Emigration and Wages: The EU Enlargement Experiment

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March 12, 2013

Abstract

The enlargement of the European Union provides a unique opportunity to study the impact of the lifting of migration restrictions on the migrant sending countries. With EU enlargement in 2004, 1.2 million workers from Eastern Europe emigrated to the UK and Ireland. I use this emigration wave to show that emigration significantly changed the wage distribution in the sending country, in particular between young and old workers. Using a novel dataset from Lithuania, the UK and Ireland for the calibration of a structural model of labor demand, I find that over the period of five years emigration increased the wages of young workers by 6%, while it had no effect on the wages of old workers. Contrary to the immigration literature, there is no significant effect of emigration on the wage distribution between high-skilled and low-skilled workers.

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

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†I am grateful to Gaia Narciso for all her support and encouragement. Furthermore, I would like to thank the editor, two anonymous referees, Catia Batista, Karol Borowiecki, Christian Danne, Tommaso Frattini, Daniel Hamermesh, Emma Howard, Tara McIndoe-Calder, Julia Anna Matz, Annaïg Morin, Gianmarco Ottaviano, Giovanni Peri, Theodore Talbot, Janis Umblijs, Pedro Vicente, Michael Wycherley and the participants at numerous conferences and seminars for helpful suggestions. The author gratefully acknowledges funding from the Irish Research Council for the Humanities and Social Sciences (IRCHSS) and the Department of Economics at TCD. Part of this paper was written during a research visit at Bocconi University. All errors are mine.

1 Introduction

Lifting the barriers to migration can lead to welfare gains of up to 150% of world GDP.[1] However, while a large body of literature has quantified the gains from migration for the receiving countries and the migrants, little is known about the impact of emigration on the sending countries. Given that migration is heavily restricted, there are few episodes of large migration waves that can be exploited to assess the impact of the lifting of these restrictions on the sending countries.[2]

This paper exploits a large emigration wave from Eastern Europe to analyze the impact of emigration on the wages of non-migrants in the sending countries. Following EU enlargement in 2004, the UK, Ireland, and Sweden opened their labor markets to workers from Eastern Europe, which prompted a migration wave of 1.2 million workers over 3 years. Indeed, the most-affected sending countries - Latvia, Lithuania, Poland and Slovakia - experienced an outflow of up to 9% of their workforce.[3]

To estimate the wage effects of emigration, I use a structural factor demand model (Card & Lemieux, 2001; Borjas, 2003). I first take a snapshot of the labor market prior to EU enlargement by estimating the model parameters using microdata from Lithuania. Based on observed immigration data from the UK and Ireland, I then simulate the emigration wave and calculate the wage change as the difference between the equilibrium wage before and after the migration wave. Compared to a reduced-form analysis, this approach allows me to isolate the effect of emigration from other factors that would otherwise impact wages, such as trade, FDI and TFP growth. Furthermore, it also delivers separate wage effects for groups of workers with different education and work experience, thus allowing for an assessment of the distributional impact of emigration.

The main finding is that emigration had a significant impact on the wage structure, and particularly on the wage distribution between old and young workers, causing a substantial wage increase for young workers yet no effect on the wages of old workers. By contrast, I find no

[1] Clemens (2011).

[2] See Kerr & Kerr (2011) for a review of the immigration literature. Estimates for the gains on the side of the emigrants can be found in Chiswick (1978), Borjas (1995), and Algan *et al.* (2010).

[3] Own calculations from work permit data.

difference in the wage effects between high- and low-skilled workers. These wage effects can be decomposed into an own-wage effect, caused by the emigration of workers with the same observable characteristics, and general equilibrium effects, caused by the change in the skill distribution of the workforce. The own-wage effect is positive; namely, a decrease in the number of workers increases their wage, while the sum of the general equilibrium effects, caused by the change in the demographics of the workforce, is negative. The own-wage effect dominates for young workers, who represented the majority of emigrants, while for older workers the two effects cancel each other out.

These findings stress the importance of labor market externalities in the assessment of the welfare impacts of emigration. Eastern Europe experienced a large outflow of young workers – a *youth drain* – from all education levels. Through the price mechanism of the labor market, the wages of young workers increased more than the wages of older workers. However, most literature on the sending countries assumes away these labor market effects, focusing instead on the human capital externalities. In this literature, high-skilled emigration changes the incentives of non-migrants to invest in education, which can have a negative "brain drain" or a positive "brain gain" effect (Gibson & McKenzie, 2011; Docquier & Rapoport, 2012) on economic growth. While indirect effects may be important for developing countries, this paper finds that the direct wage effects of emigration play a significant role in middle-income countries.

Given that the emigration wave from Eastern Europe was a sudden shock to labor supply, it allows for the identification of a short-run effect on wages. Moreover, the results have a clear interpretation, since all migrants left within a short period in time. By contrast, previous studies on the wage effect of emigration by Mishra (2007) and Aydemir & Borjas (2007) focus on longer time horizons, both finding a positive long-run impact in Mexico between 1970 and 2000. However, the results have to be interpreted *as if* all workers had left the economy at once, despite actually having left gradually over the last 50 years (Hanson & McIntosh, 2010). Dustmann *et al.* (2012) study a case similar to that in this paper — emigration from Poland, although the emigration wave in their period of study was rather small, with 2% of the workforce emigrating between 1998 and 2007. Recent evidence from quasi-natural experiments (Elsner, 2013; Gagnon, 2011) shows that emigration increases wages even in the short run. However, both studies use a reduced-form approach, only allowing them to determine an average effect. In this paper, I show that these wage effects only benefit the young workers. Moreover, a comparison with the reduced-form results of Elsner (2013) demonstrates the importance of the general equilibrium effects, without which the predicted wage changes would be considerably higher.

This paper also highlights the importance of wages as an adjustment channel to labor supply shocks in countries of origin. By contrast, the small effects of immigration on wages in migrant-receiving countries found in most studies imply that other channels are more important. Hanson & Slaughter (2002) and Lewis (2003) find that labor supply shocks in US states are mainly absorbed within industries. Industries switch to technologies that are more complementary to the increased type of labor, while there is little evidence of a change in the output mix towards goods produced intensively using the type of labor that has increased most (i.e. the Rybczynski effect). Gandal *et al.* (2004) and González & Ortega (2011) find similar results for the large immigration waves in Israel and Spain, respectively. Dustmann & Glitz (2011) show that the switching of industries to complementary technologies can be explained by firm entry and exit, given that new firms have no adjustment costs. However, the non-negligible wage effects of emigration found in this paper imply that other adjustment channels must play a lesser role than in receiving countries, with further research required to shed light on this issue.

Finally, this paper reveals that migration affects sending and receiving countries along different skill dimensions. In contrast to most studies on immigration, which find the main distributional effect between high-skilled and low-skilled workers (Borjas, 2003; Manacorda *et al.*, 2011; D'Amuri *et al.*, 2010), I find a significant distributional effect between old and young workers. The wage effect is larger in Eastern Europe than in the main receiving countries, which can be explained by the low degree of substitutability between old and young workers in transition countries: old workers in Eastern Europe were educated under socialism, while young workers received their education in a market economy. Therefore, young workers cannot easily be replaced by old workers, resulting in a stronger reaction of wages on emigration.

The remainder of the paper is structured as follows. Section 2 provides a historical overview and stylized facts concerning the emigration wave from Eastern Europe after 2004. Section 3 sets up the structural model. Section 4 describes the data sources that are used for the estimation of the structural parameters in Section 5. Section 6 details the simulation of the migration wave and calculates the wage effects. Section 7 concludes.

2 EU Enlargement, Migration and Wages: Stylized Facts

This section provides an overview of EU enlargement and the subsequent migration wave from the new to old member states of the EU. In 2004, eight former socialist countries from Central and Eastern Europe joined the EU, with the high wage differentials between Western Europe and the accession countries creating a large incentive for workers from these countries to emigrate.[4] *Freedom of Movement*, a basic principle of the EU, guarantees every worker from the New Member States the right to migrate to any EU country and take up employment. However, only Ireland, the UK and Sweden immediately opened their labor markets and experienced a large influx of immigrants. Most other countries in Western Europe were concerned with potential negative consequences for their labor markets and welfare systems, and restricted the access for workers from the New Member States for up to 7 years. Between 2004 and 2007, 1.2 million workers migrated from Eastern Europe to the UK (770,000), Ireland (416,000) and Sweden (19,000).[5]

Most migrants came from Poland, Latvia, Lithuania and Slovakia. Despite Poland having the

[4] The difference PPP-adjusted GDP per capita, a proxy for wage differentials, amounted to 37% in Lithuania and 40% in Poland, compared to the UK. Source: Eurostat.

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

highest number of emigrants, Lithuania and Latvia had the highest share of emigrants. Between 2004 and 2007, 9% of all Lithuanian workers and 6% of all Latvian workers received a work permit in Ireland or the UK. While some workers only migrated for a short period, the majority stayed in the destination country for longer periods, with evidence from the Irish Central Statistics Office (2009) suggesting that around 60% of migrants from the New Member States stayed for at least two years after having received a work permit.

This study takes Lithuania as an example to study the impact of emigration on the wages of stayers. Lithuania presents an interesting case as it had the highest share of emigrants among the accession countries. At the same time, the results are externally valid with respect to other transition countries. For instance, Poland, Slovakia and Latvia share the same history of transition as Lithuania since the fall of the Iron Curtain in 1990. In addition, they were in a similar economic situation at the time of EU enlargement, with comparable levels of GDP per capita and unemployment.[6] Accordingly, an outflow of 9% of the workforce should have similar impacts on the wage structure in all four countries.

The number of work permits per year issued to Lithuanians increased sharply from 6,400 in 2003 to 40,000 in 2006.[7] Around the same time, Lithuania experienced a phase of high economic growth, with GDP per capita growing in total by 37.5% between 2002 and 2006, which was also accompanied by a phase of considerable wage increases. The graph on the left in Figure 1 shows the changes in average real wages for workers in different education and experience groups.

Although all groups gained, the wage changes were not spread evenly across groups of workers. Indeed, young workers with a work experience of up to 20 years gained considerably more than old workers. Furthermore, wage changes were on average larger for low-skilled workers. These uneven wage changes resulted in a change in the wage distribution between young and old workers, and high- and low-skilled workers.[8]

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

7 See Table 1B.

8 See the Online Appendix A.1 for more details on wage inequality.

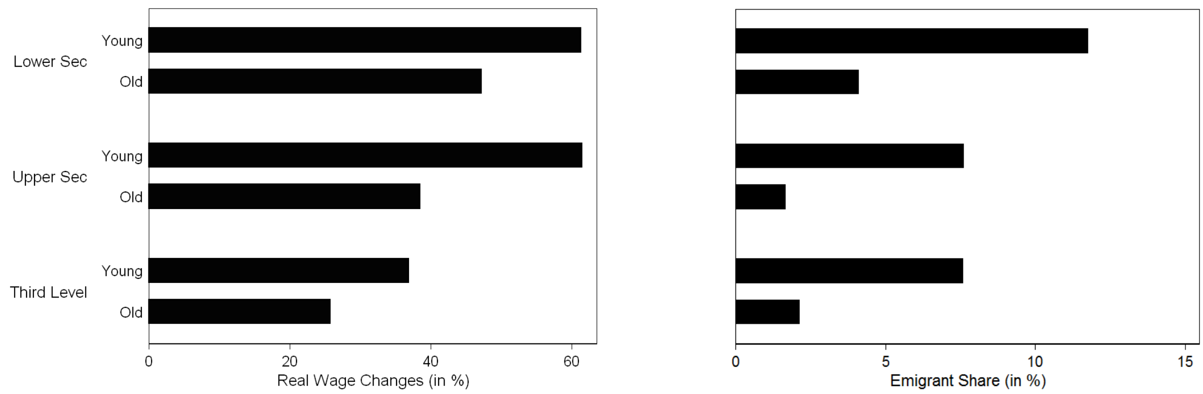

Figure 1 – Real Wage Changes and Emigrant Shares, Lithuania 2002-2006.

Note: The figure on the left shows the real wage changes in Lithuania from 2002 to 2006; the figure on the right displays the share of emigrants per skill group. A skill group is defined by education and work experience. Workers with 20 years and less of work experience are defined as young, and those with 21 and more years as old. The real wages are deflated by the HCPI. The emigrant share is measured as the share of the workers in a skill group that emigrated between 2002 and 2006.

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

Figure 1 (right graph) illustrates the magnitude of the emigration wave between 2002 and 2006 for each skill group. Similarly to the wage changes, the emigrant shares were higher for young workers, who were around 3.5 times more likely to emigrate than old workers. Surprisingly, there was little selection of emigrants with respect to the education groups: workers of all three education levels had almost identical emigrant shares, with slightly higher shares among workers with lower secondary education. Certainly, there was no evidence of a brain drain.

The changes in the level and distribution of wages could be caused by numerous factors. On the supply side, emigration leads to a smaller number of workers, and given constant labor demand, the workers who did not emigrate represent a more scarce resource and consequently their wages increase. On the demand side, domestic and foreign investment, trade integration or TFP growth can have a positive influence on wages. The structural model outlined in the next section allows me to disentangle the effect of emigration from these other channels.

3 Structural Model

The structural model lays out a system of labor demand curves for workers with different observable skills. To model the heterogeneity in observable skills, the workforce is divided into 12 skill groups, defined by education and work experience. Workers with the same observable characteristics are perfect substitutes and compete in the same labor market. Across skill groups, workers with similar skills are closer substitutes than those with fundamentally different skills. Emigration of workers of a particular skill group shifts the labor supply, and, given a downward-sloping labor demand curve, increases the wages of the stayers in this skill group. In addition, emigration of workers from one group alters the relative skill supply of the entire workforce, which shifts the labor demand curves of all other groups. The extent of these general equilibrium effects depends on the degree of substitutability between skill groups, and needs to be determined empirically.

3.1 Aggregate Production

The notation and analysis in this section follow Card & Lemieux (2001), Borjas (2003) and Ottaviano & Peri (2012). The aggregate production function consists of three building blocks. In Equation (1), physical capital K_t, labor L_t and total factor productivity A_t are combined to produce an aggregate output Q_t, which has a price of 1. The second building block, Equation (2) is a CES aggregate of three education groups, which are imperfect substitutes. The third building block, Equation (3) combines workers with the same education yet different work experience, which accounts for the difference in skills between workers of different experience levels. The difference in skills can arise due to old and young workers acquiring their qualifications at different times, or because old workers may have gathered more experience in their job, and thus have more human capital than younger workers.

$$
\begin{aligned}
Q_t &= A_t L_t^{\alpha} K_t^{1-\alpha} & (1)\\
L_t &= \left[\sum_i \theta_{it} L_{it}^{\frac{\sigma_{ED}-1}{\sigma_{ED}}}\right]^{\frac{\sigma_{ED}}{\sigma_{ED}-1}} & (2)\\
L_{it} &= \left[\sum_j \gamma_{ijt} L_{ijt}^{\frac{\sigma_{EXP}-1}{\sigma_{EXP}}}\right]^{\frac{\sigma_{EXP}}{\sigma_{EXP}-1}} & (3)
\end{aligned}
$$

$\alpha \in (0,1)$ is the share of labor in aggregate income. The labor force L_t, described in Equation (2), 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). Each education group consists of four work experience groups L_{ijt}, as described in Equation (3). The efficiency weights θ_{it} and γ_{ijt} reflect the contribution of each labor input to the overall output of the entire labor force and each education group, respectively, with $\sum_i \theta_{it} = 1$ and $\sum_j \gamma_{ijt} = 1$. The elasticities of substitution between education groups (σ_{ED}) and experience groups (σ_{EXP}) are crucial for the further analysis. The lower the value of these parameters, the harder it is to substitute two groups of workers in the production process, and the steeper the demand curves for education and experience groups.

Work experience is calculated as the exposure to the labor market, age $-$ *schooling* $- 6$.[9] For the division of an education group into experience groups (j), I choose intervals of 10 years of work experience (0-10 years, 11-20 years, 21-30 years, 31+ years), as the result of a trade-off between many skill groups and many observations per skill group. Shorter intervals allow for a more differentiated picture of the labor market, despite coming at the cost of a loss in precision. With a given number of observations, a high number of skill groups means that the calculation of the average wage and labor input per skill group are based on a small number of observations, and consequently averages become less precise. Aydemir & Borjas (2011) show that

[9] The time spent in school is 10 years for lower secondary education, 12 years for upper secondary education, and 15 years for third-level education.

this attenuation bias can have a significant impact on the estimates of the structural parameters. Given the available dataset, the choice of 10-year intervals represents a compromise that reduces attenuation bias whilst allowing for a differentiated picture of the labor supply and wage changes.[10]

3.2 Labor Market Equilibrium

Labor markets are perfectly competitive and clear in every period. The real wage w_{ijt} of each skill group L_{ijt} equals its marginal product. Differentiating $\partial Q_t / \partial L_{ijt}$ and taking logs yields the labor market equilibrium, described by the log-linear demand curve

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

where $\frac{1}{\sigma_{EXP}}$ is the slope coefficient, while all other terms on the right-hand side of equation (4) are intercepts that vary along the dimensions indicated by the indices, i.e. time, education and experience. Any change in one of the factors on the right-hand side alters the marginal product, which leads to a change in the real wage *ceteris paribus*. Hence, the wage of group ij depends on its own labor supply, as well as the labor supply of all other groups of workers. 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.

From equation (4), it is possible to generate an estimating equation for σ_{EXP}, controlling for all other factors that affect the real wage. For the case of EU enlargement, these controls are particularly important, given that EU accession was accompanied by increased FDI inflows, a deeper trade integration and the inflow of EU structural funds, which have an impact on labor demand and ultimately on wages. Controlling for such factors is possible because the variation

[10] Most of the literature, e.g. Borjas (2003), Brücker & Jahn (2011), D'Amuri *et al.* (2010), Katz & Murphy (1992), Manacorda *et al.* (2011), Ottaviano & Peri (2012) uses 5-year experience groups. In the Online Appendix A.4 I also report results for 5-year and 20-year cells.

in all terms on the right-hand side of equation (4) except $\left(-\frac{1}{\sigma_{EXP}}\log L_{ijt}\right)$ can be absorbed by dummies and interaction terms. A vector of time dummies absorbs all variation across skill groups over time, while interaction terms between time and education dummies absorb variation within education groups over time. The parameters γ_{ijt} and the labor input L_{ijt} both vary along the dimensions time, education and experience, so that the inclusion of an interaction of the respective dummies would absorb all the variation, and the model would be fully saturated. However, in this case, $\frac{1}{\sigma_{EXP}}$ could not be identified. To circumvent this problem, I assume that the relative productivity of each experience group is constant over time, so that the variation of γ_{ijt} is absorbed by an interaction of education and experience dummies, δ_{ij} and an error term ε_{ijt}. This is a standard assumption in the literature[11] and in the time horizon of 5 years, it is plausible that the relative productivity of an experience group does not fundamentally change. Moreover, as a robustness check, I add an additional set of time*experience interaction terms to the estimating equation in Section 5.

σ_{EXP} can then be consistently estimated from

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

4 Data and Descriptive Statistics

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

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

[11] See Borjas (2003), Ottaviano & Peri (2012).

for this lack of suitable emigration data is that there is no legal obligation for migrants in most European countries to de-register once they have emigrated. The consideration of the case of Lithuanian emigration after EU enlargement has the advantage that Lithuanians were only allowed to migrate to the UK, Ireland and Sweden within the EU, given that all other old EU countries kept their labor markets closed for a transitional period up to 2011. Consequently, I can obtain the number of emigrants from the register data of the destination countries. However, since the numbers of migrants to Sweden were relatively small[12], I will neglect Sweden and only use census and work permit data from Ireland and the UK.

4.1 Lithuanian Household Budget Survey

The Lithuanian Household Budget Survey (HBS) is conducted annually by the Lithuanian Statistical Office, with a random sample of 7,000-8,000 households. The sample is representative at the individual level and includes all people aged 18 or older, with information available on their age, education, income from employment, and personal characteristics such as marital status, number of children and place of residence. However, the HBS does not contain information on sectors or occupations.

Table 1A displays the summary statistics for the HBS. Real wages are calculated as the gross monthly income from employment, deflated by the HCPI in 2005 prices. Income data is self-reported, and can thus be subject to a misreporting bias if workers systematically under- or over-report their income. However, a comparison of the average monthly wages in Table 1A with the average monthly wages for men and women working in the private sector from the Lithuanian live register in Table 1C shows that this bias is negligible, as the difference is minor.

I restrict the sample to private sector workers of working age, i.e. 18-64 years, and exclude public sector workers from the sample, given that wage determination in the public sector is not usually based on the market mechanism of supply and demand, but rather on seniority.

[12] See Wadensjö (2007).

Additionally, I drop the following observations: if the variable *disposable income* is negative, if the socioeconomic status is *pensioner* or *other*, and if workers are self-employed or own a farm.

For each worker, the highest obtained degree counts for their 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 less than the equivalent of a B.Sc degree. Third-level degrees are all degrees at least equivalent to a B.Sc and would allow workers to apply for an international M.Sc program.

While this clustering may appear fairly broad, given that the Lithuanian education system offers a variety of educational tracks,[13] these broad categories are necessary to match the characteristics of the stayers with those of the emigrants. The HBS contains 12 education groups, while the data on the emigrants only distinguishes between 5 groups. Furthermore, broad categories ensure that the number of observations within each group is sufficiently large to allow for the calculation of reliable average wages and emigration numbers. For a more detailed discussion of the construction of education and experience groups, see the Online Appendix A.2.

4.2 Irish Census

For the simulations, I use immigration data from the two main receiving countries, Ireland and the UK. The Irish Census is conducted by the Irish Central Statistics Office (CSO) every 4-5 years and contains all people living in Ireland and present on 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 Lithuanian immigrants in Ireland by gender, age and education. The census reflects a lower bound to the number of emigrants, as it only captures migrants present on the survey night. Accordingly, people who travelled to Ireland for a summer job or a period shorter than one

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

year may not be included in the census.

For the calculation of the number of emigrants, I only use data on migrants whose education is finished, accounting for 93% of Lithuanians in the 2002 census and 85% in 2006. As can be seen 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 average age did not change significantly over time, while the gender distribution of migrants in 2006 is slightly skewed towards men. Comparing the Lithuanian migrants in the Irish census with the workers in Lithuania, a similar education distribution is noted, although migrants are on average 13 years younger than stayers.

4.3 Work Permit Data: PPS and NINo Numbers

The number of workers who obtained a work permit in Ireland and the UK represents an upper bound to migration from Lithuania to these countries. Every worker who moves to Ireland or the UK and wishes to take up employment has to apply for a Personal Public Service (PPS) number in Ireland or a National Insurance Number NINo in the UK.[14] Accordingly, this data captures all workers that emigrated from Lithuania to one of those two countries, regardless of how long they stay in the host country. Given that there is no obligation for working to de-register in their home country, it is not possible to measure how many people returned to Lithuania and how much time they spent in the host country. However, double counts are unlikely, as workers retain their PPS and NINo numbers no matter how frequently they move back and forth between Lithuania and Ireland or the UK. The PPS and NINo numbers could actually undercount the number of migrant workers coming to Ireland and the UK, as some workers might not have registered when they came to work for a short period in time or wanted to avoid having to pay income taxes. However, such workers who only migrated for a short period in time and did not register for that reason can hardly be seen as emigrants, because they were part of the Lithuanian workforce for the entire time. Assessing the number of workers who migrated for a longer period without

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

registering is difficult, yet it should be small given the high number of migrants who actually *did* register. In summary, even if the work permit data might slightly undercount the actual number of migrants, for the simulations this means that the actual labor supply shock might be larger, so that the predicted wage changes resulting from emigration are lower than the actual ones.

4.4 Calculation of Emigration Rates

To simulate the effect of the migration of different skill groups on wages, the labor supply shock $\frac{\Delta L_{ij}}{L_{ij}}$ has to be quantified for each skill group. 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}.[15] L_{ij} can be directly computed from the HBS. Let the sample of a skill group ij contain $l = 1, ..., L$ workers. The number of workers in this skill group is the sum of the sampling weights p_{ijl}. Thus, $L_{ij} = \sum_{l=1}^{L} p_{ijl}$.[16]

The shift in labor supply ΔL_{ij} cannot be taken directly from the data, but rather needs to be computed from several Irish and UK data sources. This is due to the fact that I have detailed data on Lithuanian migrants living in Ireland from the Irish census, yet only aggregate figures on the migrants coming to the UK.[17] To compute the labor supply shifts, I assume that the skill distribution of migrants coming to Ireland is the same as the distribution of those coming to the UK. This assumption can be justified by the fact that there was little visible sorting behavior of migrants from the New Member States between Ireland and the UK with respect to age and education, as shown in more detail in Online Appendix A.3. While there may have been a sorting behavior with respect to occupations, for example immigrants in Ireland work more in the

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

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

[17] The UK labor force survey, the most accessible quarterly representative survey of the workforce in the UK, cannot be used to extract reliable data on the skill distribution of a particular country, due to the low number of observations per country.

Table 1 – Summary Statistics

	2002	2003	2005	2006
A: Lithuanian HBS				
Number of workers				
All	3950	4136	4042	3874
% Men	58.8	59.3	60	59.7
Education				
% Lower Secondary	8.8	10.4	10.76	9.9
% Upper Secondary	69.0	69.2	67.62	67.5
% Third-level	22.2	20.4	21.6	22.6
Age	42.9	42.5	43.1	43.4
Real Wages (monthly in LTL)				
All	1084	1142	1339	1532
Men	1185	1252	1440	1688
Women	940	988	1189	1303
B: Lithuanians in the Irish Census				
Number of workers				
All	1274			11501
% Men	52.7			57.0
Education				
% Lower Secondary	16.6			20.0
% Upper Secondary	63.4			62.3
% Third-level	20.0			17.6
Age	29.5			30.7
C: Other				
Work Permits issued to Lithuanians				
UK (NINo)	1430	3140	10710	24200
Ireland (PPS)	2709	2394	18680	16017
Monthly Wage (Statistical Office)				
Men	1173	1227	1420	1676
Women	998	1029	1167	1356
HCPI (2005=100)	97.3	96.3	100	103.8
Unemployment Rate	13.8%	12.4%	8.3%	5.6%

Note: HBS: Number of private sector workers between 18 and 64 years. Education groups and work experience are determined as described in Section 4. Real wages in Litas (LTL) are deflated by the harmonized consumer price index (HCPI).

The Irish census was only conducted in 2002 and 2006. Data from the Irish census contains all Lithuanian workers who finished their education.

TABLE 2 – EMIGRATION RATES 2002-2006

		Education		
		Lower Sec	Upper Sec	Third-Level
	0-10 Years	16.6%	14.4%	12%
Work	11-20 Years	8.5%	4.3%	2.9%
Experience	21-30 Years	9.6%	2.1%	2.6%
	31+ Years	1.9%	1%	1.4%

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

construction sector and immigrants in the UK more in the service sector, this study focuses on more broadly defined skill groups, for which the distribution is similar.

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

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

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

Table 2 summarizes the calculated emigration rates per skill group, revealing the selection pattern of emigrants regarding age and education. Most emigrants are young, with a work experience of 10 years and less, while very few older workers emigrated. Among all emigrants, workers with a lower secondary education were over-represented, while those with a third-level degree were slightly under-represented. Weighted by the size of the skill groups, the aggregate emigration rate in the Lithuanian workforce is 5%.

5 Estimation of Structural Parameters

5.1 Identification and Estimation of σ_{EXP}

Using equation (5), I estimate σ_{EXP} with the number of workers per skill group as a labor input L_{ijt}.[18] An estimation of the demand curve with OLS does not yield consistent estimates, with the results suffering from simultaneity bias. The equation is a demand curve, yet 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. Accordingly, an exogenous labor supply shifter that does not shift labor demand is needed to disentangle the labor demand and supply curves and identify the slope of the demand curve. Given an appropriate instrument, $\frac{1}{\sigma_{EXP}}$ can be consistently estimated with a two-stage-least-squares (2SLS) estimator.

Most of the literature, e.g. Borjas (2003), Aydemir & Borjas (2007), Ottaviano & Peri (2012), uses immigration as an instrument for labor supply. For the current study, the corresponding instrument would be emigration from Lithuania. To be valid as an instrument, it has to be uncorrelated with labor demand over and above the correlation absorbed by the dummies and interaction terms in the estimating equation (5). However, in light of the scale of the emigration wave following EU enlargement, the emigration of workers of a specific skill group could also shift the demand for workers in this particular group.

To overcome the problem of identification in the presence of simultaneity bias, I propose a new instrument for labor supply, *birth cohort size*, which follows the logic that the size of a birth cohort should be highly correlated with labor supply today. The sign of the correlation depends on the

[18] Ottaviano & Peri (2012) 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, given that the HBS does not include data on working hours, the number of workers serves as a proxy.

labor supply behavior of different age cohorts: if all cohorts have equal employment-to-population rates, one would expect a positive correlation between the size of a birth cohort and the size of a skill group; while on the other hand, if older workers have a lower labor force participation than young workers, and at the same time birth rates were higher in earlier years, it is possible that the correlation between birth cohort size and the size of a skill group is negative.[19] The instrument naturally varies across experience groups, but also across education groups, as workers with a third-level education were born 5 years before workers with a lower secondary education with the same amount of work experience.

To ensure validity as an instrument, the size of a birth cohort must not be correlated with labor demand today, over and above the deterministic factors already controlled for in the first stage. In other words, the size of a birth cohort 50 years ago may well be correlated with contemporaneous demand shifters such as physical capital or total factor productivity, but these correlations are absorbed in the first stage with the time dummies δ_t. The only possible violation of the exclusion restriction would be an impact of the birth cohort size on the stochastic part of the estimating equation, the error term ε_{ijt}. However, it is implausible that the size of a birth cohort, which was determined at least 18 years ago, leads to a stochastic shift in labor demand today.

Figure 2 shows the number of births per year from 1945 to 1984, the years in which most workers in the sample were born. As can be seen, older cohorts were larger. Moreover, there is a large variation in the number of births over time, which can potentially be exploited in the IV regressions. The data in this time series is annual, while the observations in the sample are skill groups that consist of 10 subsequent age cohorts, and thus the question arises as to which measure predicts the number of workers of a skill group today most accurately. There are three options: 1) the total number of births; 2) the average number of births; and 3) the median number of births per skill group. As an example, take 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

[19] Naturally, the size of a birth cohort is not a perfect predictor for the labor supply today, because it does not take into account demographic factors such as emigration, deaths or early retirement. However, as long as the birth cohort size is *sufficiently correlated* with labor supply, it is suitable as an instrument.

Figure 2 – Number of Births per Year in Lithuania.

Note: Total number of people born per year in Lithuania. The data are not available for the time of the Second World War (1939-1945). *Source:* Statistics Lithuania.

between 1974 and 1984. The total number of births is the sum over all people born between 1974 and 1984, the average number of births is the average in this time span and the median number of births is the corresponding median. Taking the average, the sum or median of the number of births ensures sufficient variation in the calculated size of the birth cohort, given that the different time spans of the birth years of any two skill groups and the size of their birth cohort. As an example, consider workers with a work experience of 0-10 years in the HBS of 2002, whose birth years differ depending on their education. Workers with 0-10 years of work experience and a lower secondary education were born between 1976 and 1986, whereas those with a third-level degree were born five years earlier, between 1971 and 1981. Consequently, despite the same level of work experience, the cohort sizes of these two groups differ.

The choice of the instrument depends on its statistical power, i.e. the correlation of the instrument with the endogenous regressor. As it turns out in the first-stage regressions, the total number and average number of births are only weakly correlated with labor supply, and consequently cannot be used as instruments.[20] The F-Statistic of the median number of births is 16.085, which is a sufficiently high correlation of the instrument with the endogenous regressor.

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

The reason for the weak correlation of the first two instruments is their sensitivity to outliers in the number of births. As can be seen in Figure 2, the number of births was subject to high fluctuations and the sum and average are sensitive to large changes in the number of births. These jumps dilute the ability of the instruments to predict the labor supply of a whole *10-year* skill group. However, the median is not sensitive to such jumps, and hence it represents a better predictor for labor supply.

Table 3 – Regression results for σ_{EXP}

	Dependent variable: log real wage						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	OLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
	all	all	all	all	men only	21-64 yrs	21-55 years
log nr of workers	-0.114	-0.631***	-0.631***	-0.680**	-0.573**	-0.591***	-0.584***
	[0.072]	[0.173]	[0.177]	[0.293]	[0.241]	[0.130]	[0.123]
Obs	48	48	48	48	48	48	48
R^2	0.9742	0.9416	0.9416	0.9440	0.9317	0.9474	0.9541
Clustered SE	no	no	yes	no	no	no	no
Controls γ_{jt}	no	no	no	yes	no	no	no
First stage coefficient		-0.033	-0.033	-0.047	-0.0003	-0.036	-0.036
		[0.009]	[0.009]	[0.031]	[0.000]	[0.008]	[0.009]
F-Stat		16.1	8.0	3.2	5.5	20.8	16.8
σ_{EXP}	8.77	1.58	1.58	1.47	1.75	1.69	1.71

Note: The table shows the estimation results for the elasticity of substitution between workers of different experience groups, σ_{EXP} (Equation 5), which is computed as the negative inverse of the coefficients. Controls are as in Equation (5). Standard errors in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3 reports the estimation results for σ_{EXP}, with all regressions weighted with sampling weights. While I report the OLS results for comparison, as previously explained, they are not reliable owing to simultaneity bias. Column (2) displays the results of the 2SLS estimation, using birth cohort size as an instrument. The first stage coefficient is negative, indicating that older cohorts, who were larger in number than younger cohorts, are associated with fewer workers today. With an F-Statistic of 16, the instrument has sufficient power. The IV estimate is -0.63, which implies a σ_{EXP} of 1.58.

The econometric analysis may prompt a number of concerns. Firstly, skill groups may be serially correlated over time, which can be accounted for using clustering of the standard errors at the education-experience level. However, as there are only 12 clusters, the asymptotic properties of the clustered standard errors can be problematic (Angrist & Pischke, 2009). Column (3) reports clustered standard errors, highlighting that clustering increases the standard errors minimally, yet decreases the power of the instrument. Another problem is the small number of observations, as with 4 available survey rounds and 12 skill groups, the results are based on 48 observations. Nevertheless, note that the coefficients in Table 3 Columns 2) and 3) are precisely estimated, and the statistical significance is robust to the clustering of standard errors. The estimated parameter of 1.58 will enter the baseline simulations in the next section, but as I will show, the results hold qualitatively — they have the same sign yet the effects are smaller — if I use values from studies on other countries such as Germany and the UK.

The estimating equation (5) does not contain an interaction *time*experience*, which could bias the results if the relative productivity of an experience group changes over time. This could represent an issue if there is a positive selection of emigrants within an experience group; namely if workers with better unobservable characteristics leave, the remaining workers are on average less productive. As shown by column (4) in Table 3, the point estimate does not differ substantially from the baseline, although the instrument has less power due to the high degree of saturation.

Columns (5) to (7) report the results of further robustness checks. The regression in Column (5) is based on men only, and thus addresses a potential concern about different labor supply behavior between men and women. Furthermore, the data contains no information on work hours per week, and men are typically more likely to work full time than women. Columns (6) and (7) leave out the youngest and oldest age groups (18-20 years, and 56-64 years), which only leads to a small change in the estimates of σ_{EXP}.

Concerns might arise regarding the validity of the exclusion restriction in the estimation of σ_{EXP}, given the negative coefficient in the first stage stems from a combination of old workers having large birth cohorts and at the same time lower labor force participation than young workers. The Online Appendix A.4 presents estimates based on alternative instrumental variables — emigration from Lithuania, and emigration from Poland. For both instruments, the estimated elasticity of substitution falls in the same range as the estimates using birth cohort size as an instrument. Moreover, the baseline specification yields the same result as the reduced-form result in Elsner (2011). In sum, the IV estimates yield an elasticity between old and young workers in the range between 1.47 and 1.71. Despite the small number of observations, the coefficients can be estimated with reasonable precision, and the estimates are robust to different sample selections and instrumental variables.[21]

The estimates for σ_{EXP} in the baseline scenario are lower in magnitude than those found in previous studies using a similar model for the United States, the UK and Germany. For the US, the estimates range between 3.5 found by Borjas (2003) to 5 in Card & Lemieux (2001) to 7 in Ottaviano & Peri (2012). Meanwhile, Manacorda *et al.* (2011) estimate a yet higher elasticity of around 10 for the UK, whereas the estimates for Germany in D'Amuri *et al.* (2010) are lower with 3.1. The fact that the elasticities for Lithuania are lower than those listed above means that workers with different work experience are less substitutable in Lithuania than in Germany, the UK or the United States, with this smaller value being plausible for two reasons. First, the aforementioned studies estimate a long-run elasticity between skill groups, while I estimate a short-run elasticity. In the long run, workers of any age can adjust their skills to changes in the labor market, which is not possible in the short run. Consequently, any two skill groups are closer substitutes in the long run than in the short run.

A second reason lies in the history of the country. Given that Lithuania was part of the Soviet Union until 1990, older workers received their education and gathered their first work experience in a centrally-planned economy, whereas younger workers were educated and grew up in the environment of a market economy. Consequently, the skills of young workers should be immediately applicable to the labor market, whereas older workers may need some time for adjustment and re-training, which can lead to a low degree of substitutability between old and

[21] The Online Appendix A.4 also presents estimates for 5-year and 20-year experience groups.

young workers. A recent paper by Brunello *et al.* (2012) backs this explanation, showing that men who were educated under socialism in transition countries have lower returns to education than those who were educated under a free market economy.

The low degree of substitutability between old and young workers is also reflected in the occupational distribution, with a lower correlation in the occupational distribution between old and young workers in Lithuania ($\rho = 0.7$) than in Germany or the UK (in both $\rho = 0.95$). Accordingly, this means that old and young workers are more likely to work in the same occupations in the UK and Germany than in Lithuania.[22]

5.2 Estimation of σ_{ED}

As a next step, I estimate the elasticity of substitution between education groups, σ_{ED}. Because the model is based on a nested CES production function, and education groups are on a higher nest than experience groups, estimating this parameter requires a higher level of aggregation, resulting in a lower number of observations.

With an estimation based on only 12 observations, it will not be possible to provide a precise and credible estimate for σ_{ED}. While estimating σ_{ED}, or at least determining reasonable values for it, is not an end in itself, σ_{ED} will enter the simulations of the migration wave on real wages. Therefore, the importance of precise estimates depends on the importance of σ_{ED} for the wage changes: the larger the role of different education groups in the migration wave, the more important it is to obtain a precise estimate for σ_{ED}. As shown in the previous section, Table 2, the emigration rates are very similar across education groups, yet differ considerably across experience groups. Therefore, the parameter that matters most for the simulations is σ_{EXP}, while the value of σ_{ED} should not have a large influence on the simulated wage changes.

To find a sensible value for σ_{ED}, I propose two solutions. First, I use a very large ($\sigma_{ED} \to \infty$) and a very small value ($\sigma_{ED} = 1$) for the simulations, and demonstrate how the simulated wage

[22] These results are based on the European Labour Force Survey, including employees in 9 one-digit occupational categories (variable ISCO1D). The results are similar for other years.

changes differ accordingly. Second, to obtain some value for the baseline scenario, I estimate σ_{ED} based on the available data, with the estimation equation for this parameter derived in the same way as equation (5),

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

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

In theory, σ_{ED} can be identified from equation (7). However, owing to the small number of observations, it is not possible to identify σ_{ED} without imposing further restrictions. Otherwise, the model would be too saturated and the coefficient for $-1/\sigma_{ED}$ cannot be statistically distinguished from zero.

TABLE 4 – OLS RESULTS FOR σ_{ED}

Dependent variable: log real wage

	(1)	(2)	(3)	(4)
$\log \bar{L_{it}}$	-0.616***	-0.622***	-0.622***	-0.064
	[0.039]	[0.016]	[0.017]	[0.049]
Time trend	no	yes	no	no
Year dummies	no	no	yes	no
Educ-specific time trend	no	no	no	yes
Observations	12	12	12	12
Adj.R^2	0.9676	0.9935	0.9938	0.9999
σ_{ED}	1.62	1.61	1.68	15.625

Note: The table shows the estimation results for the elasticity of substitution between workers of different education groups, σ_{ED} (Equation 7), which is calculated as the negative inverse of the estimated coefficients. Robust standard errors in brackets. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table 4 shows the results of the OLS regressions. Surprisingly, the coefficients are highly

[23] The γ_{ij} are calculated from the coefficients of the δ_{ij} in equation (3) with $ij = 11$ as the base category, so that $\delta_{11} = 0$. Then, $\gamma_{ij} = \exp(\delta_{ij}) / \left(1 + \sum_i \sum_j \exp(\delta_{ij})\right)$.

significant in the first 3 specifications, and only when δ_{ij} is approximated by linear time trends is the model too saturated to produce a significant coefficient. Despite the caveats that apply to these estimates, σ_{ED} lies within the range found in other studies.Krusell *et al.* (2000), as well as Ciccone & Peri (2005) estimate a σ_{ED} of 1.5, Borjas (2003) 1.3 and Card & Lemieux (2001) 2.25.

6 Simulation of Wage Effects

6.1 Simulation Equation

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

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

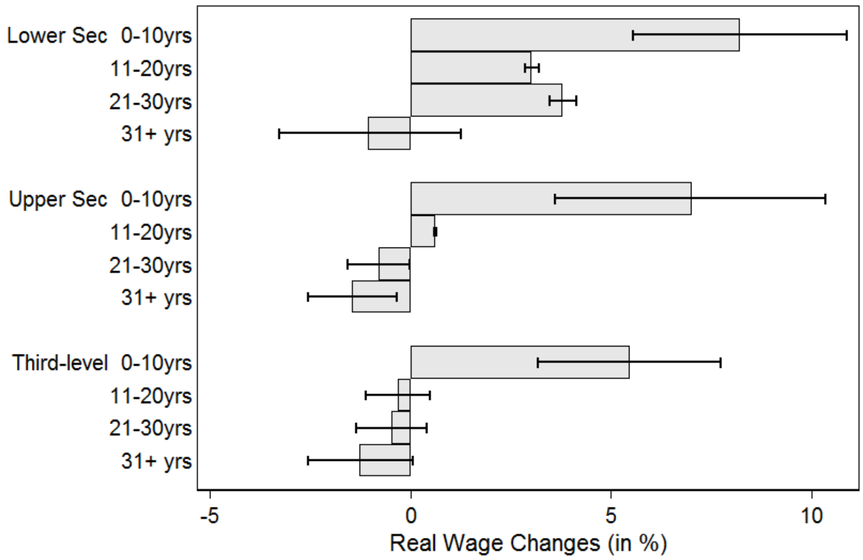

Figure 3 – The Impact of Emigration on Wages

Note: The figure displays the predicted wage changes, based on the simulation of the emigration wave after 2004 on the Lithuanian labor market. Parameters: $\alpha = 0.8$, $\sigma_{ED} = 1.68$. $\sigma_{EXP} = 1.58$. The thin lines denote 95%-confidence bands, which are calculated from Monte-Carlo simulations using the estimates for σ_{ED} and σ_{EXP}. Labels on the y-axis denote education and work experience.

6.2 Model Calibration and Simulation Results

Figure 3 displays the simulated wage changes for the baseline scenario. The 95% confidence bands have been calculated using Monte Carlo-simulations, in which the values for σ_{EXP} and σ_{ED} are drawn independently from a normal distribution with 10,000 replications, $\frac{1}{\sigma_{EXP}} \sim N(0.63, 0.173)$ and $\frac{1}{\sigma_{ED}} \sim N(0.62, 0.01)$.[25]

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[24] A_t, α, θ_{it} and γ_{ij} are held constant. Expressions L_t and L_{it} in equation (8) are labor aggregates and as such can be expressed in terms of L_{ijt}. 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. s_i and s_{ij} are calculated from the sampling weights in the HBS using the information on all men and women in the sample. The Δs measure the change in a variable from 2002 to 2006.

[25] In the Online Appendix A.5.2 Figure 7 I draw $\frac{1}{\sigma_{ED}}$ from a uniform distribution between zero and one, in order that $\sigma_{ED} \in [0, \infty]$. Despite the wider confidence bands, the wage increases for the youngest group are statistically significant).

A general pattern emerges, whereby emigration caused an increase in the wages of young workers, while the wages of old workers decreased. Young workers gained between 5.5% and 8.2% from emigration, whereas for workers with a work experience between 10 and 30 years, the model predicts wage changes close to zero, except for workers with a lower secondary education. Old workers with more than 30 years of work experience lost around 1% from emigration.

These results suggest that emigration had a significant impact on the wage distribution between old and young workers, with the youngest cohort becoming significantly smaller and this change in the composition of the workforce changing the wage structure. Despite most of the predicted wage changes being statistically significant, only the wage changes for young workers are of economic significance. This can be seen when comparing the simulated wage changes caused by migration with the total wages changes for Lithuanian workers between 2002 and 2006 in Figure 1. 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; however, the wage changes of workers with a work experience higher than 10 years are solely driven by other factors, such as domestic and foreign investment or productivity growth.

Having noted that the predicted wage changes differ considerably between young and old workers, the question arises as to which factors drive these results within the model. Due to the nested structure of the production function, there is a variety of channels through which a labor supply shock can affect wages, and the Online Appendix A.6 presents a decomposition of the wage changes into an own-wage effect and higher-order effects. Section A.7 in the online appendix compares the predicted wage changes from the structural model with wage changes predicted by a simple reduced-form analysis, clearly showing the importance of higher-order effects for the overall effect of emigration on wages. The large effects predicted by the own-wage elasticity are dampened by changes in the composition of the workforce, and a general decrease in labor demand due to a smaller consumer base. For skill groups with a predicted wage change equal or close to zero, the positive own-wage effect and negative higher-order effects balance each other out.

The wage effects found in this section are consistent with a story of an increase in bargaining power. Emigration of similar workers renders stayers a more scarce resource, thus resulting in higher wages. Another explanation could lie in the difference in the occupational distribution of old and young workers. Accordingly, if young workers tend to work in sectors with a high flexibility of work contracts and a high fluctuation of employees, they are more likely to switch to a better-paid job once emigration leads to labor shortages in the sector. This possibility should be more likely in the service sector, which only evolved in Lithuania in the last 15-20 years, and less likely in the manufacturing sector or agriculture. I elaborate on this further in Online Appendix A.8, showing that young workers were indeed over-represented in occupations that are generally associated with greater flexibility.

To show the sensitivity of the results to changes in key parameters, I conduct a series of robustness checks that are presented in the online appendix. For the calculation of emigrants per skill group, I assumed the skill distribution of emigrants going to Ireland to be the same as that of emigrants going to the UK. Section A.5.1 shows the simulations based on Irish data only, while Section A.5.2 re-calibrates the model using different elasticities of substitution. The first exercise produces standard errors for $sigma_{ED}$ being uniformly distributed on the interval $[0, \infty]$, whereas the second exercise uses parameter value from studies on other countries (US, UK, Germany) that use a similar empirical strategy, showing how the choice of parameters changes the predicted wage changes.

7 Conclusion

This paper exploits the large and sudden emigration wave from Eastern Europe after EU enlargement in 2004 to study how emigration affects the wages of non-migrants. Using Lithuanian microdata, I find that emigration significantly changed the wage distribution, causing an increase in wages on average; however, the wage effect was concentrated among young workers, whose wages increased by around 6% over the period of 5 years, while the wages of older workers were not affected. Contrary to previous literature (Borjas, 2003; Aydemir & Borjas, 2007; Docquier *et al.*, 2011), I find no significant effect of emigration on the wage distribution between high- and low-skilled workers. The difference in the wage effects of different experience groups can be explained by the demographics of the emigration wave, which mostly consisted of young workers from all education groups.

The quasi-experimental character of EU enlargement allows me to study an important issue of immigration policy. Most high-income countries have strict immigration laws in place, thus restricting migration from low- and middle-income countries. Given the large wage differentials between high-income countries and the rest, lifting these barriers to migration results in substantial migration flows, which have welfare impacts on both the sending and receiving countries. The "EU enlargement experiment" represents a rare example of the lifting of migration restrictions, and shows that workers in middle-income countries respond to the opening of labor markets in high-income countries, with between 6 and 9% of the workforce of Latvia, Lithuania, Poland and Slovakia having emigrated to the UK and Ireland. Moreover, the most mobile workers have higher emigration rates. For instance, young workers are typically more mobile and have lower moving costs than old workers. In this light, it is unsurprising that emigrants were on average 13 years younger than non-migrant workers in Eastern Europe.

The results of this paper inform policymakers in middle-income countries about the labor market impacts of the liberalization of migration. Many middle-income countries are in the same situation as the Eastern European countries in 2004, facing a large wage differential and have a well-educated and highly mobile workforce. Other examples are EU candidates such as Croatia, Serbia, or Turkey, which might see a similar outflow of workers as those countries that joined the EU in 2004.

This paper should also encourage further research on the absorption of labor supply shocks in countries of origin. A growing body of literature shows how receiving countries absorb labor supply shocks (Hanson & Slaughter (2002), Gandal *et al.* (2004), among others), finding that changes in labor supply caused by immigration are not absorbed through changes in wages, but rather through shifts in production technologies within industries. While this paper has shown that wage responses can be an important absorption channel in countries of origin, further research is needed to determine which other channels are important in countries of origin, and especially in low- and middle-income countries.

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