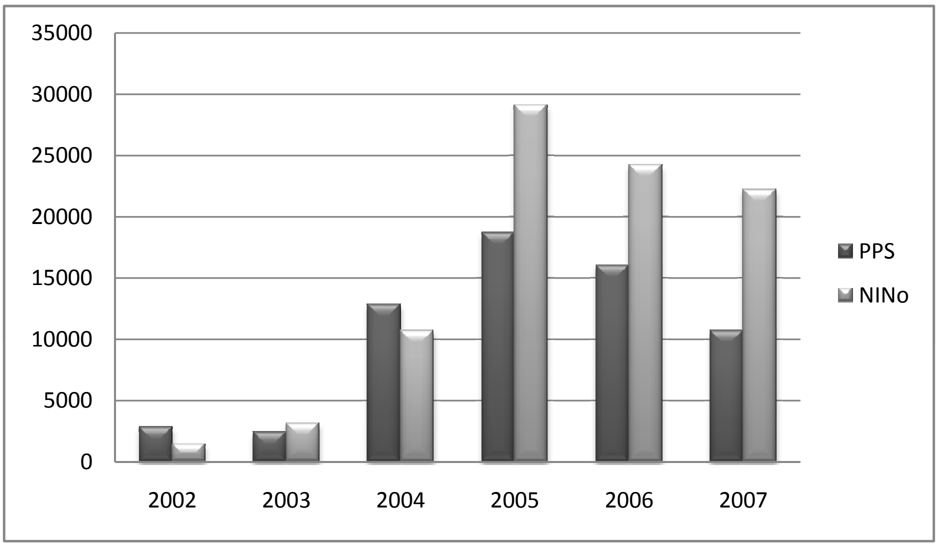

Figure 9: Skill distribution of Lithuanian migrants in Ireland. Source: Irish census 2006

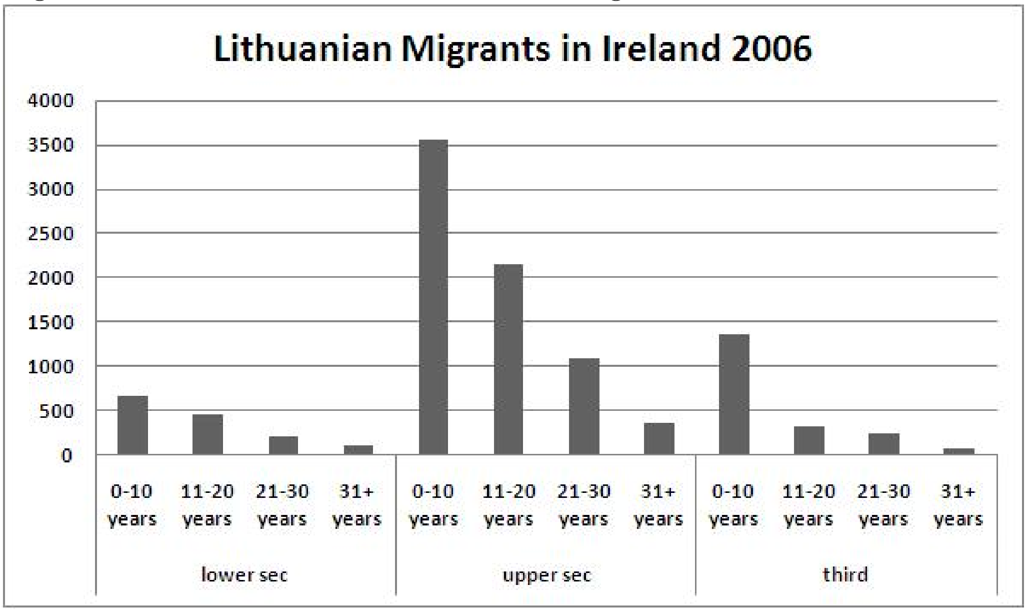

Figure 10: Number of emigrants 2004-2007 relative to the total workforce in 2003. Number of emigrants calculated from the work permit numbers in Ireland (PPS) and the UK (NINo). Workforce from Eurostat.

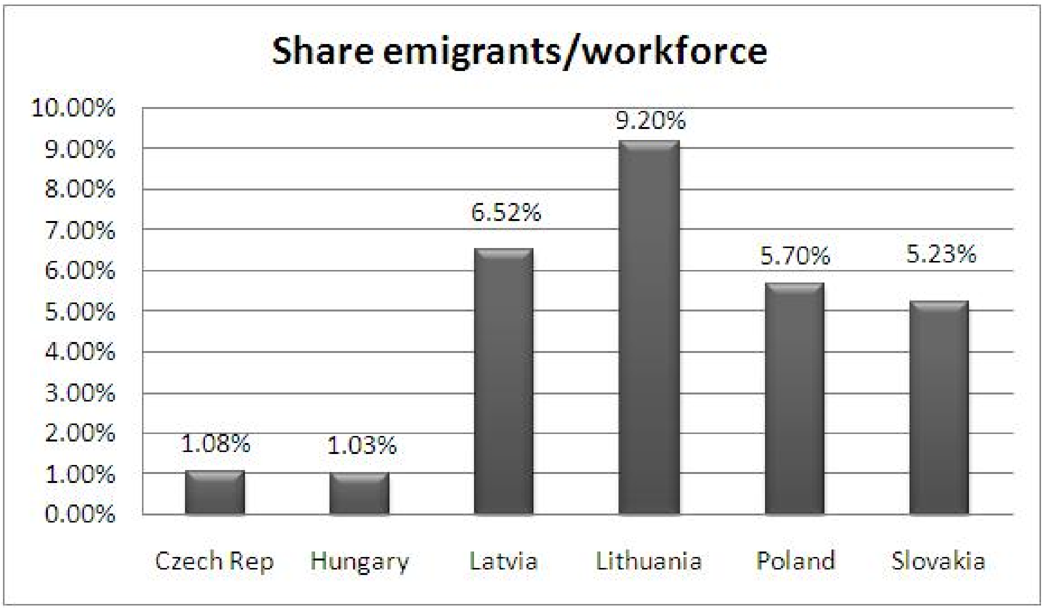

Figure 11: Correlation of emigration rates Poland - Lithuania