Essays on the Causes and Consequences of International Migration

Benjamin Elsner

Department of Economics
Trinity College
University of Dublin

Thesis submitted to Trinity College, University of Dublin in fulfilment of the requirements for the degree of Doctor of Philosophy (Ph.D.)

2012

Declaration

I declare that this thesis has not been submitted as an exercise for a degree at this or any other university and is entirely my own work. All research contained herein that is not entirely my own but is based on research that has been carried out jointly with others is duly acknowledged in the text wherever included.

I agree to deposit this thesis in the University's open access institutional repository or allow the library to do so on my behalf, subject to Irish Copyright Legislation and Trinity College Library conditions of use and acknowledgement.

Benjamin Elsner

19/12/2012

Date

Summary

This thesis is a collection of three essays on the economic consequences of international migration.

The first chapter studies the impact of emigration on wages in the sending countries. It exploits a change in the migration laws in Europe following EU enlargement in 2004 which triggered an emigration wave of 1.2 million workers within 3 years. Using data from Lithuania, the UK and Ireland, I find that emigration led to an increase in the wages of stayers. For a 10 percentage-point increase in the emigration rate, wages increased on average by 6.6%. This effect is statistically significant for men, but not for women.

Chapter 2 is closely related to the first chapter, but extends the analysis along two important dimensions. First, it looks at the distributional impacts between different education and experience levels, and second, it incorporates general equilibrium effects that may become important when a significant share of the workforce emigrates. Using the same data as in chapter 1, I estimate the parameters of a structural model of labor demand, and simulate the post-enlargement migration wave as a labor supply shock. The model shows that emigration had a significant effect on the wage distribution in the sending countries. Moreover, general equilibrium effects dampen the large wage response found in chapter 1. As a result, emigration only increased the wages of young workers, while it had no significant effect on older workers.

The third chapter analyzes the impact of migrant networks on the migration decisions of future migrants. Many workers in developing countries use existing diaspora networks to obtain information about their job prospects abroad. However, not all networks have the same knowledge about the labor market. We first argue that networks that are well-integrated in the host society have a better knowledge about the labor market than less integrated networks such as ethnic enclaves, and are able to provide more accurate information. From a theoretical model we derive two hypotheses. First, migrants with access to a well-connected network make fewer mistakes in their decisions; they are more likely to migrate if they are better off abroad, and are more likely to stay if they would be worse off. Second, migrants with access to a well-integrated network emigrate earlier. Because they receive better information, they require fewer positive signals to be convinced that migration is beneficial. We test these hypotheses using data on recent Mexican immigrants in the US. We find robust support for the first hypothesis, but not for the second.

Acknowledgements

First and foremost, I would like to thank my advisor Gaia Narciso for all her support and guidance she offered me in the last 4 years. She constantly encouraged me to keep an eye out for relevant questions and to go down the extra mile in order to turn them into fruitful research ventures, which is a skill that should greatly benefit me in my research career.

I am also very grateful to many people who gave me valuable feedback on my ongoing work and acted as mentors, in particular Catia Batista, Carol Newman, Giovanni Peri, Jacco Thijssen, Pedro Vicente, and Michael Wycherley. My work greatly benefitted from many discussions over a coffee or lunch with Karol Borowiecki, Christian Danne, Emma Howard, Julia Anna Matz, Corina Miller, Tara McIndoe-Calder, Theodore Talbot, Conor O'Toole, and Janis Umblijs, and their competent and honest feedback.

I am confident to say that I had the best PhD colleagues I could imagine. With many of them I became friends for life, and I will greatly miss our lively discussions, coffee breaks and the occasional drinks in the Duke and elsewhere.

The Department of Economics in TCD and the Institute for International Integration Studies provided an inspiring research environment. Doors were always open for PhD students and the feedback and mentoring from the faculty ensured that I was able to get through the PhD without excessive frustration. I am also very grateful to the members of the Development/Micro Working Group for their honest feedback, which brought my research projects on the right track at an early stage. Special thanks also go to the secretaries Colette Ding, Patricia Hughes, and Colette Keleher, the PhD coordinators Patrick Honohan, Pedro Vicente, and Michael Wycherley, without whom the PhD would have been much more complicated.

Going through 4 years of PhD work would not have been possible without funding from the Strategic Innovation Funds (SIF) and the Irish Research Council for the Humanities and Social Sciences (IRCHSS). The TCD Student Travel Funds and the Department of Economics generously supported my conference travels.

During the spring term in 2011 I was fortunate enough to spend three very productive months at Bocconi University in Milan. I am thankful to Gaia Narciso and Gianmarco Ottaviano for arranging this research visit.

Above all, I would like to thank my parents, Christine and Josef, for all the love, warmth and support they gave me over the years. Every bit of stress and

frustration was gone every time I took a break and recharged my batteries in Bavaria. I am also very happy to be moving closer to them, so that we should be able to spend more time with each other.

For the moment I am leaving Dublin, but I will always be more than happy to return and enjoy everything this wonderful city has to offer. I got to know many amazing people here; above all, I have had the luck to meet Suzanne here, and I'm inifinitely grateful for every moment I can share with her. Suzanne, thanks for showing me that there is so much more to life than my work, and I'm looking forward to future chapters in our life.

To my parents, Christine and Josef,
For everything

Contents

List of Tables

List of Figures

Part I

Introduction

This thesis contains three chapters on the economic causes and consequences of international migration.

The first two chapters analyze the impact of emigration on the wage structure in the migrant sending countries. While most of the literature on the wage effects of migration has focused on the receiving countries, we know very little on the effect of migration in the sending countries. In both chapters I exploit the enlargement of the European Union in 2004, which triggered a large migration wave from Eastern Europe to the UK and Ireland.

The first chapter asks whether this emigration wave had a positive effect on wages in the sending country. A simple supply-and-demand framework would predict that emigration makes the remaining workers a more scarce resource and leads to an increase in wages. The size of the wage increase depends on the demand elasticity — the reaction of labor demand to a change in wages. Most studies on the receiving countries found the demand elasticity to be very small, and thereby migration to have little effect on wages (Friedberg & Hunt, 1995; Kerr & Kerr, 2011). If labor markets in the sending countries are different, the wage effects of migration may be more or less pronounced than in the receiving countries. For the estimation I use a skill group approach as in Borjas (2003), which clusters the workforce into several skill groups defined by education and work experience. In a reduced-form regression this approach relates real wages to the share of emigrants per skill group and exploits the variation in wages and emigration rates within skill groups over time. Identification is based on an exogenous change in the migration laws following EU enlargement. Workers were only allowed to move to the old member states of the EU after the enlargement in 2004, even though the incentives to migrate had existed long before 2004. Using data from Lithuania and the two main receiving countries, Ireland and the UK, I find that emigration had, on average, a positive effect on the workers that stay behind. Yet the effect is only statistically significant for men, not for women.

While the first chapter provides robust evidence for an average wage effect, it has two important limitations. First, the reduced-form approach does not allow for an analysis of the distributional effects of emigration. In Eastern Europe, distributional effects are potentially large, as the emigration wave after EU enlargement led to an exodus of young workers, while old workers stayed behind. Second, it does not account for aggregate demand effects. If a share of the workforce leaves the country, this can dampen aggregate demand, which in turn decreases wages.

In the second chapter I overcome these limitations by using a structural model to estimate the effect of the post-EU-enlargement emigration wave on the wage structure in the sending countries. Following Card & Lemieux (2001), Borjas (2003), and Ottaviano & Peri (2011), I use a nested CES labor demand framework that allows for different degrees of substitutability between workers with different education and experience and that incorporates aggregate demand effects. I first estimate the structural parameters of the model, which I use to calibrate the model on the Lithuanian labor market. Based on stock and flow data from the UK and Ireland I simulate the post-enlargement emigration wave and calculate the effect of emigration on the wages of different groups of workers. The results show that only the youngest cohort gained from emigration. There are two channels that lead to this result. First, most of the emigrants were young, so that the own-wage effect is higher for young workers. Second, the emigration wave dampened aggregate labor demand, which decreased the wages for all workers. For young workers the difference of both effects is positive, while for older workers the two effects cancel each other out.

The third chapter, co-authored with Gaia Narciso and Jacco Thijssen, studies the impact of diaspora networks on migration decisions. These networks play an important role in passing on information about job prospects to future migrants, but not all networks have the same knowledge about the labor market in the receiving country. We argue that networks that are more integrated in the society of the receiving country have a better knowledge of the labor market than ethnic enclaves. Members of an enclave mostly have connections with other members and receive little information from the world outside the enclave. Therefore, misinformation about job prospects is more persistent in ethnic enclaves.

In a theoretical decision model we show that migrants who receive information from an enclave are more likely to make an error in their migration decisions — they migrate although they would be better off staying and they stay although they would be better off emigrating. In addition, we show that the quality of information affects the timing of the migration decision. Migrants with access to a less-integrated network need more information about their job prospects and, hence, migrate later. We test these theoretical predictions empirically using data on Mexican migrants in the US. Our results are consistent with the first hypothesis; migrants who were connected to more integrated networks were more successful and made less mistakes in their decision. Our second hypothesis, however, is not confirmed by the data. The quality of the network seemingly has no impact on the timing of migration decisions.

Part II

Emigration and its Impact on Wages

Chapter 1

Does Emigration Benefit the Stayers? Evidence from EU Enlargement

I have presented this work at the Annual Meeting of the EEA (Glasgow 2010), the Annual Conference of the Irish Economic Association (Belfast 2010), the 3rd RGS Doctoral Conference (Bochum 2010), the 6th meeting of the Irish Society of New Economists (Limerick 2009), and in internal seminars at Trinity College Dublin. Throughout this project I received valuable suggestions from my thesis advisor, Prof. Gaia Narciso. I am also grateful to the Irish and Lithuanian statistics offices for their help with the data. The European Economic Association selected this paper for the FEEM award, given to the three best papers by an economist under the age of 30 at the annual conference in Glasgow 2010. This article has been conditionally accepted for publication at the Journal of Population Economics.

1.1 Introduction

Migration affects both sending and receiving countries. While a vast literature documents the impact of migration on wages and employment in the receiving countries, there is only sparse evidence on its impact on the sending countries.[1]

In this paper I exploit the emigration wave from Lithuania after the enlargement of the European Union to study the effect of emigration on wages in the sending countries. With EU enlargement in 2004, Lithuanian workers were allowed to migrate without restrictions to the United Kingdom (UK), Ireland and Sweden. Between 2004 and 2007, around 9% of the workforce took this opportunity and emigrated to the UK and Ireland. The large emigration wave – caused by a change in the institutional framework – makes Lithuania an ideal case study of a sending country.

To identify the effect of emigration on wages, I use the skill-group approach proposed by Borjas (2003). This approach clusters the workforce in a number of skill groups – defined by gender, education, and work experience – and compares emigration rates and real wages within each skill group before and after EU enlargement.

Using microdata from Lithuania, and work permit and census data from the UK and Ireland, I show that emigration has a significant positive effect on the wages of stayers. Groups with larger emigration rates had higher wage increases. A 10% increase in the emigration rate predicts an average increase in real wages of 6.6%. This positive effect, however, is only statistically significant for men, but not for women. Given that emigration was triggered by an exogenous change in migration laws, the results can be interpreted as causal.

The positive effect of migration on wages is consistent with a simple supply-and-demand framework. Migration decreases labor supply, which - given a downward-sloping labor demand curve - leads to an increase in wages. The absence of a statistically significant effect for women is surprising, given that women accounted for 40% of all emigrants. Potential explanations are a positive self-selection of female emigrants, or endogenous responses in labor supply, i.e. women who had not been working previously filled the job of women who emigrated.

The institutional arrangements in the European Union allow me to overcome data constraints that are inherent in the study of sending countries. Sending countries typically do not keep records of emigrants, which makes it difficult to quantify the number of emigrants. With EU enlargement, workers from the new member states were only allowed to migrate to the UK, Ireland, and Sweden. Therefore, it is possible to calculate the number of Lithuanian emigrants from the census and work permit data of

[1]See Kerr & Kerr (2011) and Clemens (2011) for reviews of the literature on the economic effects of migration on receiving and sending countries.

these countries.

To be certain, identification faces several challenges. One challenge is omitted variable bias. Wages are determined by numerous factors other than migration, for example FDI inflows, trade, or unemployment. If these factors are omitted from the model, the results may be biased. To tackle this problem, I add a rich set of dummy variables and interaction terms to the regression, which account for changes in the returns to education and experience, and differences in the age-earnings-profile across education groups. In addition, I control for FDI, exports, and unemployment at the regional level. The results are not sensitive to the inclusion of these variables, however.

An additional challenge is self-selection. Average wages may increase, simply because workers from the lower end of the wage distribution have left the country. Given the data on emigrants from the UK and Ireland, it is not possible to assess directly whether emigrants within a skill group were negatively selected. An inspection of the wage distribution in Lithuania before and after EU enlargement, however, does not indicate a negative selection. Moreover, as the receiving countries have on average higher skill requirements, selection should be positive, and the results would be downward-biased.

This paper adds to the literature on the wage effect of emigration, as it shows that emigration increases wages in the short run. Previous literature has looked at long-standing migration movements. Using the same approach as this study, Mishra (2007) and Aydemir & Borjas (2007) show that emigration from Mexico to the US has led to a long-run increase in wages in Mexico. Bouton *et al.* (2011) find similar results for Moldova. This paper, by contrast, exploits a sudden emigration shock to show that emigration increases wages even in the short run.[2]

The EU enlargement was one of the rare occasions in which high-income countries opened their borders for workers in middle-income countries. The results of this study are therefore of interest for middle-income countries that may face a similar situation in the future. If the US, for example, opened its borders for workers from South America, it would be helpful for policymakers in the sending countries to know what fraction of the population they can expect to emigrate, and what consequences this emigration wave has on the labor market.

1.2 EU Enlargement and Migration

The EU enlargement in May 2004 was a milestone in the process of European integration. 15 years after the fall of the Iron Curtain, 8 former socialist countries from

[2]In a recent paper, Gagnon (2011) uses the emigration wave from Honduras after Hurricane Mitch, and finds wage effects that are similar to those in this paper.

Central and Eastern Europe became members of the European Union. At the time of EU enlargement, the new member states were still in the process of economic transition. Compared to Western Europe, economic output in the new member states was considerably lower, which also translated into substantial wage differentials. In 2004, wage differentials were highest in Latvia and Lithuania, where workers earned on average 30% of the PPP-adjusted wage in the UK.[3]

As wage differentials are a major driving force of international migration, the migration potential in the new member states before EU enlargement was substantial. Studies that estimated the migration potential from the new member states before the enlargement predicted that between 3% (Bauer & Zimmermann, 1999; Boeri & Brücker, 2001) and 5% (Sinn, 2004) of the population of the new member states would migrate within 15 years.

With freedom of movement being a core principle of the European Union, the enlargement would have allowed workers from the new member states to work in any other EU country. Policymakers in the old member states, however, feared that a large immigration wave from Eastern Europe could depress wages, increase unemployment (Zaiceva & Zimmermann, 2008), and impose a burden on the welfare state, and decided to give the old member states the option to restrict access to their labor markets until 2011. Only the UK, Ireland, and Sweden opened their labor markets in 2004.

Given the restrictions in other potential destination countries — above all Germany and France — and the good economic conditions in the UK and Ireland, it was no surprise that these two countries were the destination for the majority of workers from Eastern Europe. Between 2004 and 2007 the UK issued around 770,000 and Ireland around 400,000 work permits to workers from the new member states, while only 19,000 workers went to Sweden (Wadensjö, 2007). Elsner (2011) shows that the magnitude of the emigration wave was particularly large in Lithuania. 9% of all Lithuanian workers received a work permit in the UK and Ireland — in Latvia and Slovakia the share was 6%, in Poland 5%.[4] Most of the emigrants were young, and had a medium to high education level (Zaiceva & Zimmermann, 2008).

A number of studies have evaluated the economic consequences of this migration wave.[5] Most studies on the receiving countries did not find the effects of the immigration wave on wages and employment to be large (Barrett, 2009; Blanchflower & Shadforth, 2009). On the side of the sending countries, the evidence is purely descriptive. Kaczmarczyk *et al.* (2009) and Hazans & Philips (2009) illustrate that wages in Poland

[3]Own calculations from Eurostat.

[4]Hungary and the Czech Republic, on the contrary, had outflows of less than 1%.

[5]See Constant (2011) for a review of the most recent literature and Kahanec & Zimmermann (2009) for a collection of country studies on EU enlargement. Barrell *et al.* (2010) illustrate the macroeconomic consequences of migration on the sending and receiving countries.

and the Baltic States increased while unemployment decreased after EU enlargement. This paper extends the existing literature, as it presents a first econometric evaluation of the effect of the post-enlargement migration wave on the source countries.

1.3 Data and Descriptive Statistics

To analyze the effect of emigration on wages, one would ideally like to use a micro-dataset that contains information on both emigrants and stayers. Such a dataset, however, is usually not available for the sending countries. In most countries, emigrants are not obliged to de-register, which makes it difficult for the sending countries to keep reliable records on their emigrants. Following Mishra (2007), I use data from the two main destination countries — Ireland and the UK — to calculate the number of Lithuanian emigrants for different groups of workers and match them with stayers from the same groups. The remainder of this section describes the datasets used in this study and explains the calculation of the number of emigrants.[6]

1.3.1 Lithuanian Household Budget Survey

The core dataset of this study is the Lithuanian Household Budget Survey (HBS), which is available for the years 2002, 2003, 2005 and 2006. The HBS is an annual survey of 7,000-8,000 households; it is representative at the individual level and contains information on income and expenditure, as well as individual characteristics such as sex, age, education and place of residence. The HBS does not contain information on occupations, industries, or sectors.

The sample contains employees aged 18-64 working in the private sector. I exclude public sector workers because wages in the public sector are typically determined by seniority pay and not by supply and demand. In addition, I drop workers with zero or negative disposable income, pensioners, self-employed workers and workers whose main income comes from their own farm.

The variable *income from employment*, deflated by the HCPI, gives information on real monthly gross wages. As we can see in Table 1.1a), real wages increased by around 40% between 2002 to 2006. Along with the wage level, the standard deviation of wages increased.

A potential concern with household budget surveys is over- or under-reporting of income, which can bias the results. To assess the degree of misreporting bias, I compare the self-reported real wages from the HBS in Table 1.1a) with the wages from the live register from the Lithuanian Statistical Office in Table 1.1b). It is reassuring that both

[6]The entire section on data is similar to Elsner (2011), which uses the same data sources.

sources report similar average real wages, so that misreporting should not bias the results.

1.3.2 Irish Census

To obtain the stocks of Lithuanian migrants in Ireland and to determine the migrants' skill distribution I use data from the Irish census in 2002 and 2006.

The Irish census is carried out every 4-5 years and covers the entire population that is present in Ireland in the census night. For the 2002 and 2006 censuses, the Central Statistics Office (CSO) of Ireland provided a tabulation of the number of Lithuanians by their educational attainment, gender and age.

Table 1.2 reports the characteristics of Lithuanian migrants in Ireland in 2002 and 2006. Most migrants had an upper secondary education and were in their 20s. The number of men in 2006 was 30% higher than the number of women. The difference in the number of Lithuanians in Ireland between 2002 and 2006 shows that the majority must have migrated to Ireland around or after the time of EU enlargement. Notably, the education distribution did not change significantly over time, even though the stock of migrants in 2006 was 10 times higher than in 2002.

Comparing the migrants in Table 1.2b) to the stayers in Table 3.3a), we can see that the migrants were on average younger and less educated than stayers. The share of workers with a lower secondary education is larger among migrants, while there are relatively less migrants with an upper secondary or a third-level education. Migrants were on average 12 years younger than stayers.

1.3.3 Irish and UK Work Permit Data

To obtain the total number of Lithuanian emigrants, I use work permit data from the UK and Ireland. While the census data reflects a lower bound to the number of migrants, the work permit data is an upper bound of the migration flows from Lithuania to the UK and Ireland. Work permit data captures every person who comes to the UK and Ireland and wants to take up employment, be it for a permanent position or for a temporary job. The number of workers who left the Lithuanian workforce permanently should therefore be lower than the number of work permits.

Figure 1.1 shows the number of work permits granted to Lithuanians between 2002 and 2007. In total, the number of Lithuanian migrants to the UK and Ireland amounted to 150,000. As we can see, the migration wave set in with EU enlargement in 2004 and reached its peak in 2005.

As a measure of the number of work permits I use national insurance numbers

Table 1.1: Summary statistics Lithuania

	2002	2003	2005	2006
a) Lithuanian HBS				
Observations				
men	2,322	2,411	2,426	2,314
women	1,628	1,725	1,616	1,560
Education				
lower secondary	8.81%	10.42%	10.76%	9.91%
upper secondary	69.01%	69.17%	67.62%	67.48%
third-level	22.18%	20.41%	21.62%	22.61%
Monthly Earnings (LTL)				
men	1,185	1,252	1,440	1,688
	(856)	(913)	(981)	(1,134)
women	940	988	1,189	1,303
	(684)	(686)	(890)	(985)
b) Lithuanian Statistical Office				
Monthly Earnings (LTL)				
men	1,173	1,227	1,420	1,676
women	998	1,029	1,167	1,356

Note: a): Summary statistics for all employees between 18 and 64 years. Education groups: lower secondary education (10 years or less of schooling), upper secondary education (more than 10 years of schooling, but no finished third-level education), third-level degree (at least 15 years of schooling and B.Sc equivalent). Percentages of educational distribution relative to all men and women in a given year. Monthly earnings are deflated by the HCPI. Standard errors of monthly earnings in parentheses.

b) monthly earnings are average gross monthly real earnings in LTL.

Table 1.2: Summary statistics Irish census

	2002	2006
Observations		
men	978	12,085
women	904	9,293
Education		
lower secondary	16.6%	20.1%
upper secondary	63.4%	62.3%
third-level	20.0%	17.56%
Age		
<20	3.5%	2.8%
20-29	53.3%	60.7%
30-39	26.0%	24.6%
40-49	23.3%	9.4%
50+	3.9%	2.5%

Note: This table displays the summary statistics of the Irish census. Education groups: lower secondary education (10 years or less of schooling), upper secondary education (more than 10 years of schooling, but no finished third-level education), third-level degree (at least 15 years of schooling and B.Sc equivalent). Percentages of education and age distribution relative to all men and women in a given year.

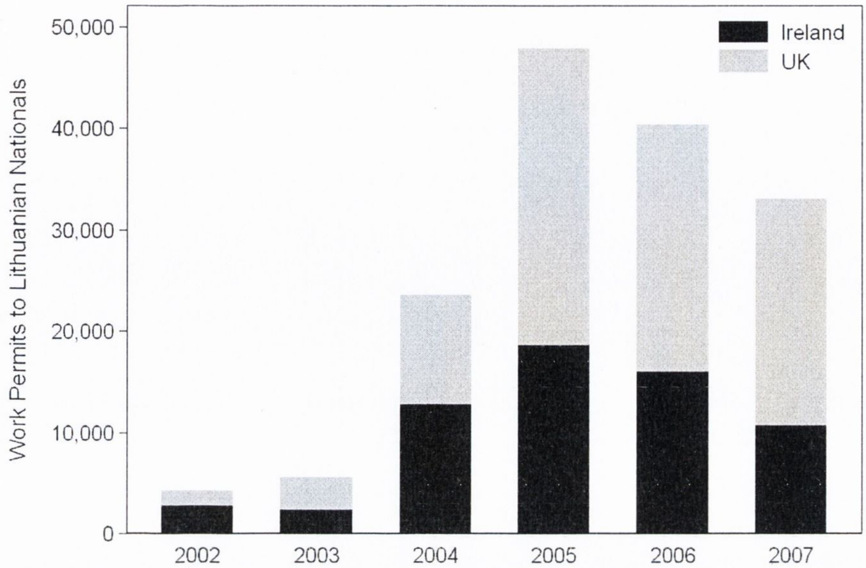

Figure 1.1: Lithuanian immigrants to the UK and Ireland, 2002-2007

Notes: Number of Lithuanian immigrants to the UK and Ireland between 2002 and 2007, as measured by the number of work permits (PPS Number in Ireland, National Insurance Numbers in the UK).
Sources: Irish Department of Social and Family Affairs, UK Department for Work and Pensions.

(NINo) for the UK and personal public service numbers (PPS) for Ireland.[7] The work permit statistics reflect actual migration, because workers only receive a work permit if they are physically present in the destination country. To obtain a work permit, a worker has to report in person to the Social Welfare Office in Ireland or the Department for Work and Pensions in the UK and produce a proof of address. If a worker moves back-and-forth between Lithuania and either the UK or Ireland, she keeps her work permit, so that repeated migration does not cause double counts.[8]

1.3.4 Calculation of Emigrant Numbers

From the census and work permit data I now construct measures for the number of emigrants by gender, education, experience, and year. For the baseline specification I use a combination of all data sources, as the census is likely to under-estimate, and the work permit data is likely to over-estimate the number of emigrants. Moreover,

[7]For further information about PPS and NINO numbers, see http://www.welfare.ie and http://www.direct.gov.uk. In 2004 the UK introduced a Worker Registration Scheme (WRS) for workers from the new member states. Compared to the data from the WRS, NINo offers the advantage that it provides information on immigration before 2004. The WRS and NINo numbers after 2004 are similar.

[8]Double counts are only possible if workers received a work permit in both destination countries. Although there does not seem to be any evidence of large numbers of workers registering in both countries, I am aware that double counting could downward-bias the estimates.

only the Irish census contains information on the skill distribution of migrants, while the UK and Irish work permit data only contains information on the inflows per year. Census data from the UK is not available for the time around EU enlargement, as the census was carried out in 2001 and 2011.[9]

To construct measures for the number of emigrants, I take the skill distribution of Lithuanian migrants from the Irish census and multiply it with a weighting factor which accounts for migrants to the UK. The calculation of the share of emigrants is based on the assumption that the skill distribution of Lithuanian immigrants in Ireland is the same as the skill distribution of Lithuanians in the UK. As shown by Elsner (2011), this assumption is justified, as the education and age distribution of migrants from the 8 New Member States in Ireland and in the UK is almost identical. In addition, Hazans & Philips (2009) show that even though migrants from Latvia, Lithuania and Estonia work in different sectors in Ireland and the UK — in Ireland more in construction and trade, in the UK more in agriculture and services — their education and age profile is the same in both countries.

To make use of all available rounds of the HBS I construct measures for the emigration rates in 2003 and 2005 from the censuses in 2002 and 2006, assuming that the skill distribution of migrants arriving in 2003 is the same as in 2002, and likewise that the skill distribution of migrants in 2005 is the same as in 2006. Table 1.2 suggests that the education distribution has been constant between 2002 and 2006, which implies that the education distribution has neither changed between 2002 and 2003, nor between 2005 and 2006. The age distribution, on the other hand, has changed between 2002 and 2006; the cohorts arriving after 2002 have been on average younger than the cohorts before 2002. Nevertheless, given that 2002 and 2003 are both before and that 2005 and 2006 are both after EU enlargement, it is plausible to assume that workers coming in 2003 had roughly the same age distribution as those coming in 2002, and workers arriving in 2005 had the same age distribution as those arriving in 2006.

For $t = (2002, 2006)$, the number of emigrants M^t_{ghj} is

$$M^t_{ghj} = IE^t_{ghj}\left(1 + \frac{NINO_t}{PPS_t}\right). \tag{1.1}$$

IE^t_{ghj} is the number of Lithuanians in Ireland in a gender(g)-education(h)-experience(j) cell at time t. $NINO_t$ and PPS_t are the numbers of British and Irish work permits issued to Lithuanians in year t. The first term in parentheses (1 in this case), accounts for the number of migrants in the Irish census. The second term, $\frac{NINO_t}{PPS_t}$, accounts for

[9] Other UK datasets, the Labour Force Survey and the European Community Household Panel have few observations on immigrants in each round, and they group immigrants from Eastern Europe by region, not by country.

migrants to the UK. If, for example, in 2006 the number of work permits in the UK was 50% higher than the number of work permits in Ireland, this factor is 1.5.

For the year 2003 I take the skill distribution from 2002 and weight it with the inflows of 2003. Analogously, for the year 2005 I use the skill distribution from 2006. The number of emigrants for 2003 and 2005 are

$$M_{ghj}^{2003} = IE_{ghj}^{2002}\left(\frac{PPS_{2003}}{PPS_{2002}} + \frac{NINO_{2003}}{PPS_{2002}}\right) \quad (1.2)$$

$$M_{ghj}^{2005} = IE_{ghj}^{2006}\left(\frac{PPS_{2005}}{PPS_{2006}} + \frac{NINO_{2005}}{PPS_{2006}}\right). \quad (1.3)$$

The first term in parentheses, $\frac{PPS_{2003}}{PPS_{2002}}$ and $\frac{PPS_{2005}}{PPS_{2006}}$ accounts for the changes in inflows between 2002 and 2003, and between 2005 and 2006.[10] As in Equation (1.1), the second term in parentheses represents the number of migrants to the UK.

To calculate the emigration rate m per skill group and year I divide the number of emigrants from Equations (1.1) to (1.3) by the population in Lithuania of the same group,

$$m_{ghjt} = \frac{M_{ghj}^{t}}{\sum_i p_{ghjt}^{i}}. \quad (1.4)$$

The population of skill group ghj in year t is the sum of the sampling weights p_{ghjt}^{i} of all workers i in the Lithuanian HBS that belong to this group.[11]

One might be concerned that the calculated emigration rate may over-estimate the actual change in labor supply, in case migrants from other countries had come to Lithuania and taken up the jobs of the workers who left. In fact, the Lithuanian immigration statistics show an increase in the number of immigrants between 2002 and 2006. A closer look, however, indicates that this increase was in large parts driven by return migrants from the UK.[12]

The share of emigrants could also be under-estimated, if workers moved to other countries besides the UK and Ireland. A particular concern may be emigration to Russia. Russia is potentially an important destination, as most Lithuanians speak Russian as a second language and both countries have strong economic ties. The Russian immigration statistics, however, do not give any evidence for mass immigration from

[10] $\frac{NINO_{2003}}{PPS_{2002}}$ actually consists of two factors: $\frac{NINO_{2003}}{PPS_{2003}}$, which accounts for the size of migrant flows to the UK relative to Ireland and $\frac{PPS_{2003}}{PPS_{2002}}$, accounting for the change in migration flows to Ireland from 2002 to 2003. By multiplication of those two terms, PPS_{2003} cancels out.

[11] The sampling weight p_{ghijt} is the inverse probability that observation i is included in the sample.

[12] Source: Statistics Lithuania.

Lithuania; immigration in the 2000s amounted to 200-300 Lithuanians per year.[13]

1.4 Empirical Framework

The theoretical underpinnings for the empirical strategy are derived from a simple supply-and-demand model of a labor market. Emigration decreases the labor supply, which shifts the labor supply curve inwards. Given a constant, downward-sloping labor demand curve, emigration makes the remaining workers a more scarce resource, and leads to an increase in wages.

1.4.1 The Skill Group Approach

To identify the average effect of emigration on wages, I use the skill-group approach proposed by Borjas (2003), which considers emigration rates and wages at the national level and exploits the variation in both variables within skill groups over time. If emigration indeed increased wages, we should observe higher wage increases in groups with a higher share of emigrants.

A skill group is defined by the observable characteristics *education* and *work experience*. The workforce consists of 27 skill groups – 3 education and 9 experience groups. The 3 education groups are lower secondary education (at most 10 years of schooling), upper secondary education (11-14 years of schooling), and third-level education (at least 15 years of schooling).[14]

A higher number of education groups would be desirable, as it would allow for more variation in emigration and wages across education groups. The available data, however, imposes a constraint on the number of education groups. The datasets from the sending and receiving countries differ in their classification of education groups; the HBS contains 12, the Irish census only 5 categories. Choosing 3 broad education groups makes it possible to consistently match emigrants and stayers with the same education level.

Each education group is divided into 9 experience groups: 0-4 years, 5-9 years, 10-14 years, ..., 40+ years of work experience. The work experience is calculated as the exposure to the labor market, i.e. the time since finishing education, *experience = age - education - 6*. The value for education is 10 years for lower secondary, 12 years for upper secondary, and 15 years for third-level education.

[13]The available immigration figures are 376 in 2000, 213 in 2005, and 228 in 2006. The Russian statistical office does not report immigration statistics for the time between 2000 and 2005. Source: www.gks.ru; the author can produce the table on request.

[14]See Appendix 1.A.2 for a detailed description of the educational tracks.

1.4.2 Empirical Model

The empirical model is a regression of individual wages on the share of emigrants in the individual's skill group, estimated from pooled cross-sectional data. The baseline estimating equation is

$$w^i_{ght} = \delta m_{ght} + \boldsymbol{X^{i\prime}_{ght}\beta} + year + educ + exper + \varepsilon^i_{ght}. \tag{1.5}$$

w^i_{ght} is the log real wage of individual i with education g, experience h in year $t = 2002, 2003, 2005, 2006$. m_{ght} is the emigration rate for individual i's skill group. The coefficient of interest, δ, denotes the percentage change in real wages associated with a 1 percentage-point change in the emigration rate.

The dummy variables $year$, $educ$, and $exper$ absorb changes in average wages over time, and differences in average wages across education and experience groups. $\boldsymbol{X^i_{ght}}$ is a vector of individual control variables, which include gender, marital status, whether individual i has children under 18, and whether she lives in a city. ε^i_{ght} is an error term. Because m_{ght}, the regressor of interest, is a group variable defined by education, experience and time, I cluster the standard errors at the year, education, and experience level.

The model in Equation (1.5) has the advantage that it uses a low number of degrees of freedom, but it potentially comes at the cost of omitted variable bias. The $year$, $educ$, and $exper$ dummies reduce this bias, but there could be factors that have an impact on wages over and above what is absorbed by the dummies. Examples are changes in the returns to education or experience, or demand shifters such as FDI or exports. To account for these factors, I extend the baseline model with the interaction terms $(year * educ)$, $(year * exper)$, and $(educ * exper)$. The interactions $(year * educ)$ and $(year * exper)$ absorb changes in the returns to education and experience; $(educ * exper)$ accounts for differences in the age-earnings profile across education groups.

The inclusion of interaction terms has the additional advantage that they absorb cross-wage effects. If the underlying theoretical model has a heterogeneous workforce with several skill groups, the impact of emigration depends on the demographic characteristics of the emigrants compared to the stayers (Card & Lemieux, 2001; Borjas, 2003). Emigration in one skill group affects the marginal product of all other groups, and has a larger wage impact on groups that are close substitutes. After controlling for cross-wage effects, δ measures the own-wage effect, i.e. the average effect of the emigration of workers from a specific skill group on the wages of that same group.

1.4.3 Identification Issues

Sources of variation: skill groups vs. occupations vs. geography

The skill-group approach overcomes identification problems inherent in the migration literature, by focusing on migration and wages at the national level. A large number of studies have used geographic variation of migration and wages to identify the impact of immigration on the wages of natives.[15] The small and insignificant effect typically found in these studies can be the result of unobserved adjustment in local labor markets or of the endogenous location choice of migrants. If migrants locate in areas with more flexible labor markets, they may be absorbed without depressing the wages of natives, or immigration can trigger the outflows of natives (Card, 2001). In addition, if migrants locate in areas that experience an economic boom and high wages, a spurious positive correlation between the share of immigrants and wages may appear. The skill group approach, by contrast, eliminates the endogeneity in the location choice of migrants. Endogeneity bias could only arise if migrants were able to choose their skill group, but this is not possible as workers generally make their education decision before they enter the workforce.

Some studies overcome the bias resulting from endogenous location choice by exploiting variation in migration rates and labor market outcomes within occupations at the national level (Card, 2001; Friedberg, 2001). If the occupation is predetermined by the immigrants' education and training, and if immigrants cannot easily switch to occupations with higher wage growth, it is possible to estimate a causal effect of immigration on wages and employment.

Although the within-occupations approach can provide a clean identification, it requires information on the occupation *before* emigration, which is not available for Lithuanian workers in Ireland and the UK. The only available information is the migrants' current occupation *after* emigration. In the context of EU enlargement, however, it is not possible to use this information to infer the occupation before emigration. As shown by Kahanec *et al.* (2009, p. 20), Drinkwater *et al.* (2009) and Saleheen & Shadforth (2006), immigrant workers from the new member states were overrepresented in typical low-skilled occupations, although their education level was on average higher than the level of natives. The skill group approach, by contrast, clusters the workforce in broader categories and makes emigrants and stayers comparable.

[15] See Friedberg & Hunt (1995) and Kerr & Kerr (2011) for a review of this literature and Longhi *et al.* (2010) for a meta-analysis.

Endogeneity issues

The marginal effect of emigration on wages only has a causal interpretation if emigration is exogenous. Ideally, one would run an experiment, in which the emigration rate is randomly assigned across skill groups. After controlling for all other factors in Equation (1.5), the average change in wages could then be exclusively attributed to emigration. As reality does not permit such experiments, identification has to rely on quasi-experimental variation in emigration rates.

Identification in this study is based on an exogenous change in migration laws after the EU accession of Lithuania in 2004. Only when the country joined the European Union were workers actually allowed to emigrate and take advantage of the higher wages in Western Europe. As Figure 1.1 shows, few Lithuanians migrated to Ireland and the UK before 2004, while the large migration wave began in 2004. Using the variation in emigration rates and real wages within skill groups from 2002 to 2006, the model in Equation (1.5) compares the emigration rates and wages for each skill group in the two years before and the two years after EU accession. The increase in emigration rates was caused by an exogenous policy change. Therefore, the changes in real wages, over and above the dummies and interaction terms, can be attributed to emigration.

A potential concern about the exogeneity of EU enlargement is that workers could have anticipated the lifting of migration barriers and accumulated destination-specific human capital. In the lead-up to EU enlargement, workers in Lithuania could have indeed anticipated that they were allowed to emigrate, as the country began its accession negotiations in 1999. Yet the destinations for migration only became clear in 2003, when the old member states decided on temporary restrictions of their labor markets. Germany, for example, only decided in spring 2004 that it would keep its labor markets closed for workers from the new member states (Deutscher Bundestag, 2004).

While in theory the causality runs from migration to wages, the direction of causality is less clear empirically. Wages can be a push factor for migration, as low wages create an incentive for workers to emigrate. In this case the relation between migration and wages should be negative, as skill groups with low wages should have high emigration rates. In the Lithuanian case, however, reverse causality should not confound the results. The emigration wave was triggered by the country's EU accession, and workers from all skill groups emigrated despite considerable wage increases. Moreover, if the estimate of δ is positive, reverse causality can at most downward-bias the result.

Equation (1.5) only identifies the wage effect if labor demand is constant. Shifts of the labor demand curve, unless controlled for, can bias the estimates. One such demand shifter is capital adjustment. Based on the idea of a Solow (1956)-type framework, emigration leads to a decrease in the capital stock, which offset the wage effect of emigration in the long run. This paper, by contrast, studies a short-run effect, so that capital adjustments should not affect the results. Moreover, it is unlikely that firms decrease their capital stock in a period of high economic growth, as Lithuania experienced in the 2000s.

One might be concerned that the Lithuanian economy underwent structural changes around the time of EU enlargement In particular, EU enlargement did not only change the migration laws; Lithuania gained access to a free-trade area and received EU structural funds, which may cause an increase in labor demand. If EU enlargement changed the trade and investment patterns, we would expect a shift in the level of exports and FDI, or a change in the trend of both variables. The aggregate data does not suggest that EU accession has led to substantial shifts in the trade and investment patterns. As we can see in Figure 1.2, none of these variables show a structural break after EU enlargement.[16]

The overall time trend in the trade and investment patterns — and of other factors that affect wages, such as TFP growth — is accounted for by the year dummies in Equation (1.5). In addition, if a factor shifts labor demand for high-skilled workers more than for low-skilled workers, or for young workers more than for old workers, the interactions $(year * educ)$ and $(year * exper)$ absorb these differential demand shifts. The only demand shifts I cannot control for with interaction terms, are skill group-specific demand shifts, because an interaction $(year * educ * exper)$ would completely saturate the model.

Self-selection of migrants

As it is only possible to observe the wages of workers who decide not to migrate, self-selection arises as a potential source of bias.

Negative self-selection of migrants leads to an upward-bias in the estimates. If most emigrants are selected from the lower end of the wage distribution, the average wage of the remaining workers increases. Yet, this increase is not caused by a decrease in labor supply, but by a change in the composition of the workforce. Analogously, if most emigrants are selected from the upper end of the wage distribution, the estimates will be downward-biased.

The selection of migrants can occur along two dimensions: between and within skill groups. When we compare the education distribution of stayers in Table 3.3 and of

[16]Between 2004 and 2006 Lithuania received EU structural funds of EUR 1.5bn, which is 8% of the country's real GDP in 2004. The largest share of the funds, which were spread across 3,500 projects, went into infrastructure projects (European Commission, 2007).

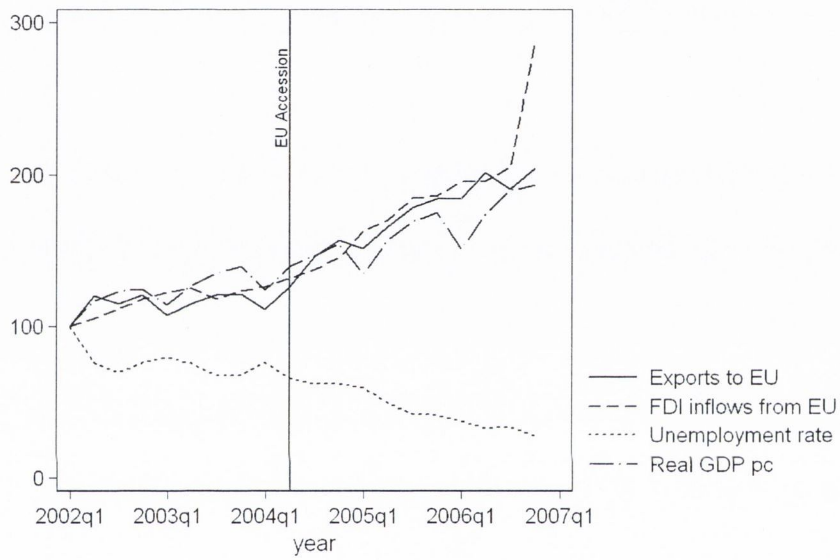

Figure 1.2: FDI, exports, GDP per capita, and the unemployment rate in Lithuania, 2002-2006

Notes: The graph shows the time series for exports to the EU, FDI inflows from the EU, real GDP per capita and the unemployment rate. All variables are normalized to 100 (first quarter in 2002). None of the variables shows a structural break around EU enlargement.

Source: Statistics Lithuania

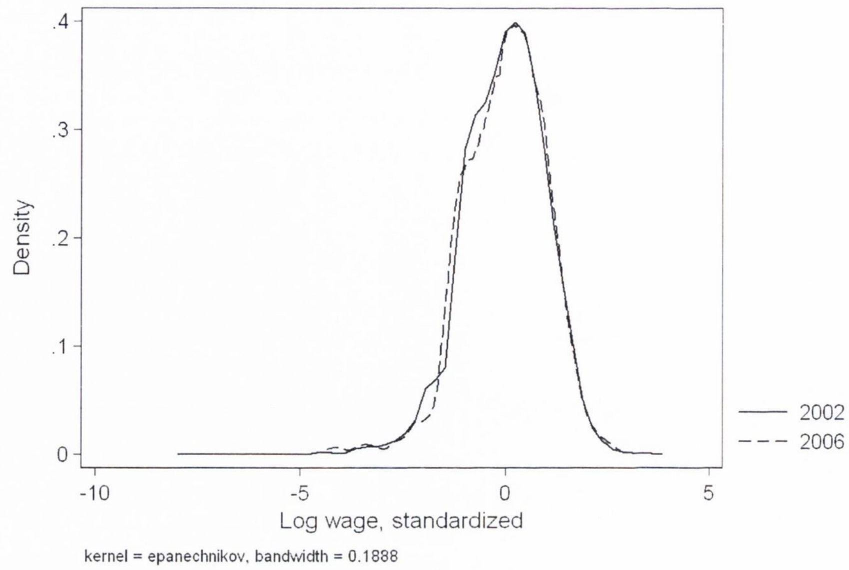

Figure 1.3: Standardized wage distribution in Lithuania, 2002 and 2006

Notes: The graph shows a Kernel density plot of the log real wages in 2002 and 2006. This plot allows for a comparison of the wage distribution before and after EU accession. It shows that the shape of the distribution has only changed slightly, despite the emigration of 9% of the workforce.
To make the distribution comparable across years, wages are standardized to their z-scores, i.e. the wage of an individual minus the mean wage, divided by the standard deviation of wages, $z_i = (w_i - \bar{w})/\sigma_w$. The mean of the distribution is zero.
Source: Lithuanian Household Budget Survey

migrants in Table 1.2, we can see that, between skill groups, emigrants were negatively selected. Negative selection, however, does not bias the results, as the dummies and interaction terms in Equation (1.5) account for it.

Selection within skill groups — a selection pattern that can not be observed from the summary statistics — can be a source of bias. It is difficult to determine the direction and size of this bias, as the data has no information on counterfactual wages, i.e. the wages emigrants would earn had they stayed in Lithuania. The standardized wage distribution in Lithuania before and after EU enlargement does not give evidence of selection bias. If migrants were on average negatively selected, we would expect the probability mass to shift to the right. As we can see in Figure 1.3, the shape of the wage distribution is almost identical in 2002 and 2006. [17]

Moreover, given the difference in the economic situation between Lithuania and

[17]Figure 1.4 in Appendix 1.A.3 plots separate wage distributions for men and women. For men, there have been some changes to the left of the mean, but no substantial shifts in the probability mass. By contrast, for women the probability mass moved to the left of the mean, indicating a positive selection.

Ireland and the UK, it is unlikely that migrants are on average negatively selected. First, migrants are, by definition, more mobile than stayers. If mobility is positively correlated with ability, migrants should be on average more skilled than stayers, and earn higher wages.

Second, because of the foreign language requirements, and because of minimum wages, the skill requirements are on average higher in the UK and in Ireland than in Lithuania. Most jobs, in particular in the service sector, require fluency in English and a good knowledge of British or Irish culture. In addition, the minimum wages in the UK and Ireland are considerably higher than in Lithuania, which creates an additional hurdle for low-skilled migrants. Only the more productive migrants get a job that pays them at least the minimum wage.[18] As the UK Home Office (2009) shows, more than 80% of immigrants from the accession countries were officially employed, so that the minimum wage is binding for the majority of immigrants.

Third, since there was little migration from Lithuania to Ireland and the UK prior to EU accession, migrants could not rely on large migrant networks that support them in finding a job and facilitate assimilation. As suggested by the literature on migrant networks (Carrington *et al.*, 1996; McKenzie & Rapoport, 2010), small networks are usually associated with a positive selection of migrants.

Closely related to the issue of self-selection is the question whether some of the workers were unemployed before they emigrated. If this was the case, emigration could have decreased unemployment and — in the most extreme case — have no effect on wages. In fact, Figure 1.2 shows that unemployment had been falling between 2002 and 2006. While I cannot exclude that emigration played a role in reducing unemployment, the unemployment rate does not show a structural break after EU accession. Even the emigration of 9% of the workforce did not cause a sudden drop in the unemployment rate.

If being unemployed is associated with lower ability, and if migrants are on average positively selected within skill groups, then most of the migrants should be employed at the time of emigration. While the Lithuanian unemployment data is not detailed enough to calculate unemployment rates per skill group, it is possible to control for unemployment at the regional level, which I do in a robustness check in Appendix 1.A.1. Moreover, for the unlikely case that many emigrants were unemployed right before emigration, the estimates of the wage effect would be downward-biased, as the calculated emigration rate would be higher than the actual one.

[18] In 2004, minimum wages were EUR 7 in Ireland and GBP 4.85 in the UK.

Table 1.3: The wage effect of emigration

Dependent variable: log real wage						
	(1)	(2)	(3)	(4)	(5)	(6)
Sample:	all	all	all	all	men	women
Emigration rate	0.665**	0.391	0.426	0.401	1.245***	0.283
	[0.2937]	[0.3132]	[0.3154]	[0.3236]	[0.2950]	[0.3910]
Emigration * male		0.799***	0.793***	0.777***		
		[0.2936]	[0.2912]	[0.2852]		
Year dummies	yes	yes	yes	yes	yes	yes
Education dummies	yes	yes	yes	yes	yes	yes
Experience dummies	yes	yes	yes	yes	yes	yes
FDI, unemp., exports	no	no	yes	no	no	no
Year * region	no	no	no	yes	no	no
Observations	9970	9970	9970	9970	6771	3199
Adjusted R^2	0.3463	0.3468	0.3568	0.3638	0.3371	0.3222

Robust standard errors in brackets

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

Note: This table shows the OLS results for the econometric model in Equation (1.5), a regression of log real wages on the emigration rate, interactions of the emigration rate with a dummy for men (emig*male), a vector of personal characteristics.

Standard errors are clustered at the time-education-experience level. All observations are weighted with survey weights.

FDI stocks (in logs), unemployment rate and exports (in logs) are measured at the regional level. Year*region is an interaction of year and region dummies.

1.5 Empirical Analysis

1.5.1 Estimation Results

Table 1.3 presents the results of the estimated impact of emigration on the real wages of stayers. The wage effect for men and women, reported in Column (1), indicates that emigration predicts a significant increase in wages. A one percentage-point increase in the emigration rate increases real wages on average by 0.67%.

While this effect may be large and statistically significant on average, the wage effects can differ between men and women. To analyze the difference in the wage effect between men and women, I interact the emigration rate with a dummy for men. As column (2) shows, the coefficient of the interaction term indicates a large and statistically significant difference in the wage effect of emigration for men and women. For a one percentage-point increase in the emigration rate, the wages of men increased on average by 1.1%, while the marginal effect for women is smaller and statistically insignificant. From columns (5) and (6) we can see that these results also hold if the sample is split between men and women.

In Column (3) I control for FDI inflows, exports, and unemployment at the regional level. Each of these factors can confound the analysis, if they affect wages over and above what it absorbed by the dummy variables. The three variables are measured at the regional level, so that the wage of a person can be matched with the FDI, unemployment, and exports in the region the person is living in. It is reassuring that the most obvious potential confounding factors, FDI, exports, and unemployment, do not change the results of the more parsimonious specification in Column (1).

Next, I include an interaction of region and year dummies into the basic model to ensure that no other factors affect wages at the regional level. The *region*year* interactions absorb all economic factors that affect a region over time but are unrelated to emigration. The results of this specification, displayed in Column (4), are not different from the previous result.

An obvious problem with controls at the regional level is that the demand shifters are the same for all skill levels. If, for example, the demand shift is larger for high-skilled than for low-skilled workers, this change in returns to education cannot be captured with the controls of the basic model. To account for changes in returns to education, I re-estimate the basic model with an interaction of year and education dummies. As we can see in Column (1) of Table 1.4, the estimated wage effect is the same when we account for changes in returns to education.

In a similar fashion, the returns to experience can change over time. Technological progress, for example, can benefit young workers more than old workers. To account for changes in returns to experience, I include an interaction of year and experience dummies. Column (2) of Table 1.4 indicates that changes in returns to education explain part of the wage increases. The point estimates are 0.3 lower compared to the benchmark case.

Part of the initial results can also be driven by differences in the age-earnings profile across education groups. The basic model in Equation (1.5) estimates a separate intercept for every education level, every experience level, and every year. The difference in wages for old and young workers, however, may be larger for high-skilled workers than for low-skilled workers, or vice versa. An interaction of education and experience dummies absorbs the difference in the age-earnings profile between education groups. The results in Column (3) of Table 1.4 suggest that the age-earnings profiles differ in fact by education level. Taking them into account increases the point estimates for men

Table 1.4: Estimation of the wage effect with additional controls

Dependent variable: log real wage							
A. Men	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Emigration rate	1.117***	0.825**	1.497***	0.292	1.372***	1.464***	0.833***
	[0.3218]	[0.3998]	[0.3145]	[0.3953]	[0.3127]	[0.3265]	[0.2649]
Observations	6771	6771	6771	6771	6771	6771	6771
Adjusted R^2	0.3374	0.3375	0.3382	0.3382	0.3385	0.3387	0.3392
B. Women							
Emigration rate	0.310	-0.039	0.622*	-0.012	0.642	0.817*	1.035
	[0.4166]	[0.4986]	[0.3217]	[0.4632]	[0.3859]	[0.4569]	[0.6657]
Observations	3199	3199	3199	3199	3199	3199	3199
Adjusted R^2	0.3225	0.3291	0.3302	0.3302	0.3305	0.3364	0.3375
Controls							
year*educ	yes	no	no	yes	yes	no	yes
year*exper	no	yes	no	yes	no	yes	yes
educ*exper	no	no	yes	no	yes	yes	yes

Robust standard errors in brackets

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

Note: This table shows the estimation results of the effect of emigration on wages with a number of additional controls. Year*educ accounts for changes in returns to education. Year*exper accounts for changes in returns to experience. Educ*exper accounts for fundamental differences in wages between experience groups within an education group. Furthermore, all regressions include year dummies, education dummies, experience dummies, and a vector of personal characteristics.

Standard errors are clustered at the time-education-experience level. All observations are weighted with survey weights.

and women by 0.3.

The inclusion of interaction terms changes the estimates, which suggests that returns to education, returns to experience, and difference in age-earnings profiles explain part of the wage changes. To see how the interactions jointly affect the results, I include two interactions at a time in Columns (4)-(6) in Table 1.4. The results are mixed, with results similar to the baseline case in Columns (5) and (6), and no statistical significance and low point estimates if year*education and year*experience are included. Column (7) displays the estimates with all three interactions included. In this specification – the same as in Borjas (2003) and Mishra (2007) – the only possible variation is within skill groups over time. Despite the large number of regressors, I find a large and statistically significant positive effect of emigration on the wages of men, and a statistically insignificant effect on the wages of women.

1.5.2 Discussion of the Results

The results show that emigration has a positive impact on wages on average, which is consistent with a supply-and-demand framework. Emigration leads to labor shortages, which — given a downward-sloping labor demand curve — causes an increase in real wages. EU enlargement increased the workers' bargaining power vis-a-vis their employers, which enabled them to negotiate higher wages.

The estimated effect is statistically and economically significant. The marginal effect of 0.67 means that a one percentage-point increase in the emigration rate increases real wages on average by 0.67%, which is in line with Elsner (2011), who estimates the demand elasticity with the same data in a structural model. If 5% of the Lithuanian workforce emigrated permanently, the model predicts that wages increase by 3.3% over 5 years. Given average wages in Lithuania increased by 40% over the same period (see Table 3.3), emigration can explain 8% of the overall wage increases. If we focus on the marginal effect for men, emigration even explains 16% of the wage increases.

The difference in wage effects for women and men is striking. There are several potential explanations for the absence of a significant effect for women. One explanation is that the data from the UK and Ireland over-estimate the number of women that have left the Lithuanian workforce. If women that emigrated to the UK and Ireland were not part of the workforce before emigrating, the actual number of emigrants would be smaller than the number in the data. Another explanation could be that EU enlargement gave a higher bargaining power to men than to women. If men are the main earners of the family, it is easier for men than for women to use the option to emigrate as a credible threat when negotiating their salaries. A third possibility is a labor supply response in Lithuania. If women that emigrated were replaced by women that had not been part of the workforce before, then there are fewer labor shortages for women and the wage increases are lower. Yet another explanation is self-selection of emigrant women. If women were on average selected from the upper end of the wage distribution — as suggested by Figure 1.4 in the online appendix — then the average wage of the remaining women decreases.

1.6 Conclusion

In this paper I study the effect of emigration on the wages of stayers. According to a simple supply-and-demand framework, emigration reduces labor supply and causes an increase in real wages. Using the emigration wave from Lithuania after EU enlargement, I test this hypothesis.

With EU enlargement, workers from Lithuania were allowed to emigrate to the UK and Ireland; around 9% of the Lithuanian workforce emigrated after the country joined the European Union. I exploit this exogenous change in migration laws and the resulting emigration wave to identify the effect of emigration on wages, using variation within demographic groups over time. The estimated impact of emigration on wages is significant. A one-percentage point increase in the emigration rate increases real wages on average by 0.66%. This effect, however, is only significant for men, not for women. The magnitude of the effect is larger than in previous studies (Mishra, 2007; Aydemir & Borjas, 2007), which looked at the long-run effect. The results of this study indicate that emigration can have a larger effect in the short run than in the long run

The results can inform policymakers about the effects of a large emigration wave on the labor markets in the sending countries. There are a number of middle-income countries that could face a similar emigration wave, once their workers are allowed to emigrate. Examples are EU candidate countries like Croatia, Serbia, Montenegro, or Turkey, which exhibit large wage differentials vis-á-vis Western Europe.

This study opens several avenues for future research. As more migration data becomes available, it is important to check the validity of the results for a larger number of countries. While the immigration literature has found very small effects of migration on wages in the receiving countries, the limited evidence on the sending countries shows that the effects can be significant. To be certain that this effect is not only limited to a small number of countries, we require evidence from more countries.

EU enlargement occurred during an economic boom in Western Europe so that workers from Eastern Europe could easily find jobs after emigration. With the financial crisis, starting in 2008, the prospects for migrants in most of Western Europe have become less positive, and many migrants are returning to their home countries. These two states of the European economy – boom before 2008, followed by a crisis – could be used to identify to what degree migration and return migration is driven by wage differentials and differences in the employment rates. Moreover, in looking at workers that emigrated immediately after EU enlargement, it would be interesting to investigate which workers stayed and which workers returned to their home countries, and what determined the timing of the decision to return.

1.A Appendix

1.A.1 Robustness Checks

The calculation of the emigration rates is based on a number of assumptions. Table 1.5 demonstrates how the results change when the assumptions are dropped. Panel A) shows the results for the baseline model in Equation (1.5); in panel B) I add a rich set of interaction terms. Columns 1) and 2) show the sensitivity of the results with respect to changes in the cell size. The coefficients are lower for 2-year cells and larger for 10-year cells. Panel i) displays the estimates for men and women together. The coefficient is statistically significant for 2-year cells but not for 5-year cells. The statistical significance of the effect for men is not affected by the cell size.

In Column 3) I drop the data for 2003 and 2005, as I do not have precise emigration data for these years. We first look at panel A): The coefficient for men and women jointly is larger than in the baseline and statistically significant at the 5% level. The interaction of the emigration rate and the male dummy in ii) is similar to the baseline, and significant at the 10% level. In the saturated model in panel B) none of the coefficients is statistically significant.

Column 4) displays the results for Irish data only. This exercise clearly underestimates the number of emigrants, as around 60% of all Lithuanian emigrants went to the UK. As a consequence, the coefficients are significantly larger than in the baseline scenario.

1.A.2 Education Groups

The Lithuanian education system offers a variety of educational tracks and degrees.[19] I aggregate the different education levels into three broad education groups for two reasons: Firstly, the Irish census only includes five different education groups (*primary and lower, lower secondary school, upper secondary school, third-level - no degree* and *third-level degree*), so that a matching of the educational attainment of emigrants and stayers is only possible if broader education groups are considered. Secondly, in some cases different educational tracks in Lithuania lead to comparable degrees. For example, the *basic school*, which students finish at the age of 16, and the *stage I of vocational training*. Both of those tracks lead to a basic school leaving certificate. Thus, students holding either of those comparable degrees can be seen as close substitutes on the labor market and should be equally affected by the emigration of workers with comparable characteristics. Tables 3.3 and 1.2 show the distribution of the education levels in the Lithuanian HBS as well as in the Irish census.

[19] http://www.euroguidance.lt provides an overview of the Lithuanian education system.

Table 1.5: Robustness checks

Dependent variable: log real wage

	(1) 2yr cells	(2) 10yr cells	(3) 2002 & 2006	(4) Irish data
A) without interactions				
i) all				
Emigration rate	0.535***	0.295	1.020**	2.089**
	[0.194]	[0.462]	[0.419]	[0.996]
ii) men/women				
Emigration rate	0.242	0.645	0.764	1.236
	[0.230]	[0.444]	[0.476]	[0.995]
Emig*male	0.634**	1.055***	0.842*	2.761***
	[0.274]	[0.348]	[0.434]	[0.745]
B) with interactions				
i) all				
Emigration rate	0.417*	0.334	0.576	1.332
	[0.218]	[0.694]	[0.648]	[1.341]
ii) men/women				
Emigration rate	0.217	1.442**	0.690	1.663*
	[0.226]	[0.808]	[0.704]	[0.952]
Emig*male	0.532*	1.625**	0.637	2.773***
	[0.272]	[0.638]	[0.601]	[0.826]

Robust standard errors in brackets
*** p<0.01, ** p<0.05, * p<0.1

Note: This table displays the coefficients for a series of robustness checks: 1) 2-year experience cells, 2) 10-year experience cells, 3) only data from 2002 and 2006, 4) only Irish data. Emig*male is an interaction term of the emigration rate and a male dummy. Year dummies, education dummies, experience dummies and personal characteristics are controlled for. Panel A) are estimates of the baseline model in Equation (1.5). Panel B) enhances the baseline model by the interaction terms $year * educ$, $year * exper$, and $educ * exper$. Robust standard errors in brackets. Standard errors are clustered at the education-experience-year level. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

I therefore define the education groups as follows: *Lower secondary school and less, upper secondary school* and *third-level degree.*

Lower Secondary School and Less People with 10 years of schooling or less. As the Lithuanian HBS contains very few observations with primary school education or less, I merge these with the category lower secondary school. Therefore, in terms of the Lithuanian classification, this category includes highschool dropouts, workers who only finished primary school, those with a *basic school* leaving certificate (usually obtained at the age of 16) and those who pursued *stage I of vocational training,* which also leads to a *basic school* leaving certificate. In the Irish census, this group consists of *primary school and less* and *lower secondary school.*

Upper secondary school This category includes all workers having a degree higher than a basic school leaving certificate (i.e. at least 11 years of schooling), but do not hold a degree that would allow them to enter a masters' programme at a university in Lithuania or abroad. The dominant degree in this category is the Lithuanian A-level, usually obtained at the age of 18. The other degrees of this category are *stages II, III and IV of vocational training* and certificates from non-university third-level institutions.
In the Irish census, this category contains all workers with an *upper secondary school* degree or a third-level education that does not lead to a university degree.

Third-level degree All workers with at least 15 years of schooling and a degree that enables them to apply for a university masters' degree in Lithuania or abroad. Workers with a masters' or a PhD degree are also included in this category.

1.A.3 Figures

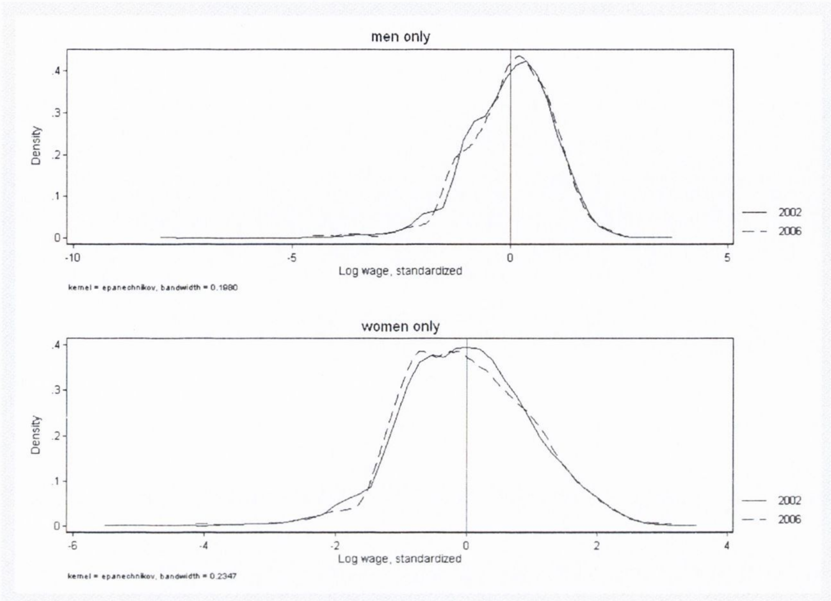

Figure 1.4: Standardized wage distribution for men and women in Lithuania, 2002 and 2006

Note: The graph shows a Kernel density plot of the log real wages in 2002 and 2006 for men and women. To make the distribution comparable across years, wages are standardized to their z-scores, i.e. the wage of an individual minus the mean wage, divided by the standard deviation of wages, $z_i = (w_i - \bar{w})/\sigma_w$. The mean of the distribution is zero.

Source: Lithuanian Household Budget Survey

Chapter 2

Emigration and Wages: The EU Enlargement Experiment

I have presented this work in research seminars at UCD, Mainz, TCD, NUIM, SSE Riga, Bocconi, FEEM, OEI Regensburg, U Edinburgh, IZA, LMU Munich, U Stirling, as well as at the Norface conference (London 2011), 7th ISNE (Dublin 2010), SAEe (Málaga 2011), VfS (Frankfurt 2011), RES PhD Meeting (London 2012), EEA (Málaga 2012). Part of this chapter was written during a research visit at Bocconi University in Milan. I received valuable suggestions from numerous people, above all from Gaia Narciso, Giovanni Peri, and Pedro Vicente. The article is available as an IZA Discussion Paper nr 6111.

2.1 Introduction

Lifting the barriers to migration can lead to welfare gains of up to 150% of world GDP.[1] A large literature has quantified the gains from migration for the receiving countries and the migrants. Yet little is known about the impact of emigration on the sending countries. Because migration is heavily restricted, there are few episodes of large migration waves which 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. With EU enlargement in 2004, the UK, Ireland, and Sweden opened their labor markets for workers from Eastern Europe, which was followed by a migration wave of 1.2 million workers over 3 years. 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 before EU enlargement by estimating the model parameters using microdata from Lithuania. Based on immigration data from the UK and Ireland I simulate the emigration wave and calculate the wage change, the difference between the equilibrium wage before and after the migration wave. This approach allows me to isolate the effect of emigration from other factors that would otherwise have an impact on wages, such as trade, FDI, and TFP growth. The methodology also delivers separate wage effects for groups of workers with different education and work experience, allowing for an assessment of the distributional impact of emigration.

I find that emigration had a significant impact on the wage structure, particularly on the wage distribution between old and young workers. It caused a wage increase of 6% for young workers, while it had no effect on the wages of old workers. By contrast, I find no difference in the wage effects between high-skilled 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; a decrease in the number of workers increases their wage. The sum of the general equilibrium effects, caused by the change in the demographics of the workforce, is negative. For young workers, who were the majority of emigrants, the own-wage effect dominates, while for older workers the two effects cancel each other

[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. See Figure 2.1.

out.

These findings stress the importance of the 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 for older workers. Most of the literature on the sending countries, however, assumes away these labor market effects and focuses 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, 2011) 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. The results are therefore relevant for policymakers in middle-income countries, since candidates for EU membership like Croatia, Serbia, or Turkey, or Latin American countries have well-educated workforces and may face a similar emigration wave in the future. This paper shows emigration has a positive effect on the non-migrants, despite the large outflow of workers.

As 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 studies find a positive long-run impact in Mexico between 1970 and 2000, but the results have to be interpreted *as if* all workers left the economy at once, even though they actually left gradually over the last 50 years (Hanson & McIntosh, 2010). Recent evidence from quasi-natural experiments (Elsner, 2010; Gagnon, 2011) shows that emigration increases wages even in the short run. Both studies, however, use a reduced-form approach, which only allows them to determine an average effect. In this paper, I show that the these wage effects only benefit the young workers. Moreover, a comparison with the reduced-form results of Elsner (2010) demonstrates the importance of the general equilibrium effects, without which the predicted wage changes would be considerably higher.

Finally, this paper reveals that migration affects sending and receiving countries along different skill dimensions. I find a significant distributional effect between old and young workers, 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). 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, which results in a stronger reaction of wages on emigration.

The remainder of the paper is structured as follows. Section 2.2 gives a historical overview and stylized facts about the emigration wave from Eastern Europe after 2004. Section 2.3 sets up the structural model. Section 2.4 describes the data sources, which I use for the estimation of the structural parameters in Section 2.5. Section 2.6 details the simulation of the migration wave and calculates the wage effects. Section 2.7 concludes.

2.2 EU Enlargement, Migration and Wages: Stylized Facts

In 2004 eight former socialist countries from Central and Eastern Europe joined the EU. For workers from these countries the high wage differentials between Western Europe and the accession countries created a large incentive 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 their welfare systems and restricted the access for workers from the New Member States for up to 7 years. 1.2 million workers migrated between 2004 and 2007 from Eastern Europe to the UK (770,000), Ireland (416,000) and Sweden (19,000).[5]

Figure 2.1 illustrates the magnitude of the emigration wave by comparing the number of emigrants to the size of the workforce. Most migrants came from Poland, Latvia, Lithuania and Slovakia. Although Poland had the 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 of time. Evidence from the Irish Central Statistics Office (2009) suggests that around 60% of migrants from the New Member States stayed for at least two years after having received a work permit.

This study takes Lithuania as an example to study the impact of emigration on the wages of stayers. Lithuania makes an interesting case, as it had the highest share of emigrants among the accession countries. At the same time, the results are externally

[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).

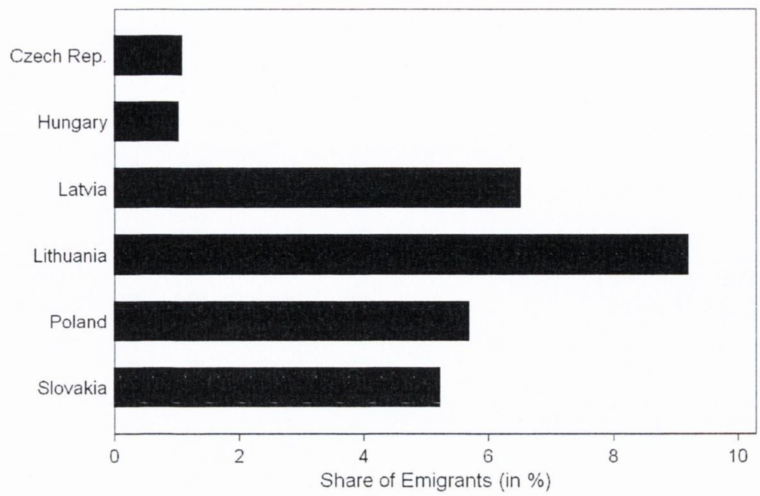

Figure 2.1: Emigrant shares in Central and Eastern Europe

Note: This figure shows the share of emigrants to the UK and Ireland between 2004 and 2007, relative to the total workforce.

Source: Own calculations, based on Irish PPS Numbers, UK National Insurance Numbers (NINo), Eurostat.

valid with respect to other transition countries. 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] An outflow of 9% of the workforce should therefore have similar impacts on the wage structure in all four countries.

The number of work permits per year issued to Lithuanian workers 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. Between 2002 and 2006, the GDP per capita grew in total by 37.5%. The high growth was also accompanied by a phase of considerable wage increases. The graph on the left in Figure 2.2 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. Young workers with a work experience of up to 20 years gained considerably more than old workers with less than 20 years of work experience. In addition, workers with an education level below third-level degree experienced higher wage increases than workers with a third-level degree.

[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 2.1c.

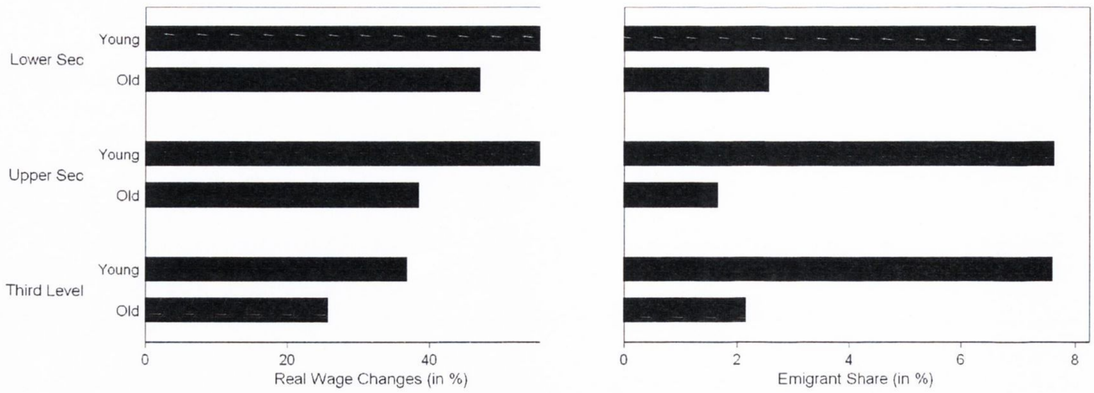

Figure 2.2: Real wage changes and emigrant shares in Lithuania

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, 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 2.4 for details.

Figure 2.2 (right graph) illustrates the magnitude of the emigration wave between 2002 and 2006 for each skill group. Similarly to the wage changes, the emigrant shares were higher for young workers than for old workers. Young workers were around 3.5 times more likely to emigrate than old workers. Surprisingly, there was no visible selection of emigrants with respect to the education groups. Workers of all three education levels had almost identical emigrant shares, which is evidence against a brain drain.

The relative changes in real wages had a significant impact on the wage inequality between experience and education groups. In particular, the wage premium for old workers changed remarkably, as the graph on the left in Figure 2.3 shows. In 2002 old workers earned on average 8% more than young workers. This wage gap was reversed in 2006. The wage premium for workers with a third-level degree compared to those with a lower secondary education decreased slightly over time, while the premium of workers with an upper secondary education remained stable. In sum, the wage inequality between education groups decreased over time.

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

The aim of this study is to isolate the role of emigration in the total change in wages,

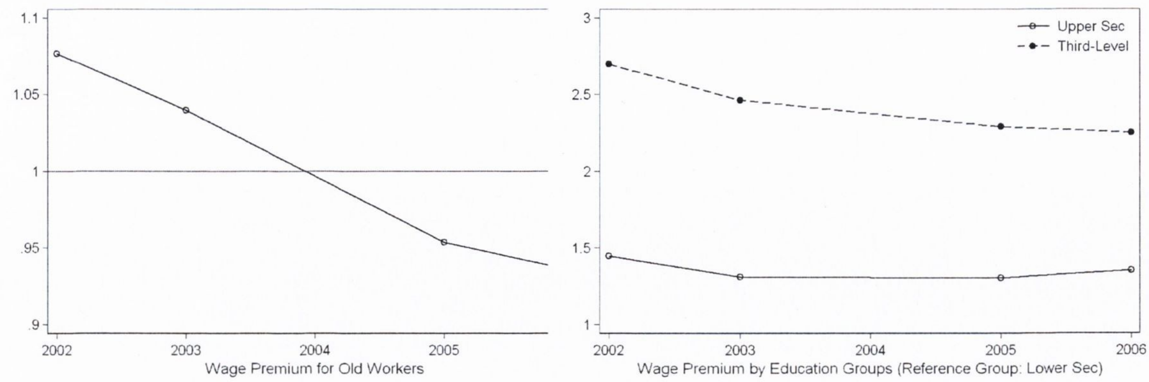

Figure 2.3: Wage premia by work experience and education

Note: The figure on the left illustrates the development of the wage premium for old workers (i.e. workers more than 20 years of experience) compared to young workers. The figure on the right shows the wage premium for college-educated workers (dashed line) and for workers with an upper secondary education (solid line), compared to workers with a lower secondary education. *Source:* Own calculations from the Lithuanian HBS.

which extends previous work by Elsner (2010) who found a positive average effect in a reduced-form approach. The current study goes a step further and investigates the impact of emigration on the wage distribution. To that end, it aims to determine *how much* different groups of workers gained or lost from emigration, *all other things equal.*

2.3 Structural Model

The structural model explains how a change in labor supply affects the wages of workers with different skills. To model this heterogeneity in observable skills, the workforce is divided into 12 skill groups, which are 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 workers with fundamentally different skills. Emigration of workers of a particular skill group shifts the labor supply and, given a downward-sloping labor demand curve, increases the wages of the stayers in this skill group. 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.

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

The aggregate production function consists of three building blocks: first, physical capital and labor are combined to produce an aggregate output. As this study focuses on a short-run effect, capital is fixed. The second building block is a CES aggregate of three education groups, which reflects the fact that workers with different education are imperfect substitutes in the labor market. The third building block combines workers with the same education but different work experience, which accounts for the difference in skills between workers of different experience levels. On the one hand, the difference in skills can arise because old and young workers acquired their qualifications at different times. On the other hand, old workers may have gathered more experience in their job, so that they have more human capital than younger workers.

2.3.1 Aggregate Production

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

$$Q_t = A_t L_t^{\alpha} K_t^{1-\alpha}. \tag{2.1}$$

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

$$L_t = \left[\sum_i \theta_{it} L_{it}^{\frac{\sigma_{ED}-1}{\sigma_{ED}}} \right]^{\frac{\sigma_{ED}}{\sigma_{ED}-1}}. \tag{2.2}$$

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

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

$$L_{it} = \left[\sum_j \gamma_{ijt} L_{ijt}^{\frac{\sigma_{EXP}-1}{\sigma_{EXP}}} \right]^{\frac{\sigma_{EXP}}{\sigma_{EXP}-1}} . \tag{2.3}$$

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

For the division of an education group into experience groups (j) I choose intervals of 10 years of work experience (0-10 years, 11-20 years, 21-30 years, 31+ years). This choice is the result of a trade-off between many skill groups and many observations *per skill group*, given the dataset. Shorter intervals allow for a more differentiated picture of the labor market, but they come at the cost of a loss in precision. With a given number of observations, a high number of skill groups means that the calculation of the average wage and labor input per skill group are based on a small number of observations. As a consequence, the averages become less precise. Aydemir & Borjas (2011) show that this *attenuation bias* can have a significant impact on the estimates of the structural parameters. Given the available dataset, the choice of 10-year intervals is a compromise that reduces attenuation bias and yet allows for a differentiated picture of the labor supply and wage changes.[8]

Figure 2.4 illustrates the nested structure of the aggregate production function. The model compresses the different degrees of substitutability between skill groups to 2 elasticities, σ_{ED} and σ_{EXP}. This simplification is necessary for the identification of the structural parameters. Ideally, one would like to estimate a separate relative labor demand curve for every skill group, but the econometric identification of the model would be impossible. With 12 skill groups the number of parameters to be estimated would amount to $12 \cdot 11 = 132$, which cannot be estimated from the small number of observations that is typically available from aggregate labor market data. Nevertheless, σ_{ED} and σ_{EXP} can be identified and given the variation in the number of emigrants across skill groups, so that we can obtain a differentiated picture of the impact of emigration on the wages of each skill group.

2.3.2 Labor Market Equilibrium

Labor markets are perfectly competitive and clear in every period. Profit-maximizing firms pay each skill group L_{ijt} a real wage w_{ijt} equal to the group's marginal product $w_{ijt} = \partial Q_t / \partial L_{ijt}$. This equation is the result of a partial differentiation of equations

[8] Most of the literature, e.g. Borjas (2003), Brücker & Jahn (2011), D'Amuri *et al.* (2010), Katz & Murphy (1992), Manacorda *et al.* (2011), Ottaviano & Peri (2011) uses 5-year experience groups. In the estimation results in Section 2.5.1 I also report results for 5-year and 20-year cells.

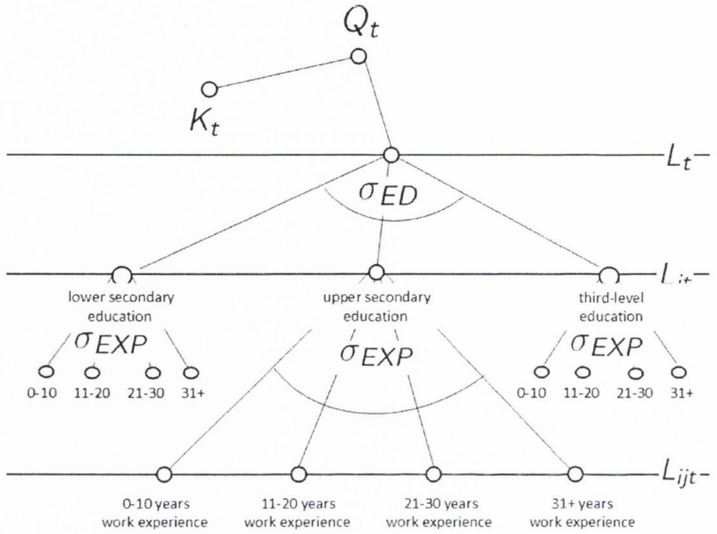

Figure 2.4: Nested CES production function

Note: This figure illustrates the nested structure of the CES production function, which is the core of the structural model. See Section 2.3 for details.

(2.1)-(2.3) and describes the firms' labor demand for skill group ijt. The log of this equation yields a log-linear labor demand curve,

$$\begin{aligned}\log w_{ijt} &= \log \alpha A_t + (1-\alpha)\log K_t + (\alpha - 1 + \frac{1}{\sigma_{ED}})\log L_t + \log \theta_{it} \\ &+ (\frac{1}{\sigma_{EXP}} - \frac{1}{\sigma_{ED}})\log L_{it} + \log \gamma_{ijt} - \frac{1}{\sigma_{EXP}}\log L_{ijt},\end{aligned} \tag{2.4}$$

where $\frac{1}{\sigma_{EXP}}$ is the slope coefficient, while all other terms on the right-hand side of equation (2.4) are intercepts that vary along the dimensions indicated by the indices, i.e. time, education and experience. Any change in one of the factors on the right-hand side alters the marginal product, which leads to a change in the real wage *ceteris paribus*. Hence, the wage of group ij depends on its own labor supply, as well as on the labor supply of all other groups of workers. Therefore, it is not only the absolute scarcity of group ij which determines its wage, but also the relative scarcity of this group compared to all other skill groups.

From equation (2.4), 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, as EU accession was accompanied by increased FDI inflows, a deeper trade integration and the inflow of EU structural funds, which have an impact on labor demand and ultimately on wages. Controlling for such factors is possible because the variation in all terms on the right-hand side of equation (2.4) except $\left(-\frac{1}{\sigma_{EXP}}\log L_{ijt}\right)$ can be absorbed by dummies and interaction terms. $\left(\log \alpha A_t + (1-\alpha)\log K_t + (\alpha - 1 + \frac{1}{\sigma_{ED}})\log L_t\right)$ only varies over time, so that a set of time dummies δ_t absorbs this variation. An interaction of time and education group dummies δ_{it} absorbs $\left(\log \theta_{it} + (\frac{1}{\sigma_{EXP}} - \frac{1}{\sigma_{ED}})\log L_{it}\right)$, which varies across education groups and over time. The parameters γ_{ijt} and the labor input L_{ijt} both vary along the dimensions time, education and experience, so that the inclusion of an interaction of the respective dummies would absorb all the variation and the model would be fully saturated. In this case $\frac{1}{\sigma_{EXP}}$ could not be identified. To circumvent this problem, I assume that the relative productivity of each experience group is constant over time, so that the variation of γ_{ijt} is absorbed by an interaction of education and experience dummies, δ_{ij} and an error term ε_{ijt}. This is a standard assumption in the literature[9] and in the time horizon of 5 years it is plausible that the relative productivity of an experience group does not change fundamentally. Moreover, as a robustness check in Section 2.5 I add an additional set of time*experience interaction terms to the estimating equation.

σ_{EXP} can be consistently estimated from

$$\log w_{ijt} = \delta_t + \delta_{it} + \delta_{ij} - \frac{1}{\sigma_{EXP}}\log L_{ijt} + \varepsilon_{ijt}. \tag{2.5}$$

2.4 Data and Descriptive Statistics

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

The number of emigrants per skill group cannot be taken from the source country, as the statistical offices usually do not keep detailed records about emigrants. An obvious reason for this lack of suitable emigration data is that in most European countries there is no legal obligation for migrants to de-register once they have emigrated. The consideration of the case of Lithuanian emigration after EU enlargement has the advantage that within the EU Lithuanians were only allowed to migrate to the UK, Ireland and Sweden, while all other old EU countries kept their labor markets closed for a transitional period up to 2011. Consequently, I can obtain the number of emigrants

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

from the register data of the destination countries. Since the numbers of migrants to Sweden were relatively small[10], I will neglect Sweden and only use census and work permit data from Ireland and the UK.

2.4.1 Lithuanian Household Budget Survey

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

To obtain the monthly real wages I deflate the variable *income from employment* using the harmonized consumer price index (HCPI).[11] Table 2.1a displays the summary statistics for the HBS. The average real wages increase for all groups between 2002 and 2006. The magnitude of the standard errors of the average wages indicates a considerable variation of wages within each skill group.

Income data are self-reported, which can be subject to a misreporting bias if workers systematically under- or over-report their income. However, a comparison of the average monthly wages in Table 2.1a with the average monthly wages for men and women working in the private sector from the Lithuanian live register in Table 2.1d shows that this bias is negligible, as the difference between both 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, as wage determination in the public sector is usually not based on the market mechanism of supply and demand, but on seniority. Additionally, I drop the following observations: if the variable *disposable income* is negative, if the socioeconomic status is *pensioner* or *other*, and if workers are self-employed or own a farm.

For each worker the highest obtained degree counts for her classification into one of the education groups *lower secondary education*, *upper secondary education* and *third-level degree*. Lower secondary education includes all workers with less than a high school degree. Upper secondary school classifies all workers with a high school degree that allows them to go to college as well as workers who obtained a degree that is less than the equivalent of a B.Sc degree. Third-level degrees are all degrees that are at least equivalent to a B.Sc and would allow workers to apply for an international

[10]See Wadensjö (2007).

[11]See Table 2.1d for the HCPI.

Table 2.1: Summary statistics Lithuanian HBS

a) Lithuanian HBS						
Survey Year			**2002**	**2003**	**2005**	**2006**
Number of Workers		All Workers	3950	4136	4042	3874
		Men	2322	2411	2426	2314
		Women	1628	1725	1616	1560
	Education	Lower Sec	348	431	435	384
		Upper Sec	2726	2860	2733	2614
		Third-level	876	844	874	876
Age			42.9	42.5	43.1	43.4
Experience			24.5	24.1	24.6	24.9
Real Wage (monthly, in LTL)		All Workers	1084	1142	1339	1533
			(799)	(836)	(954)	(1093)
		Men	1185	1152	1440	1688
			(856)	(913)	(981)	(1134)
		Women	940	988	1189	1303
			(684)	(686)	(890)	(985)
	Education	Lower Sec	689	768	946	1045
			(466)	(545)	(706)	(707)
		Upper Sec	952	1019	1203	1382
			(619)	(667)	(784)	(938)
		Third-Level	1653	1752	1964	2197
			(1076)	(1129)	(1203)	(1351)
b) Irish Census						
Number of Workers		All Workers	1274	-	-	11501
		Men	671	-	-	6557
		Women	603	-	-	4944
	Education	Lower Sec	211	-	-	2315
		Upper Sec	808	-	-	7166
		Third-level	255	-	-	2020
Age			29.5	-	-	30.7
c) Work Permit Data						
NINo Numbers	(UK)		1430	3140	10710	24200
PPS Numbers	(Ireland)		2709	2394	18680	16017
d) Aggregate Data, Lithuania						
Monthly Wage (in LTL)		Men	1173	1227	1420	1676
		Women	998	1029	1167	1356
HCPI		2005=100	97.334	96.291	100	103.788
Unemployment Rate			13.8%	12.4%	8.3%	5.6%

Note: Standard errors of average values in parentheses. HBS: Number of private sector workers between 18 and 64 years. Education groups and work experience are determined as described in Section 2.4. Real wages in Litas (LTL) are deflated by the harmonized consumer price index (HCPI).
The Irish census was conducted in 2002 and 2006 only. Data from the Irish census contain all Lithuanian workers who finished their education.
Sources: HBS and Irish census: Own calculations. Work permit data: UK Home Office, Irish Social Welfare Office. Panel d): Statistics Lithuania.

M.Sc programme. Workers holding a degree *Bakalauras*, *Magistras* or higher are classified as third-level educated.[12] Those with some college education, but a degree that requires less schooling than the two mentioned above are classified as having an upper secondary education.

This clustering may appear fairly broad, given that the Lithuanian education system offers a variety of educational tracks.[13] However, these broad categories are necessary to match the characteristics of the stayers with those of the emigrants. The HBS gives 12 education groups, while the data on the emigrants only distinguishes between 5 groups. Furthermore, broad categories ensure that the number of observations within each group is large enough to allow for the calculation of reliable average wages and emigration numbers.[14]

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

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 Polish and Lithuanian immigrants

[12]These degrees are the minimum requirement for graduate admission at the London School of Economics (LSE), see http://www2.lse.ac.uk/study/informationForInternationalStudents/countryRegion/europeEU/lithuania.aspx

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

[14]Table 2.8 in the appendix illustrates in detail the aggregation of the educational tracks into the three education groups.

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

in Ireland by gender, age and education.

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

For the calculation of the number of emigrants I only use data on migrants whose education is finished, which is 93% of Lithuanians in the census 2002 and 85% in 2006. As we can see in Table 2.1b the number of workers in the Irish census increased by a factor 10 between 2002 and 2006. Interestingly, the educational distribution and the average age did not change significantly over time. The gender distribution of migrants in 2006 is slightly skewed towards men. Comparing the Lithuanian migrants in the Irish census with the workers in Lithuania, we can see that the education distribution is similar, although the migrants are on average 13 years younger than the stayers. In 2006 workers with a lower secondary education are slightly overrepresented among the migrants (20% among migrants compared to 10% among stayers), while workers with a third-level education are slightly underrepresented (18% among migrants compared to 23% among stayers). These summary statistics indicate two types of selection behavior: migrants are more likely to be young than stayers and on average less educated, although the extent of selection across education groups is minor.

2.4.3 Work Permit Data: PPS and NINo Numbers

The number of workers who obtained a work permit in Ireland and the UK defines an upper bound to migration from Lithuania to Ireland and the UK. Every worker who moves to Ireland or the UK and wants to take up employment has to apply for a Personal Public Service (PPS) number in Ireland or a National Insurance Number NINo in the UK.[16] These data capture all workers that emigrated from Lithuania to one of those two countries, regardless of how long they stay in the host country. There is no obligation to de-register for workers in their home country, so it is not possible to measure, how many people returned to Lithuania and how much time they spent in the host country. Double counts are unlikely, however, as workers keep their PPS and NINo numbers, no matter how often they move back and forth between Lithuania and Ireland or between Lithuania and the UK. The PPS and NINo numbers could undercount the actual number of migrant workers coming to Ireland and the UK, as some workers might not have registered when they came to work for a short period in time or wanted to avoid having to pay income taxes. Workers who only migrated for a short period in time and did not register for that reason can hardly be seen as emigrants, because they were part of the Lithuanian workforce for the whole time.

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

Assessing the number of workers who migrated for a longer period without registering is difficult, but it should be small given the high number of migrants who actually *did* register. In summary, even if the work permit data may slightly undercount the actual number of migrants, for the simulations this means that the actual labor supply shock might be larger so that the predicted wage changes resulting from emigration are lower than the actual ones.

2.4.4 Calculation of Emigration Rates

To simulate the effect of the migration of different skill groups on wages, the labor supply shock $\frac{\Delta L_{ij}}{L_{ij}}$ for each skill group has to be quantified. This fraction, which can be interpreted as the emigration rate, i.e. the percentage of workers in skill group ij who emigrated, consists of the change in labor supply in a given time span ΔL_{ij} and the number of workers of the same skill group in Lithuania, L_{ij}.[17] 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, $L_{ij} = \sum_{l=1}^{L} p_{ijl}$.[18]

The shift in labor supply ΔL_{ij} cannot be taken directly from the data, but needs to be computed from several Irish and UK data sources. This is due to the fact that I have detailed data on Lithuanian migrants living in Ireland from the Irish census, but only aggregate figures on the migrants coming to the UK.[19] To compute the labor supply shifts, I assume that the skill distribution of migrants coming to Ireland is the same as the distribution of those coming to the UK. This assumption can be justified by the fact that there was little visible sorting behavior of migrants from the New Member States between Ireland and the UK with respect to age and education. There may have been a sorting behavior with respect to occupations, for example immigrants in Ireland work more in the construction sector and immigrants in the UK in the service sector but this study focuses on more broadly defined skill groups, for which the distribution is similar.

Figure 2.5 shows the education and age distribution of all migrants from the New Member States in Ireland and the UK. The share of third-level educated workers was slightly higher in the UK, while the share of workers with an upper secondary ed-

[17]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.

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

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

ucation was higher in Ireland. In the youngest group, between 18 and 24 years of age, the UK saw relatively more immigrant workers than Ireland. Consequently, the assumption that the experience distribution are the same implies that the predicted wage changes for young workers can be slightly downward-biased, meaning that the actual wage changes caused by emigration will be at least as high as those predicted by the model.

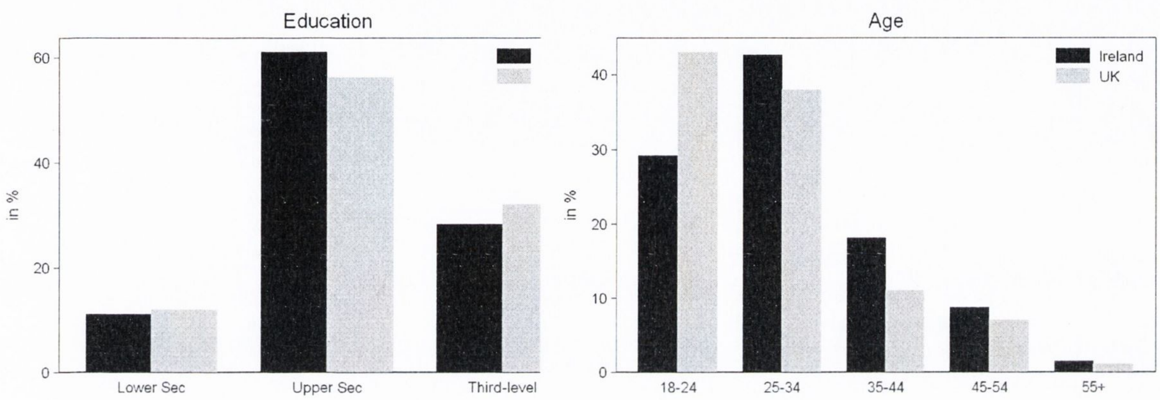

Figure 2.5: Education and age distribution of immigrants from the New Member States in the UK and Ireland

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

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

$$\Delta L_{ij} = (IE_{ij,2006} - IE_{ij,2002}) \left(1 + \frac{\text{Work permits in the UK 2002-2006}}{\text{Work permits in Ireland 2002-2006}}\right). \tag{2.6}$$

$(IE_{ij,2006} - IE_{ij,2002})$ 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 (2.6) augments the number of migrants to Ireland by a weighting factor that takes account of the number of workers who migrated from Lithuania to the UK. The 1 accounts for those who moved to Ireland and the fraction (Work permits in the UK 2002-2006)/(Work permits in Ireland 2002-2006) is the number of work permits given to Lithuanians in the UK between 2002 and 2006 as measured by the NINo numbers relative to the corresponding number in Ireland. Over the course of these 5 years 43% more Lithuanians received a work permit in the UK than in Ireland, so that the fraction is 1.43.

Table 2.2: Emigration rates 2002-2006

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

Note: The emigration rate per skill group denotes the share of workers in every skill group who emigrated between 2002 and 2006. The average emigration rate, weighted by the size of the skill group, is 5%. The emigration rates are calculated as the number of emigrants to Ireland and the UK divided by the average size of the skill group between 2002 and 2006. Sources: own calculations, as explained in Section 2.4.4.

Table 2.2 summarizes the calculated emigration rates per skill group and reveals the selection pattern of emigrants along the old-young dimension. Most emigrants are young, with a work experience of 10 years and less. Only very few older workers emigrated. Across education groups the emigration rates were balanced, so that the country did not suffer from a *brain drain*. The aggregate emigration rate, weighted by the size of the skill groups in the Lithuanian workforce is 5%.

2.5 Estimation of Structural Parameters

2.5.1 Identification and Estimation of σ_{EXP}

Using equation (2.5), I estimate σ_{EXP} with the number of workers per skill group as a labor input L_{ijt}.[20] An estimation of the demand curve with OLS does not yield consistent estimates as the results suffer from simultaneity bias. The equation is a demand curve, but the observations in the data are equilibrium points in the (w_{ijt}, L_{ijt}) space, which were determined by an interplay of supply and demand factors. To disentangle the labor demand and supply curves and identify the slope of the demand curve, an exogenous labor supply shifter is needed that does not shift labor demand, i.e. an instrumental variable (IV). Given an appropriate instrument, $\frac{1}{\sigma_{EXP}}$ can be consistently estimated with a two-stage-least-squares (2SLS) estimator.

Most of the literature, e.g. Borjas (2003), Aydemir & Borjas (2007), Ottaviano & Peri (2011), uses immigration as an instrument for labor supply. For the current study, the corresponding instrument would be emigration from Lithuania.[21] To be valid as an

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

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

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 (2.5). However, in light of the scale of the emigration wave following EU enlargement, the emigration of workers of a specific skill group could also shift the demand for workers in this particular group.

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

To overcome the problem of identification in the presence of simultaneity bias, I propose a new instrument for labor supply, *birth cohort size.* This instrument follows the logic that the size of a birth cohort should be highly correlated with labor supply today. For example, if 50 years ago many people were born, we should observe many 50-year-olds in the workforce today. Obviously, the size of a birth cohort is not a perfect predictor for the labor supply today, because it does not take into account demographic factors like emigration, deaths or early retirement. However, as long as birth cohort size is *sufficiently correlated* with labor supply, it is suitable as an instrument. An additional requirement for the instrument is that it varies across education and experience groups. As long as the birth rates change over time, the instrument varies naturally across experience groups. A decline in birth rates over time means that older cohorts are larger. Birth cohort size also varies across education groups, albeit not to the same degree as it varies across experience groups. The relevant units of observation for the instrument, however, are education experience cells. Between the survey rounds of 2002 and 2006, the birth cohorts vary considerably within the same experience level. Take as an example the youngest experience group (0-10 years) with a lower secondary education. In the 2002 survey the members of this cell were born between 1976 and 1986, in 2003 between 1977 and 1987, and so forth.

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

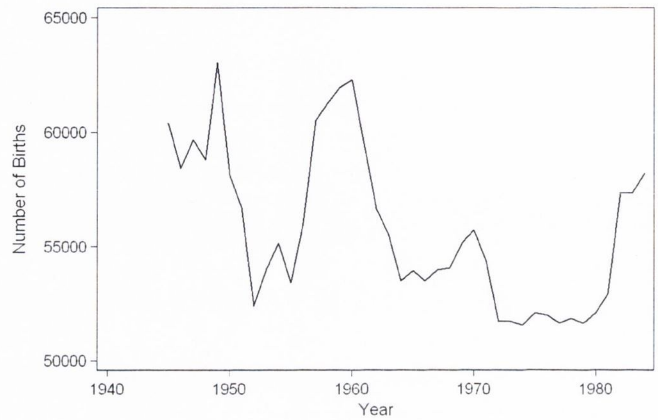

Figure 2.6: Number of births per year in Lithuania

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

The Lithuanian Statistical Office provides data on the total number of births per year from 1928 to 2010, excluding the years of the Second World war (1939-1945). Figure 2.6 shows the number of births per year from 1945 to 1984, the years in which most workers in the sample were born. As we can see there is a large variation in the number of births over time, which can potentially be exploited in the IV regressions. The data in this time series are annual, while the observations in the sample are skill groups that consist of 10 subsequent age cohorts, so that the question arises, which measure predicts the number of workers of a skill group today most accurately. There are three candidates: 1) the total number of births, 2) the average number of births and 3) the median number of births per skill group. Take as an example the skill group *upper secondary education, 0-10 years of work experience* in the HBS of 2002. This skill group consists of 11 birth cohorts, born between 1974 and 1984. The total number of births is the sum over all the people born between 1974 and 1984, the average number of births is the average in this time span and the median number of births is the corresponding median. Taking the average, the sum or the median of the number of births ensures sufficient variation in the calculated size of the birth cohort, since the time spans of the birth years of any two skill groups is different and so is the size of their birth cohort. As an example, consider workers with a work experience of 0-10 years in the HBS of 2002. Their birth years differ depending on their education. Workers with 0-10 years of work experience and a lower secondary education were born between 1976 and 1986, whereas those with a third-level degree were born five years earlier, between 1971 and 1981. Consequently, despite the same level of work experience, the cohort sizes of these two groups differ.

The choice of the instrument depends on its statistical power, i.e. on the correlation of the instrument with the endogenous regressor. As it turns out in the first-stage regressions, the total number and the average number of births are only weakly correlated with labor supply, so that they cannot be used as instruments.[22] The F-Statistic of the median number of births is 16.085, which is a sufficiently high correlation of the instrument with the endogenous regressor. The reason for the weak correlation of the first two instruments is their sensitivity to outliers in the number of births. As we can see in Figure 2.6, 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. The median is not sensitive to these jumps, so that it is a better predictor for labor supply.

Table 2.3 reports the estimation results for σ_{EXP}. All regressions are weighted with sampling weights.[23] I report the OLS results for comparison but as previously explained, they are not reliable because of simultaneity bias. The IV estimates lie consistently around -0.63, which implies a σ_{EXP} of 1.58.

The econometric analysis may give rise to 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. As there are only 12 clusters, however, the asymptotic properties of the clustered standard errors can be problematic (Angrist & Pischke, 2009). All standard errors in Table 2.3 are therefore reported without clustering. Once standard errors are clustered, the error in Column 2) increases to 0.18 and in Column 3) to 0.33). The F-Statistic of the instrument decreases to 8 in Column 2) and to 1.6 in Column 3).[24] The small changes in standard errors indicate that serial correlation is not a problem in this case.

Another problem is the small number of observations. With 4 available survey rounds and 12 skill groups, the results are based on 48 observations. Note, however, that the coefficients in Table 2.3 Columns 2) and 3) are precisely estimated, nevertheless, 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

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

[23]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.

[24]Regression outputs available on request.

Table 2.3: Regression results for σ_{EXP}

Dependent variable: log real wage

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

Note: The table shows the estimation results for the elasticity of substitution between workers of different experience groups, σ_{EXP} (Equation 2.5), which is computed as the negative inverse of the coefficients. Robust standard errors in brackets. Significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Controls: δ_t: year dummies, δ_{it}: interaction year*education, δ_{ij} interaction education*experience, δ_{jt}: interaction experience*time. σ_{EXP} is calculated as the negative inverse of the estimated coefficients.

as I will show, the results hold qualitatively — they have the same sign but the effects are smaller — if I use values from studies on other countries such as Germany and the UK.

The estimating equation (2.5) does not contain an interaction *time*experience*, which could bias the results if the relative productivity of an experience group changes over time. This could be an issue if there is a positive selection of emigrants within an experience group. If workers with better unobservable characteristics leave, the remaining workers are on average less productive. As column (3) in Table 2.3 shows, the point estimate does not differ substantially from the baseline. However, the instrument has less power due to the high degree of saturation.

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

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

A second reason lies in the history of the country. As Lithuania was part of the

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

2.5.2 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, which results 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}. Estimating σ_{ED}, or at least determining reasonable values for it, is not an end to itself, but σ_{ED} will enter the simulations of the migration wave on real wages. The importance of precise estimates depends therefore 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 2.2, the emigration rates are very similar across education groups, but they 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, for the simulations I use a very large ($\sigma_{ED} \to \infty$) and a very small value ($\sigma_{ED} = 1$), and demonstrate how the simulated wage changes differ accordingly. Second, to obtain some value for the baseline scenario, I estimate σ_{ED} based on the available data. The estimation equation for this parameter is derived in the same way as equation (2.5),

$$\log \bar{w}_{it} = \delta_t + \delta_{it} - \frac{1}{\sigma_{ED}} \log \bar{L}_{it} + \varepsilon, \tag{2.7}$$

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 (2.3).[25]

[25]The γ_{ij} are calculated from the coefficients of the δ_{ij} in equation (2.3) with $ij = 11$ as the base category,

In theory, σ_{ED} can be identified from equation (2.7). However, due 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 2.4: OLS results for σ_{ED}

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

Note: The table shows the estimation results for the elasticity of substitution between workers of different education groups, σ_{ED} (Equation 2.7), 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 2.4 shows the results of the OLS regressions. Surprisingly, in the first 3 specifications, the coefficients are highly significant. Only when δ_{ij} is approximated by linear time trends, the model is fully saturated and the coefficient becomes insignificant. Yet, despite the statistical significance, the asymptotic properties of the OLS estimator are violated due to the small number of observations. Moreover, the estimation suffers from a simultaneity bias, which could only be mitigated by an instrumental variable. Therefore, one has to be cautious in taking the results in Table 2.4 as clearly identified estimates. But despite these obvious problems, the coefficients are of a similar magnitude as 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. For the baseline simulations to follow I will use the point estimate of $\sigma_{ED} = 1.18$.

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

2.6 Simulation of the Wage Effects

2.6.1 Simulation Equation

In this section, I simulate the emigration shock that occurred after EU enlargement in this labor market and calculate the new equilibrium wage for each skill group. The calculated wage change is the difference between the equilibrium wages after and before the migration shock. The results of this simulation have a *ceteris paribus* interpretation. The fundamental structure of the labor market is held constant, so that the simulations yield the change in wages in absence of other adjustment channels. To obtain the simulation equation I differentiate equation (2.4)[26] and drop the time subscripts

$$\begin{aligned} \frac{\Delta w_{ij}}{w_{ij}} &= (1-\alpha)\frac{\Delta K}{K} - (1-\alpha)\frac{\Delta L}{L} + \frac{1}{\sigma_{ED}}\frac{\Delta L}{L} \\ &+ (\frac{1}{\sigma_{EXP}} - \frac{1}{\sigma_{ED}})\frac{\Delta L_i}{L_i} - \frac{1}{\sigma_{EXP}}\frac{\Delta L_{ij}}{L_{ij}}. \end{aligned} \tag{2.8}$$

Expressions L_t and L_{it} in equation (2.8) are labor aggregates and can as such be expressed in terms of L_{ijt}.[27] The Δs measure the change in a variable from 2002 to 2006.

2.6.2 Model Calibration and Simulation Results

Figure 2.7 displays the simulated wage changes for the baseline scenario. A general pattern emerges: emigration caused an increase in the wages of young workers, while the wages of old workers decreased. Young workers gained between 4.9% and 7% from emigration. For workers with a work experience between 10 and 30 years the model predicts wage changes close to zero. Old workers with more than 30 years of work experience lost around 1% from emigration.

These results suggest that emigration had a significant impact on the wage distribution between old and young workers. Because of the emigration wave after 2004, the youngest cohort became significantly smaller and this change in the composition of the workforce changed the wage structure. As previously shown in Figure 2.3, the wage premium for older workers was reversed into a wage penalty between 2002 and

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

[27] 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.

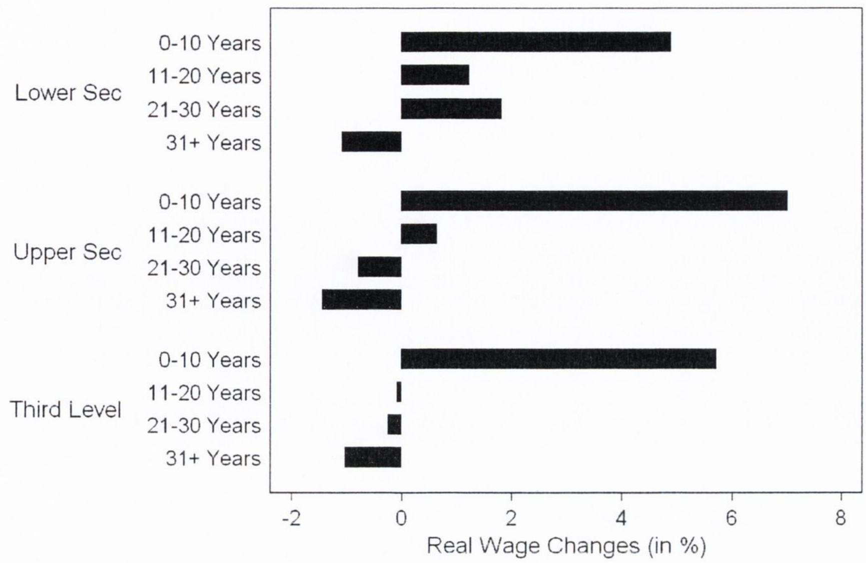

Figure 2.7: The impact of emigration on wages

Note: The figure displays the predicted wage changes, based on the simulation of the emigration wave after 2004 on the Lithuanian labor market. Parameters: $\alpha = 0.8$, $\sigma_{ED} = 1.18$. $\sigma_{EXP} = 1.58$. Labels on the y-axis denote education and work experience.

2006. Emigration cannot entirely account for these changes in the wage premium but the results give evidence that it played a significant role.

To account for the uncertainty in the estimates of the structural parameters I calculate the standard errors of the wage changes using Monte-Carlo simulations. The values of σ_{EXP} and σ_{ED} are drawn independently from a normal distribution, $\frac{1}{\sigma_{EXP}} \sim N(0.63, 0.17)$ and $\frac{1}{\sigma_{ED}} \sim N(0.85, 0.01)$.[28] The simulated standard errors reported in Table 2.3 are the average standard errors of 10000 replications. Comparing the calculated wage changes to the simulated standard errors, we can see that most wage changes are statistically significant at a significance level of 5% or lower. These simulated standard errors only take into account the uncertainty that arises from the estimation of the structural parameters. The additional uncertainty given by the assumptions about the number of migrants to the UK and the calculation of the labor aggregates are addressed in the robustness checks in Section 2.B.

Although most of the predicted wage changes are statistically significant, only the wage changes for young workers are of economic significance. This can be seen when we compare the simulated wage changes caused by migration with the total wages

[28]Note that I take the inverse of the parameters, because these are the results of the IV regressions in Section 2.5.1.

Table 2.5: Decomposition of the wage effect of emigration

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

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

changes for Lithuanian workers between 2002 and 2006 in Figure 2.2. The wages of all groups increased by between 20% and 80%, so that emigration can explain between 10% and 30% of the wage changes of young workers, but the wage changes of workers with a work experience higher than 10 years are driven solely by other factors, such as domestic and foreign investment or productivity growth.

After noting that the predicted wage changes differ considerably between young and old workers, the question arises which factors drive these results *within the model.* Due to the nested structure of the production function, there is a variety of channels through which a labor supply shock can affect wages. The total wage effect in equation (2.8) can be decomposed into four effects, which are shown in Table 2.5. The first effect is referred to in the literature as the partial effect of migration on wages. The effects 2, 3 and 4 are general equilibrium effects that reflect the re-adjustment of the labor demand for different skill groups following changes in labor supply.

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

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

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

4. **Aggregate Production Effect** $-(1-\alpha)\frac{\Delta L}{L}$. This effect is a direct consequence of the functional form of the aggregate production function. In a Cobb-Douglas production function, a decrease in aggregate labor leads to an increase in output per worker, because output decreases by less than aggregate labor. If capital were to adjust fully, this effect would disappear and the predicted wage changes would be about 1% lower.

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

2.6.3 Alternative Calibrations for σ_{EXP} and σ_{ED}

To assess the sensitivity of the simulated wage changes to changes in the estimated parameters σ_{EXP} and σ_{ED}, I present the results for a range of values. In addition, I calibrate the model on parameters from the literature.

Columns (2) and (3) in Table 2.6 show the simulation results for small and large values of σ_{ED}: $\sigma_{ED} = 1$ (Cobb-Douglas case) and for $\sigma_{ED} = \infty$, in which case any two education groups are perfect substitutes. As migration only affected the age composition of the workforce, but not the educational composition, the predicted wage changes only vary mildly with the variation in σ_{ED}.

Table 2.6 compares the baseline results with the results when the model is calibrated on parameters from the literature. As the labor demand curves in Lithuania are steeper, the first-order effects, i.e. the direct impact of a labor supply shift of a skill group on the wage of the same group, are greater with the parameter estimated for the Lithuanian labor market. On the other hand, the fact that σ_{ED} found here is smaller than the one in the literature means that the higher-order effects, i.e. the effects of the labor supply shifts of workers from one skill group on the wages of another skill group, are smaller in the Lithuanian case. Consequently, the negative wage effects I find for workers with more than 30 years of work experience disappear when calibrating the model on parameters from other studies. Despite the different magnitude in the wage changes, the main result of this study is robust to these parameter specifications.

2.6.4 Comparison of the Structural Estimates with Reduced-Form Results

It is important to note at this point that this study does not aim to explain the change in real wages in its entirety. Its aim is to back out the share of the wage changes that can be attributed to emigration. This interpretation, identifying a causal effect after controlling for all other explanatory variables, is the same as for a reduced-form approach. To assess the quality of model predictions, one has to compare the predicted wage changes from both approaches. The upper graph in Figure 2.8 compares the predicted wage changes from the structural model in this study to the estimates in Elsner (2010). The latter are positive for every skill group, since the reduced form does not take into account the complementarity effects. Once the general equilibrium effects are excluded from the structural estimates, it turns out that the predictions of both approaches are almost identical, as can be seen in the bottom graph of Figure 2.8.

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

Table 2.6: Sensitivity analysis

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

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

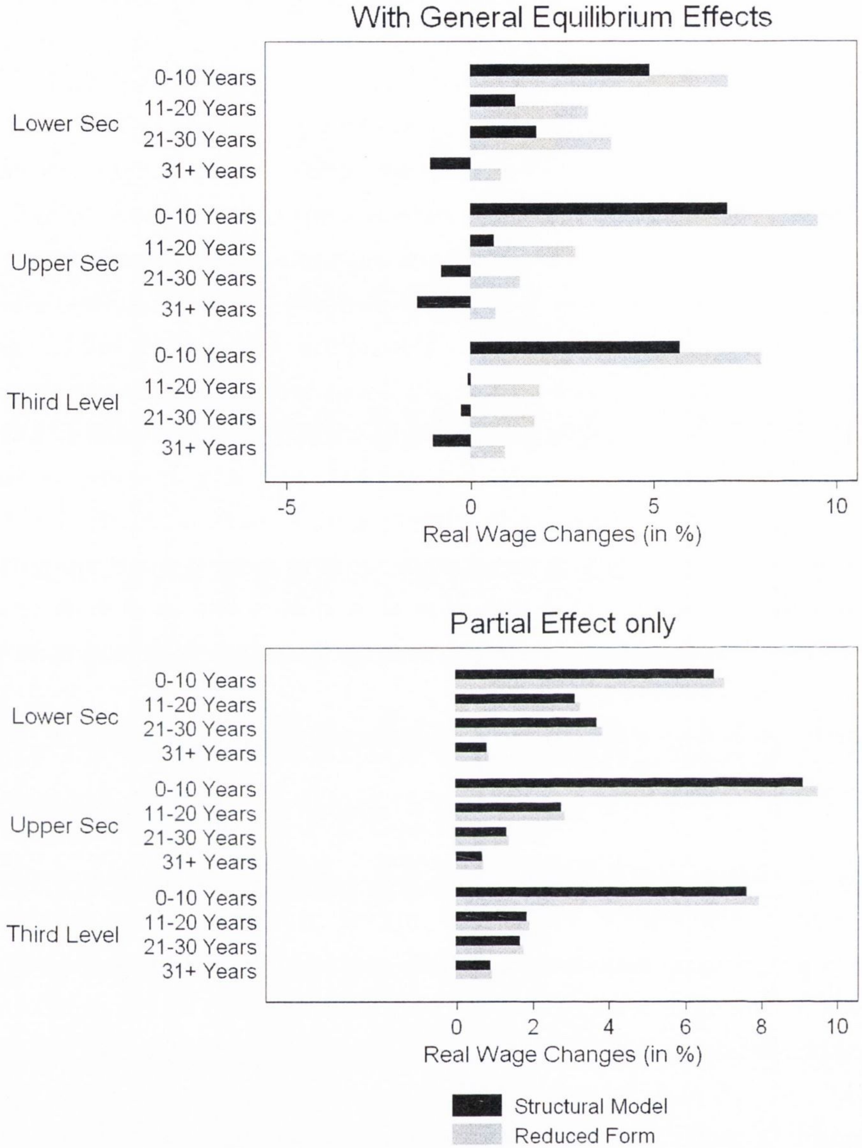

Figure 2.8: Comparison: structural model vs. reduced form

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

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

The structural model offers insights in the channels through which emigration affects the wages of stayers, but it does so at the cost of the reliance on a number of assumptions. The neoclassical demand framework presented in Section 2.3 is based on the assumption that labor markets clear and thus assumes away unemployment and wage rigidities. These factors could nevertheless play a role in the determination of wages, which would mean that the magnitude of the wage effects resulting from the simulations could be inaccurate. In fact, looking at Table 2.1d, we can see that the unemployment rate decreased substantially from 13.8% in 2002 to 5.6% in 2006, which means that labor markets became tighter over the considered period. Given the absence of information on the unemployment rate by skill group in the data, it is not possible to incorporate unemployment into the simulations. However, in the reduced-form approach Elsner (2010) controls for unemployment at the regional level and finds very similar results as in the structural model in this study. This indicates that unemployment does not alter the magnitude of the wage effect of emigration.

2.6.5 Discussion of the Results

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

One explanation why young workers gain from the possibility of emigration is the increase in bargaining power. In 2004 workers in Central and Eastern Europe were granted the possibility to emigrate at a very small cost. For stayers this means that they should be able to negotiate higher wages under the threat of emigration. Before 2004 this threat was empty due to the high emigration costs. The gain in bargaining power was lower for older workers, since they have higher moving costs and their prospects of finding work in Ireland in the UK are considerably lower than for young workers. Moreover, because of the large number of young emigrants the labor market for young workers became tighter, which means that the same number of firms competes for fewer workers. If the labor markets for old and young workers are very different from each other, a positive wage effect should be visible among young workers but not among old workers. The finding in Section 2.5 that young and old workers are less substitutable in Lithuania than in the US or Germany confirms this hypothesis.

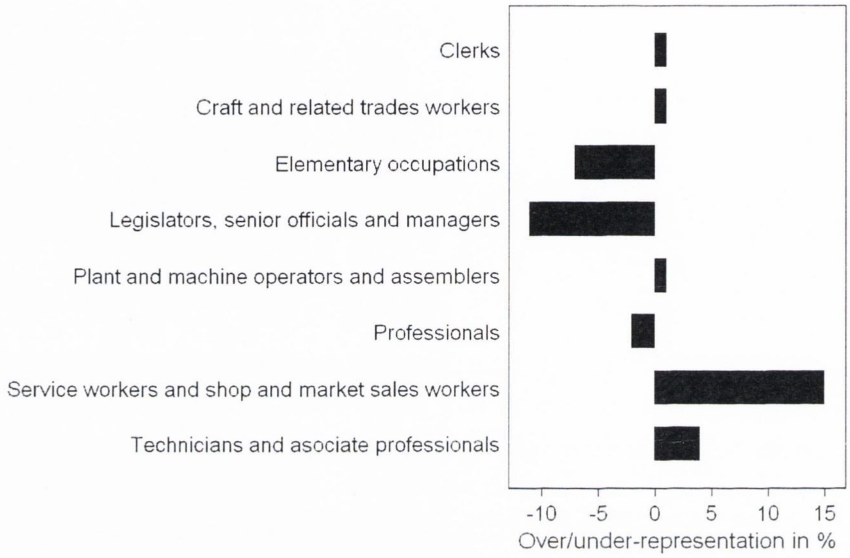

Figure 2.9: Over-/under-representation of workers aged 14-34 by occupation

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

Another explanation could be the sectoral distribution of workers. If young workers tend to work in sectors with a high flexibility of work contracts and a high fluctuation of employees, they are more likely to switch to a better-paid job once emigration leads to labor shortages in the sector. This possibility should be more likely in the service sector, which in Lithuania only evolved in the last 15-20 years, and less likely in the manufacturing sector or in agriculture. If young workers are concentrated in the service sector, they should see higher wage increases. The same logic also applies to occupations. If young workers tend to choose occupations in which it is possible to switch easily to a better-paid job, the wages of young workers should increase. Figure 2.9 gives evidence for the concentration of young workers in certain groups of occupations. Workers aged 35 and less are over-represented in among service workers and technicians, while older workers are more concentrated among *legislators, senior officials and managers* and *elementary occupations*, which includes agriculture. These occupations tend to have a higher wage rigidity than occupations related to services, so that the sectoral and occupational composition within an age group could explain part of the wage changes for young workers.

2.7 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. Emigration caused an increase in wages on average, but 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-skilled 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 consisted mostly 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, which restrict 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 the receiving countries. The "EU enlargement experiment" is a rare example for the lifting of migration restrictions. It shows that workers in middle-income countries respond to the opening of labor markets in high-income countries. Between 6 and 9% of the workforce of Latvia, Lithuania, Poland and Slovakia emigrated to the UK and Ireland. Moreover, the most mobile workers have higher emigration rates. Young workers are typically more mobile and have lower moving costs than old workers. In this light, it is not surprising 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; they face a large wage differential and have a well-educated and highly mobile workforce. Other examples are EU candidates like Croatia, Serbia, or Turkey, which might see a similar outflow of workers as countries that joined the EU in 2004.

The impact of migration on wages estimated here is larger than in most studies on the receiving countries (Borjas, 2003; Ottaviano & Peri, 2011; Manacorda *et al.*, 2011). Yet, the true winners of migration are, in fact, the migrants themselves, who can on average earn 2.5 times as much in the UK than in Eastern Europe.

Table 2.7: Regression results for σ_{EXP} - men only

Dependent variable: log real wage

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

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

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

The baseline estimation in Section 2.5.1 assigns the same level of work experience to men and women with the same age and education. This method can potentially lead to miscalculations for the work experience of women, who might have less actual work experience due to maternity leave. If this miscalculation was important, the results of the same regressions using data on men only would have to differ fundamentally from those with men and women. As we can see in Table 2.7, the results are different when using data on men only, but not fundamentally. For 10-year experience groups the estimated slope is slightly lower than in Table 2.3, 20-year it is the same. In all cases the instruments are weaker than in the specification with men and women, so that the results in Table 2.3 are more accurately estimated.

2.B Sensitivity Analysis

The simulations in Section 2.6 were based on a number of assumptions about the structural parameters and the number of emigrants per skill group. In this section I check the robustness of the simulation results to changes in these assumptions.

In addition, I re-run the simulations using parameter values from the literature.

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

2.B.1 Irish Data only

The calculation of the number of emigrants per skill group was based on the assumption that the distribution of Lithuanian migrants in Ireland is the same as in the UK. I based this assumption on previous studies, 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 2.6 with Irish data only. Column (2) in Table 2.6 shows the simulated wage changes based on Irish data only. Compared to the baseline scenario, the magnitude of the wage effects is significantly lower, but the pattern prevails: young workers gain from emigration, while old workers lose. As the emigration rates taken from the Irish census data reflect a lower bound to emigration from Lithuania, the true wage effects from emigration will be at least as large as those based on simulations with Irish data only.

2.C Tables and Figures

Table 2.8: Aggregation of education groups in the Lithuanian HBS and the Irish census

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

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

Part III

Networks and Migration Decisions

Chapter 3

Migrant Networks and the Spread of Misinformation

I developed this chapter from joint work with Gaia Narciso (TCD) and Jacco Thijssen (U York). I presented this work at the 8th ISNE conference (Dublin 2011), the 2nd TEMPO conference (Vienna 2011), the Annual Conference of the Irish Economic Association (Dublin 2012), the Econometric Society European Meeting (Málaga 2012) and the TCD Micro Working Group. We are grateful to Joanna Clifton-Sprigg, Christian Danne, Julia Matz, and Imran Rasul for helpful comments. We would also like to thank TCHPC for granting us access to a high-performance cluster.

3.1 Introduction

Prior to moving abroad, migrants face significant uncertainty about their job prospects. To assess their chances of getting a good job after emigration, migrants often seek advice from diaspora networks. But not all networks have the same knowledge about the labor market in the destination country; some networks are able to provide more accurate information than others.

In this paper we study the impact of existing diaspora networks on the success of future migrants and on the timing of their migration decisions. We argue that migrant communities that are well-integrated in the society of the host country have a greater knowledge of the labor market than ethnic enclaves, whose members typically have few interactions with the host society. Migrants with access to a well-integrated network receive more accurate information and are more likely to make the right decision; they migrate if they can expect to get a good job, and they stay if they can expect a job that makes them worse off.

We first explore the link between the information flows and the success of migrants in a 2-period decision model. Initially the migrant has some knowledge about his job prospects abroad, but not enough to convince him that he will be better off abroad. He then receives information from the network and updates his beliefs of getting a good job. The more integrated the network, the lower the degree of misinformation, and the more likely the migrant is to make the right decision.

To study the effect of networks on the timing of migration, we develop a dynamic decision model in which the migrant receives in every period a signal from the network, and faces the trade-off between migrating now under greater uncertainty, and postponing the migration decision and obtaining more information from the network. With every signal he updates his beliefs, and learns over time about his true odds of getting a good job abroad. He emigrates once he has enough evidence that migration is beneficial. This threshold is reached earlier by migrants with access to a more integrated network, as every signal contains more accurate information.

In a next step we test the theoretical predictions using data on Mexican immigrants in the US. Mexicans have had a long tradition of emigrating to the US, but their settlement patterns have changed over time. Until the 1980s most Mexicans were concentrated in a few US states, while new arrivals since the 1990s have moved to a large number of places, which means that we can exploit a significant variation in the size and skill composition of Mexican communities across the US.

Key to the empirical analysis is finding proxy variables for the quality of the network and for the success of immigrants. For the quality of the network we propose two measures: the share of high-skilled Mexicans in an area, and the degree of assimilation of Mexicans — as measured by the similarity of Mexicans and Americans in an area. To obtain a measure for the success of immigrants, we take the difference between a counterfactual income in Mexico and the actual income in the US. The more negative this measure, the more successful is the migrant.

The results confirm our hypothesis that networks affect the likelihood of making the right decision. An increase in the degree of assimilation by 10 percentage points predicts a decrease in the chances of being better off in Mexico compared to the US by 1%. This relation is robust to controls for personal characteristics, the size of the network, and employment growth. Furthermore, the results are robust to the inclusion of state fixed effects, which indicates that they are not driven by fundamental differences in job prospects between states. We also test the second hypothesis, but find no significant relation between the quality of the network and the age at immigration.

This paper contributes to four strands of the literature. First, it adds a new perspective to the literature on network effects in international migration. In large parts, the literature defines a network as the number of previous migrants in a given destination. One strand of this literature documents that migration is path-dependent; new migrants move to places where they find an established community from their home countries (Pedersen *et al.*, 2008; Beine *et al.*, 2010). Other papers argue that larger networks are associated with a negative selection of migrants. Larger networks decrease the moving costs, so that migration becomes profitable even for less-skilled workers (Carrington *et al.*, 1996; Winters *et al.*, 2001; Munshi, 2003; McKenzie & Rapoport, 2010; Beine *et al.*, 2011). As shown by Umblijs (2012), larger networks attract more risk averse migrants, while risk-loving migrants tend to move to smaller networks. This paper, by contrast, focuses on the *quality* of migrant networks as a driver of migration flows. The empirical results show that, in addition to the size of the network, its quality has an impact on the success of migrants.

Second, it adds to a small but growing literature on the role of the migrants' information on their decision to migrate. McKenzie *et al.* (2007) show that migrants have false beliefs about their employment and earnings prospects abroad. Based on a survey of Tongan migrants in New Zealand they show that prior to migration workers under-estimate both the chances of getting a job and the earnings possibilities. One explanation they offer is that migrant networks deliberately report lower earnings to their families at home to mitigate the pressure to send remittances. Another important source of information is media. Farré & Fasani (2011) show for Indonesia that access to cable TV significantly lowers internal migration, because workers have more information about their potential destinations. Our paper, by contrast, shows that information not only shapes expectations and influences the decision to migrate, it also has an impact on the success of migrants.

Third, the paper also contributes to the literature on the impact of ethnic enclaves on the labour market outcomes of immigrants. Borjas (1995) shows that enclaves create human capital externalities that persist over generations. Children in ethnic enclaves grow up in the same closed-up environment, which leads to a persistence in skill differentials compared to people outside the enclave. Yet enclaves can also have a positive impact on the labor market outcomes of immigrants. Edin *et al.* (2003) find a large positive effect of ethnic concentration on the earnings of low-skilled immigrants in Sweden. As Andersson *et al.* (2009) show, the concentration of immigrants also increases the likelihood of getting a job for new immigrants. While these papers document the impact of networks on the outcomes of immigrants that have already emigrated, our paper shows that networks can even have an impact on migration decisions *before* emigration. Not only do migrant networks provide help in finding a job once a migrant has arrived, they also provide information to potential migrants in their home country.

Finally, the paper relates to the literature on the optimal timing of migration. This strand of the literature began with Burda (1995), who shows in a real options model that increased uncertainty about job prospects can lead to considerable delays in the migration decision. Moretto & Vergalli (2008) and Vergalli (2008) show in a similar framework that the timing of migration can be driven by networks that facilitate the integration abroad. Our dynamic decision framework builds on a similar methodology, but we explicitly model the relation between networks, information flows and the migration decision, which allows us to compare the success and the optimal time to migrate for networks with different degrees of integration.

The remainder of the paper is structured as follows. In Section 3.2 we motivate and extend our argument that more integrated networks provide more accurate information. We then illustrate the basic intuition in a simple decision model in Section 3.3.1. In Section 3.3.2 we generalize the findings from the simple model in a multi-period setting and present numerical examples. In Section 3.4 we test the theoretical predictions using data on Mexican migrants in the US. Section 3.5 concludes.

3.2 Migrant Networks as Providers of Information

Our basic argument is simple: migrant communities that are more integrated in the society of their host country are able to give better information to future migrants. Members of a more integrated community have a better knowledge of the labor market and can give future migrants more accurate information about job prospects. Two examples for networks with different degrees of integration are illustrated in Figure 3.1.

The figure on the left describes an ethnic enclave. Its members, represented by the

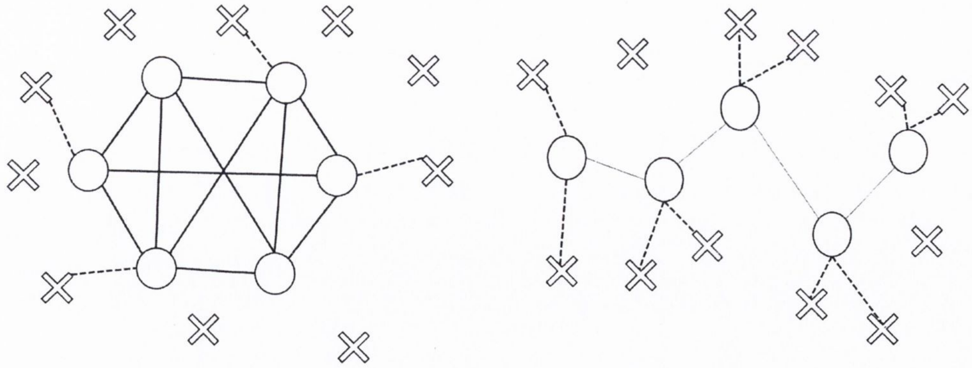

Figure 3.1: Ethnic enclave (left) and loosely connected network (right)

Note: These two panels depict models of migrant networks. The circles represent the migrant network; the crosses represent information sources outside the network, i.e. native people or the media. The network on the left is an ethnic enclave, with strong connections within the network but weak connections to the outside world. The network on the right is a loosely connected migrant network, with strong connections to the outside world and weak connections within the network.

circles, have close connections within the network, but very few connections to the outside world, represented by the crosses. Examples for such networks are Mexican neighbourhoods in Los Angeles or Chinatowns in most North American cities. The graph on the right represents a well-integrated network, whose members have weak connections among each other but strong connections to the outside world. Examples for such groups are the Germans in London or the Dutch in New York.

There are two reasons why a potential migrant receives better information from a well-integrated network than from an enclave. First, the well-integrated network has more connections to the outside world. Its members receive more information and therefore have better knowledge about job perspectives in the receiving country. In contrast to this, members of an enclave typically have little knowledge of the language of the host country (Lazear, 1999; Bauer *et al.*, 2005; Beckhusen *et al.*, 2012). An enclave may offer job opportunities within the migrant community, but it has very limited information on the labor market outside the enclave. Second, members of the well-integrated network only have weak ties among each other, so that misinformation — false beliefs about the world outside the network — is unlikely to persist. The members of an enclave, on the other hand, deal mostly with other members of the enclave. As shown by Acemoglu *et al.* (2010) and Bikchandani *et al.* (1992), misinformation is more likely to persist in such closely connected communities, as their members receive most of their information from each other.

To be certain, the two network formations in Figure 3.1 are polar cases that illustrate the differences between migrant networks, while in reality most networks will lie somewhere in between.

3.3 A Theoretical Model of Misinformation and the Decision to Migrate

Having established that migrant networks differ in their ability to provide accurate information to future migrants, we now explain how the quality of information affects the outcome and timing of the migration decision. We first develop a two-period decision model and show that a migrant with access to a better network makes less mistakes in his migration decision. In Section 3.3.2 we extend the model to an infinite-horizon setting to study how networks affect the timing of migration.

3.3.1 Intuition from a Simple Model

We focus on the decision of a single worker, which allows us to isolate the effect of a large network on one migrant from feedback effects that may arise if a whole group of people emigrates.[1] We also assume that networks already exist and that their quality is constant over time.

Consider a potential migrant whose job at home that gives a lifetime income of $\underline{w} = 0$. If he moves abroad he can either get a good job that pays him a discounted lifetime income of $w^G > 0$ or a bad job that pays $w^B < 0$. Before he emigrates it is uncertain which job he will actually get. If he migrates, he has to pay a sunk moving cost M. We assume that $w^G > M$; otherwise migration would never be beneficial. For simplicity, we assume that he is risk-neutral. He migrates if his expected income from migration minus the moving costs is greater than his income at home,

$$\mathbb{E}(U(k)) = p(k)w^G + (1 - p(k))w^B - M \geq 0, \tag{3.1}$$

where $p(k)$ is the belief probability — the belief that he gets a good job abroad — which depends on his level of information k. Initially, his best guess is a commonly known probability p_0. For example, p_0 could be the fraction of previous migrants that got a good job. If he receives information from the network he will learn more about his actual odds of getting a good job, so that his best guess changes from p_0 to some other $p(k)$.

In the first period t=1 he can decide whether to emigrate or stay. If he stays, he earns his wage at home, and he obtains additional information from the network in the second period. The signals from the network can be of two types,

[1] See Epstein (2010) for a model of informational cascades within a group of migrants.

g: he will get a good job after migration
b: he will get a bad job after migration.

A positive signal g brings him to information set $2A$, at which he knows that he has received a positive signal, but he does not know whether he is at the upper node — and he actually gets a good job — or at the lower node. A negative signal b brings him to the information set $2B$. Based on the signal he updates his beliefs from p_0 to $p(k)$, with

$$k = \begin{cases} 1 & \text{if he receives a positive signal } g \\ -1 & \text{if he receives a negative signal } b \end{cases}$$

A positive signal increases his belief probability, while a negative signal decreases it, so that $p(1) > p_0 > p(-1)$.

The signal is truthful with probability λ. If he gets a good job abroad, then the signal is positive with probability λ and negative with probability $1 - \lambda$. The opposite holds if he gets a bad job; he receives a negative signal with probability λ and a positive signal with probability $1 - \lambda$. Following our argument from Section 3.2, a network with more knowledge about the labor market sends a more truthful signal and spreads less misinformation. As it is unrealistic that a network has perfect knowledge and completely eliminates the migrant's uncertainty, we assume that $\lambda < 1$. At the same time, λ has to be greater than $\frac{1}{2}$ for the signal to convey a minimum level of truthfulness.[2]

Figure 3.2 illustrates the worker's decision problem. We assume that only $p(1)$ fulfills Equation (3.1), so that the worker only migrates if he has received a positive signal. In the second period only two actions lead to correct decisions. In the upper node of information set $2A$ he has received a positive signal, in which case he migrates and gets a good job; in the lower node of information set $2B$, he has received a negative signal, so he stays while he would get a bad job if he emigrated. The remaining two actions lead to a wrong decision — a decision that makes him worse-off than he would otherwise be. In the lower node of $2A$ he migrates despite getting a bad job abroad, while in the upper node of $2B$ he stays although he could gain from migration. Table 3.1 summarizes the probability distribution for the terminal nodes on the decision tree. Clearly, the probability of making the wrong decision (rows 2 and 3 in Table 3.1) decreases with the signal quality λ. The higher λ, the lower is the spread of misinformation.

Proposition 1 *A potential migrant with access to a better network is less likely to make errors in his decision to migrate. He is more likely to stay when his prospects abroad are bad and more*

[2]Otherwise, the signal would either be completely noisy ($\lambda = \frac{1}{2}$) or it would indicate the opposite of the true state of the world ($\lambda < \frac{1}{2}$).

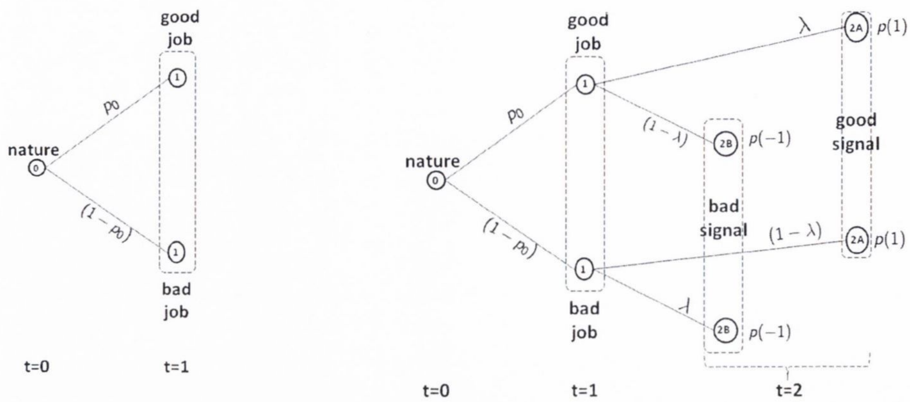

Figure 3.2: Decision tree for a potential migrant: First stage (left), second stage(right)

Note: Decision tree with 2 stages. The panel on the left shows the first stage only, the panel on the right shows both first and second stage. In the first stage the migrant only knows the a-priori odds of getting a good job, p_0. In the second stage he receives a signal from the network which is truthful with probability λ. He migrates if the signal is positive and he stays if the signal is negative.

Table 3.1: Probability distribution of terminal nodes

	Job	Signal	Action	Probability	Decision
1)	Good	Positive	Migrate	$p_0\lambda$	correct
2)	Good	Negative	Stay	$p_0(1-\lambda)$	*wrong*
3)	Bad	Positive	Migrate	$(1-p_0)(1-\lambda)$	*wrong*
4)	Bad	Negative	Stay	$(1-p_0)\lambda$	correct

likely to migrate if his prospects abroad are good.

The person only emigrates if he has enough evidence that emigration is beneficial — that is, if the number of positive signals k is at least as great as some threshold value, $k > k^*$. For simplicity we have assumed so far that one positive signal is sufficient. The result from Proposition 1, however, does not hinge on this assumption. [3]

3.3.2 Networks and the Timing of Migration

Next, we extend the simple model to a multi-period model in discrete time, which allows us to study the effect of the quality of the network on the timing of migration.[4]

[3]It is possible to extend the model from two periods to an infinite horizon, and to express the threshold k^* as a function of wages, moving costs, the discount factor, and the prior probability. As shown by Thijssen *et al.* (2004), Proposition 1 still holds in such a more general setting.

[4]The general framework in this section follows Thijssen *et al.* (2004) and Delaney & Thijssen (2011).

The setting is the same as in the 2-period model. The migrant receives a signal from the network in every period and learns over time about his true job prospects. In every period he faces a trade-off between migrating now and waiting for the next signal. He has to weigh the cost of uncertainty today against the opportunity cost of waiting for the next signal. If he migrated today he could reap the potential benefits of migration immediately, but he would also face a higher uncertainty. If he waits one more period he learns more about his prospects, but he can only benefit from migration in the next period. We model this trade-off as an optimal stopping problem, in which the potential migrant accumulates information and postpones the migration decision until he has sufficient evidence that he will get a good job. The sufficient amount of information depends on several parameters: the wages for good and bad jobs, moving costs, the discount factor, and the prior probability of obtaining a good job.

The number of good signals $g(t)$ evolves according to the law of motion $dg(t) = udt$, with $g(0) = 0$ and

$$u = \begin{cases} 1 & \text{with probability } \lambda \text{ if } w^G \text{ and } (1-\lambda) \text{ if } w^B \\ 0 & \text{with probability } \lambda \text{ if } w^B \text{ and } (1-\lambda) \text{ if } w^G \end{cases}$$

Initially the potential migrant has a prior belief p_0. With every signal he learns more about his prospects and updates his beliefs by making a best guess given the available information. If he has received n signals in total, of which g were good, his belief probability according to Bayes' rule is,

$$\begin{aligned} p(n,g) &= \frac{\mathbb{P}(n,g|G)\mathbb{P}(G)}{\mathbb{P}(n,g|G)\mathbb{P}(G) + \mathbb{P}(n,g|B)\mathbb{P}(B)} \\ &= \frac{\lambda^k}{\lambda^k + \frac{1-p_0}{p_0}(1-\lambda)^k} \equiv p(k), \end{aligned} \tag{3.2}$$

where $P(G) = p_0$ and $P(B) = 1 - p_0$ are the unconditional probabilities of getting a good or a bad job. We define $k := 2g - n$ is the excess number of good signals to bad signals.[5]

At a threshold k^* the expected gain from migration in Equation (3.1) equals zero, so that the worker is indifferent between migrating and staying. The corresponding belief probability is $p^* = p(k^*)$. If the number of signals and the belief probability exceed k^* and p^*, the migrant will have a higher expected income abroad and emigrates. If both values are below the threshold, the migrant is better-off waiting for the next signal. Starting at time $t = 0$ he will keep the option to migrate open until the number of

[5]He receives n signals, of which g are good and $n - g$ are bad. The difference between good and bad signals is $g - (n - g) = 2g - n$.

positive signals exceeds k^*. Solving Equation (3.2) for k and evaluating at $p^* = p(k^*)$, we obtain the threshold number of positive signals,

$$k^* = \frac{\log\left(\frac{p^*}{1-p^*}\right) + \log\left(\frac{1-p_0}{p_0}\right)}{\log\left(\frac{\lambda}{1-\lambda}\right)}. \tag{3.3}$$

The unique solution for k^* can be obtained from dynamic programming. Formally deriving the solution is mathematically demanding, as k^* depends on p^*, which in turn is a function of several parameters, $p^* = p(\lambda, r, w^G, w^B, M)$. To demonstrate the mechanics of the model we present a simple numerical example and refer the interested reader to the Appendix 3.A.1 for a formal derivation of k^* and p^*. We calibrate the model on the parameters listed in Table 3.2 and vary the quality of the network λ. After emigration the worker can either gain 20,000 or lose 10,000 compared to his job at home. The fixed moving costs are 10,000. He knows that on average 60% of all emigrants get a good job. The parameter values only serve illustrative purposes, but as we in the comparative statics below, the qualitative results hold for a wide range of parameters.

Table 3.2: Parameters for the simulations

w^G	20,000	gain in discounted life-time income after getting a good job
w^B	-10,000	loss in discounted life-time income after getting a bad job
M	10,000	sunk moving cost
p^0	0.6	unconditional probability of getting a good job
r	0.1	discount rate
λ	0.75	probability of a truthful signal

As we can see in Figure 3.3, a better network requires a lower number of positive signals. If the signal is truthful with a probability of 55% he requires 4 positive signals in excess of negative signals, while he only requires 2 positive signals if the signal is truthful with 95%. This leads us to the following proposition:

Proposition 2 *A potential migrant who receives signals from a high quality network emigrates earlier.*

Signals with a higher quality reduce the uncertainty more than low-quality signals. A migrant with access to a good network requires a lower number of positive signals to have sufficient evidence that emigration is beneficial.

Figure 3.4 shows how the threshold number of positive signals is related to other parameters. Changes in wages for good and bad jobs, w^G and w^B, as well as the moving costs M work through the expected income channel. An increase in the gains from

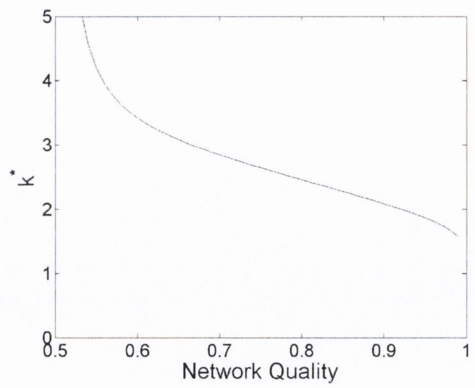

Figure 3.3: Comparative statics: change in the network quality λ.

Notes: The threshold belief probability p^* increases with the network quality λ. With a higher network quality a potential migrant demands more certainty about his prospects. Right: the threshold number of positive signals k^* decreases with the network quality λ. A better network reduces the uncertainty of migration and the potential migrant requires less positive information to emigrate.

a good job, a decrease in the losses from a bad job, or a decrease in the moving costs increase the expected gains from emigration, so that a lower number of positive signals is sufficient. The negative relation between k^* and the discount rate r is intuitive. A low discount factor puts more weight on income in the future and leads to low opportunity costs of waiting, in which case a worker needs many positive signals to convince him to migrate early. Finally, k^* decreases in the prior probability p_0. If a worker knows that the majority of migrants get a good job, he does not require many positive signals to be convinced.

From the model we hypothesise that the higher the probability of misinformation, the later a potential emigrant migrates.

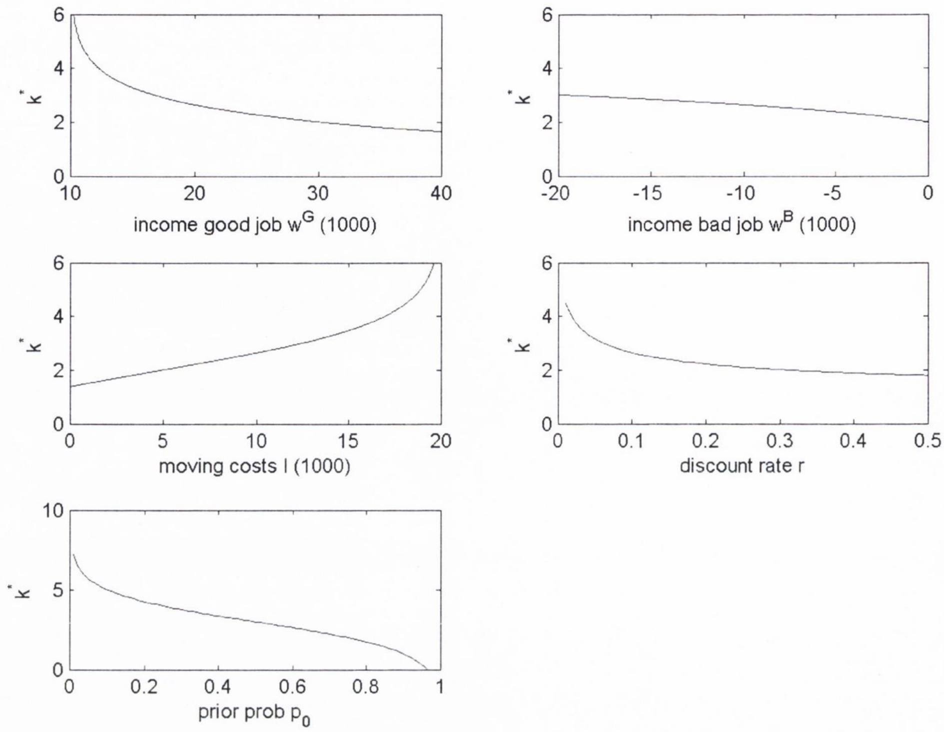

Figure 3.4: Comparative statics: variation in the model parameters

Notes: The graphs show the changes in the threshold number of positive signals k^* subject to a change in the key parameters. In each graph, the other parameters are held constant at the values stated in Table 3.2.

3.4 Empirical Investigation

We now turn to the empirical test of the theoretical predictions. The aim of this exercise is to present empirical patterns that are consistent with the theoretical predictions, and to explore the channels through which networks affect migration decisions. While previous literature concentrates on the size of the network as the main driver of migration flows, we want to see if other network characteristics have an impact on the migration outcome.

3.4.1 Empirical Strategy

The testable hypotheses are that migrants with access to a better network 1) are less likely to migrate if they actually get a bad job abroad, 2) are less likely to stay if they would get a good job abroad, 3) they migrate earlier, given migration is beneficial for them. Empirically, they translate into

1. $P(\text{emigrate}|\text{bad job}) = f(\text{network quality, controls})$

2. $P(\text{stay}|\text{good job}) = f(\text{network quality, controls})$

3. Age at immigration $= f(\text{network quality, controls})$.

The error probabilities $P(\text{emigrate}|\text{bad job})$ and $P(\text{stay}|\text{good job})$, and the timing of migration are a function of the network characteristics as well as control variables such as education, age, or gender. Guided by our theory, we expect a negative sign for the network variables in all three equations.

To test the first and third hypotheses we require data on actual migrants, which can be obtained from the receiving countries. The second hypothesis is more difficult to test, as it requires information on workers that stay at home but that would actually gain from migration. In most poor and middle-income countries there are millions of workers who would gain from migration, but only a fraction actually has the intention to emigrate. As it is hardly possible to spot the potential migrants in a source country, we only test the first and third hypotheses.

We use data on recent Mexican immigrants in the US, which offers several advantages over other available data. One advantage is that we can rely on a large number of observations. Mexicans represent a significant share of the entire US population; even in a 5% sample we have sufficient observations to produce statistically meaningful results. Another important feature of Mexican-US migration is the large degree of variation in Mexican communities across the US. Mexicans have had a long tradition of emigrating to the US, which led to well-established Mexican networks in many US cities. Yet the settlement pattern has changed in the 1990s. While until the 1980s most Mexicans went to California, Texas, and Chicago, many Mexicans in the 1990s settled in areas that had no significant Mexican community, such as Atlanta, Denver, Seattle, or Washington, D.C. (Card & Lewis, 2007). This gradual diffusion of Mexicans across the US means that we can exploit a significant degree of variation in networks and their characteristics across metropolitan areas and over time. A third advantage of Mexican data is that all immigrants come from the same country, which minimizes the impact of unobserved heterogeneity on our estimates. If instead we look at immigrants from many different countries, much of the variation in networks and the success of immigrants could be driven by unobservable characteristics of these countries. Admittedly, there may still be unobserved heterogeneity across Mexican regions, but its impact on our results should be smaller than a comparison across different countries.

3.4.2 Data and Descriptive Statistics

Data

The main dataset is the US census, which is conducted every 10 years and includes the entire population. We use the 1990 and 2000 public use 5% sample, drawn from IPUMS.[6] The 1990 and 2000 rounds have a large number of observations, which ensures that the sample is representative even if we restrict our analysis to a relatively small subpopulation – recent Mexican immigrants. Furthermore, a Mexican census is available for the same years, so that we can match the information from the US census with the wages in Mexico.

The US census is representative at the individual and the household level. It contains rich information on individual and household characteristics. Important for our analysis is information about the age at the time of immigration, birth place, current employment, education, and family situation.[7]

Among all the available datasets on Mexican-US migration, the US census is the most suitable for our study. Other Mexican-US datasets have information on networks, but they do not suit our analysis because of their sample size and representativeness.[8] To characterize the quality of Mexican networks across the United States, we require a dataset that is representative of the migrant stocks. The US census allows us to compute several proxies for the network quality in narrowly defined geographic units from 1980 until 2000, so that the success of recent migrants can be linked to network characteristics 10 or 20 years ago. A disadvantage of the census is that it has no information on the migrants' previous income in Mexico. Also, the census gives no direct information on the migrants' network of family and friends in the US, so that we have to proxy the network by the Mexicans living in the migrant's surroundings.

Ideally, we would like to directly observe the information flows between the net-

[6]Ipums: Steven Ruggles, J. Trent Alexander, Katie Genadek, Ronald Goeken, Matthew B. Schroeder, and Matthew Sobek. Integrated Public Use Microdata Series: Version 5.0 [Machine-readable database]. Minneapolis: University of Minnesota, 2010.

[7]The census includes both legal and illegal migrants, although it does not flag them as illegal migrants. Moreover, the census only includes people that stay in the US long-term; it does not include people that are on a tourist visa, or any other short-term visitors (Hanson, 2006).

[8]Other Mexican-US datasets have information on networks, but they do not suit our analysis because of their sample size and representativeness. The household surveys ENET (Encuesta Nacional de Empleo Trimestral), ENADID (Encuesta Nacional de la dinámica demográfica), and the Mexican Family Life Survey (MxFLS) are conducted in Mexico, and have little information on Mexicans that already reside in the US. The Mexican Migration Project (MMP), a survey of Mexican migrants that contains both migrants and non-migrants, has some information on family and friends in the US, and on the help of these networks in crossing the border and finding a job. Numerous studies use the MMP to analyze the effect of networks on migration decisions (Munshi, 2003; Bauer *et al.*, 2005; Amuedo-Dorantes & Mundra, 2007; McKenzie & Rapoport, 2007; Bauer *et al.*, 2007). The MMP is representative of migration flows to the US (Massey & Zenteno, 2000), but it is not representative of the stocks. Additionally, it does not have any information on the characteristics of friends and family networks in the US, which is what our analysis requires.

work and the migrant. As the census does not have such information, we only consider recent migrants, as they have most likely received information from the network they eventually moved to. The sample includes all people born in Mexico between 18 and 64 years that arrived no longer than 5 years before the census, and who were at least 18 years old when they first entered the US. We drop all Mexicans that are the only Mexicans in their census area (consistent PUMA). Moreover, we only consider workers with a positive wage income that are not enrolled in a school or college. Our sample is therefore only representative for Mexicans that went to the US and found a job. For workers with zero income we cannot distinguish between those that unemployed, those that choose not to work, and those that do not report any income. By including workers with zero income, we would over-estimate the share of workers that would be better-off in Mexico.

A potential problem regarding sample selection is the misreporting of the date of entry. Transient migrants — those who move back-and-forth between Mexico and the US — tend to report the date of their last arrival in the US, even though they had a longer history of migration to the US (Redstone & Massey, 2004; Lubotsky, 2007). [9] To reduce the bias from misreporting the year of entry, we only include those migrants that state that they lived outside the US 5 years ago (in the 1990 census) or that they lived in Mexico 5 years ago (in the 2000 census).

Another concern with data on Mexicans in the US is the undercounting of illegal migrants. The majority of Mexicans in the United States arrive as illegal immigrants and only receive their residence permit at a later stage (Massey & Malone, 2002; Hanson, 2006). The census does not ask respondents about their legal status. Yet some illegal migrants may fear negative consequences and choose not to take part in the survey, or they may not be available for some other reason. The undercount of illegal migrants can lead to selection bias, if the least-skilled migrants are more likely to be excluded. While we are aware that undercounting may bias the results, it is important to note that the extent of undercounting has decreased significantly over the last census rounds, from 40% undercount rate in 1980 (Borjas *et al.*, 1991) and 15-20% in the 1990s (Bean *et al.*, 2001; Costanzo *et al.*, 2002), to around 10% in the 2000 survey (Card & Lewis, 2007). Moreover, Chiquiar & Hanson (2005) show that undercounting only causes minor changes to the wage distribution of Mexicans in the US, which means that there is no systematic undercount of a particular skill level.

[9] One reason for the misreporting among transient migrants is the ambiguous wording of the census question. In 1990 it asked when the person "came to stay", in 2000 the question was when they "came to live" (Redstone & Massey, 2004).

Dependent variable: error measure

Next we turn to the construction of the dependent variable. Following the theory, we require a measure for an error in the migration decision — that is, a variable that equals one if the person would be better off in Mexico and zero if he is better off in the US. As we cannot observe wages before emigration, we predict a counterfactual wage from the Mexican census based on observable characteristics. A 30-year old male migrant with a college degree, for example, will have a counterfactual wage equal the wage of a typical 30-year old college-educated man in Mexico. We first use the Mexican census to regress monthly wages (variable INCEARN) on a vector of personal characteristics,

$$\text{wage} = \boldsymbol{X_{MEX}}\beta_{\boldsymbol{MEX}} + \varepsilon. \tag{3.4}$$

$\boldsymbol{X_{MEX}}$ includes a set of education dummies, a dummy for marital status, age, and age squared, as well as interactions of the education dummies with the dummy for marital status, age, and age squared. ε is an error term that captures unobservable determinants of wages. The interaction terms allow us to have a separate age-earnings gradient for each education level. Because the coefficients may differ significantly by gender, we run separate regressions for men and women. The sample consists of all people aged 18 to 64 with a wage income greater than zero.[10] From Equation (3.4) we obtain the estimated parameters $\hat{\beta}_{\boldsymbol{MEX}}$.

Using the same characteristics for Mexicans in the US, $\boldsymbol{X_{US}}$, we calculate the counterfactual wages as

$$\widehat{\text{wage}} = \boldsymbol{X_{US}}\hat{\beta}_{\boldsymbol{MEX}}. \tag{3.5}$$

To make both wages comparable, we convert the counterfactual wages into US dollars and adjust for differences in price levels using PPP data from the Penn World Tables. [11] As the wages in the US census are annual wages, we multiply the counterfactual wages by 12.

The difference between the counterfactual and the actual wages yields the losses from emigration.[12] As Figure 3.5 shows, the losses from emigration of recent migrants have a smooth distribution. In both censuses around 25% of all recent Mexican migrants would be better off in Mexico. For the baseline regressions we define the error measure as a binary variable with value one if the losses from emigration are positive,

[10] We also delete any observations with a monthly wage of 2,000,000 pesos or more, which were distinct outliers. See Appendix 3.D.1 for a description of the education groups.

[11] The PPP factor is the amount of goods in return for one dollar in the US over the amount of goods in return for one dollar in Mexico. The PPP factor was 0.48 in 1990 and 0.63 in 2000. The exchange rates were 2.83 pesos per dollar in 1990 and 9.2845 in 2000. Source: Mexican Central Bank.

[12] Annual wages in the US measured by the variable INCWAGE.

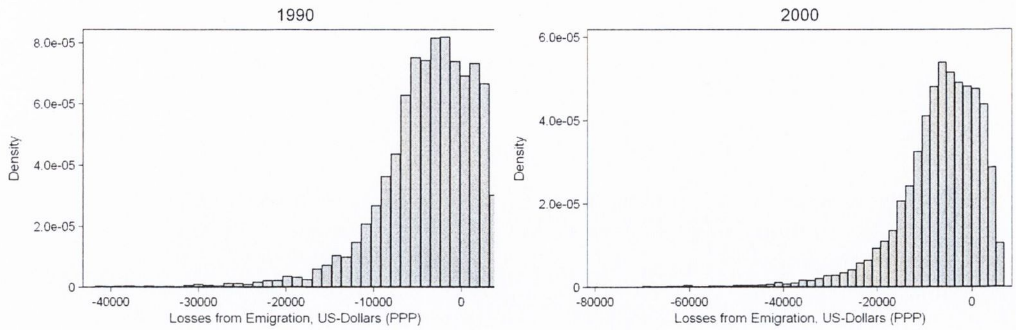

Figure 3.5: Losses from emigration, 1990 and 2000

Note: The graphs show the distribution of the losses from emigration in 1990 and 2000, which are measured as the difference between the counterfactual and the actual annual income. A Mexican in the US has positive losses from emigration if, based on his observable characteristics, he would have a higher income in Mexico than in the US. Data sources: US and Mexican census.

and zero otherwise.

Due to unobserved factors we potentially over- or under-estimate the counterfactual wages. The prediction of counterfactual wages in Equation (3.5) assigns to every Mexican in the US the average wage of a worker in Mexico with the same observable characteristics. But education, age, gender, and marital status only capture some of the factors that determine wages. Unobserved factors, such as IQ, confidence, motivation, or self-selection into a certain type of firm potentially have a large impact on wages and can explain wage differentials between workers with identical observable characteristics. If migrants are positively selected — that is, if they are on average more skilled than comparable workers in Mexico — we under-estimate the counterfactual wages and undercount the number of workers who would be better off in Mexico. If migrants are negatively selected, we over-estimate the counterfactual wages and the losses from emigration.

The literature on the selection of Mexican migrants has not reached a consensus on the direction of selection bias. Chiquiar & Hanson (2005) and Orrenius & Zavodny (2005) find that the selection of Mexican migrants occurs mostly at the center of the wage distribution. This view has been challenged by Ibarraran & Lubotsky (2007), Moraga (2011) and Ambrosini & Peri (2012), who use longitudinal data to show that Mexican migrants are negatively selected from the wage distribution. If that were the case, we would over-estimate the losses from emigration and classify too many immigrants as being better off in Mexico.

Another reason for over-estimating the losses from emigration is the misreporting of educational attainment. Education is self-reported in the census, and although respondents do not benefit from misreporting, there is evidence that migrants over-report their education level (Lubotsky, 2007), for example to make them look better in front of the interviewer or other people present at the interview .

As we are unable to correct for selection- or misreporting bias in the calculation of counterfactual wages, and as the baseline 0-1 error measure is likely to overestimate the number of people coded with one — those who would be better off in — we provide several alternative error measures. One continuous measure is the gain from returning, i.e. the difference between the counterfactual and the actual wage. In addition, we consider error measures based on the relative position in the distribution of the losses from emigration; in one measure we code as one all immigrants whose losses are above the 90th percentile, in another measure above the 75th percentile, and yet in another above the median.

Regressors of interest: network measures

The key explanatory variable is the quality of the migrant network — the ability of the network to provide accurate information about job prospects.

As we have no direct information on the network and the information flows before migration, we have to rely on proxies for the network quality. Generally speaking, we proxy network quality by the characteristics of Mexicans that had lived in the same area for at least 5 years before the census. The smallest geographic areas in the US census are the PUMAs (public use microdata area), which contain between 100,000 and 200,000 people. There are more than 2000 PUMAs across the US. PUMAs do not cross state borders, but their boundaries change from census to census, depending on internal migration in the US. For the censuses in 1980, 1990, and 2000, the US Census Bureau has constructed 543 consistent PUMAs whose boundaries are constant over time. For our analysis we use the number and characteristics of Mexicans in a consistent PUMA as a proxy for the network. For better readability, we will refer to consistent PUMAs as "PUMAs."

The first network measure is the number of Mexicans in a PUMA, which is the standard measure in the literature on network effects.[13] Given that all PUMAs are similar in size, the number of Mexicans is a measure for the geographic concentration of Mexicans.

The second network measure is the share of high-skilled Mexicans in a PUMA. The conjecture behind this measure is that high-skilled workers have a better knowledge of the labor market and can give better information to future immigrants. We classify as

[13]In the regressions to follow, we will use the natural logarithm of the number of Mexicans. As we have some PUMAs with no Mexicans, we use $\log(1 + \text{Nr of Mexicans})$.

high-skilled those immigrants who finished at least the 9th grade, which is equivalent to a high-school degree. Among all Mexicans in the US, the share of high-skilled was 42.3% in the 1990 census and 53% in the 2000 census.

Our third measure of the network quality is an assimilation index that measures how similar Mexicans are compared to Americans in the same metropolitan area. Mexicans that are highly assimilated potentially have a better knowledge of the labor market. The assimilation index, developed by Vigdor (2008), measures the statistical similarity between Mexicans and Americans with respect to a large number of observable characteristics such as gender, age, income, occupation, number of children, home ownership, employment status, etc. The index is 0 if we can perfectly distinguish Mexicans from Americans, and 100 if it is not possible to statistically distinguish a Mexican from an American. The assimilation index is based on a probit regression of the immigrant status of all Mexicans and Americans in a metropolitan area — coded as 1 if Mexican, 0 if American — on all observable characteristics. In a second step, we use for each Mexican the estimated coefficients from the probit regression to predict the probability of being Mexican. The assimilation index per PUMA is then calculated as 100 minus the average probability of being Mexican.[14] For each census round we use the assimilation index of 10 years before as an explanatory variable.[15]

Descriptive statistics

Table 3.3 displays the descriptive statistics for the census rounds in 1990 and 2000. The average new migrant is in his late 20s, male, and has a lower secondary education.

Between 1990 and 2000 the losses from emigration decreased; new immigrants were on average more successful in 2000. At the same time, the increase in the standard deviation indicates a larger degree of variation in the success of new migrants. The change in the mean can be caused by at least two factors. One possibility is that real wages have increased more in the US than in Mexico. Another factor is that migrants coming after the census in 1990 were more skilled; the share of high-skilled immigrants — those with more than 9 years of education — increased by 8 percentage points, while the share of high-school dropouts decreased by 6 percentage points. Besides having better education, it is also possible that immigrants in 2000 had better unobservable skills.

Another noteworthy development is the number of Mexicans per PUMA. It decreased on average from 1990 to 2000, while its standard deviation increased. These changes confirm the observation by Card & Lewis (2007) that the 1990s have seen a

[14]See Appendix 3.B for a more detailed description of the assimilation index.

[15]We can only use 10-year lags, as the census is only carried out every 10 years.

Table 3.3: Summary statistics: Mexicans in the US

	1990			2000		
	Obs	Mean	SD	Obs	Mean	SD
Dependent variables						
Losses from emigration	15,988	-4,046	5,694	35,466	-6,973	8,954
1 if losses > 0	15,988	0.25	0.43	35,466	0.21	0.41
Age at immigration	15,988	26.6	8.6	35,466	26.9	8.4
Network measures						
Nr of Mexicans	15,988	89,026	94,346	35,466	85,355	112,927
Share High-skilled	15,988	0.38	0.10	35,466	0.46	0.09
Assimilation index	14,561	0.63	0.13	29,031	0.62	0.15
Control variables						
High-school dropouts	15,988	0.24	0.42	35,466	0.14	0.34
Lower secondary	15,988	0.45	0.50	35,466	0.49	0.50
Upper secondary	15,988	0.27	0.44	35,466	0.33	0.47
Some college	15,988	0.05	0.21	35,466	0.04	0.21
Male	15,988	0.70	0.46	35,466	0.70	0.46
Married	15,988	0.46	0.50	35,466	0.51	0.50
Nr children	15,988	0.69	1.33	35,466	0.66	1.22
Employment growth	-	-	-	28,920	8.1	10.9

Note: Summary statistics for Mexicans that migrated to the US no longer than 5 years before the census. Losses from emigration are the difference between the counterfactual income in Mexico and the actual income in the US. The second dependent variable takes value 1 if a person has positive losses from migration and zero otherwise. The network variables are measured at the level of consistent PUMAs (public use microdata area). *Share high-skilled* is the share of Mexicans with more than 9 years of education. The *assimilation index* takes value 1 if migrants cannot be statistically distinguished from natives. Employment growth is the growth of employment in a metropolitan area from 1990-1995. Sources: census data from the IPUMS 5% public use samples.

Table 3.4: Summary statistics for selected areas in 2000

	Losses	Error	Age mig	Nr Mexicans	Assim.	High-skilled
Albuquerque	-4,374	33%	26.4	51,106	59	44%
Atlanta	-7,879	18%	27.4	20,839	73	46%
Boston	-6,061	40%	29.5	2,281	99	82%
Chicago	-8,119	20%	27.7	149,514	59	47%
Dallas	-7,463	18%	26.1	130,570	52	41%
Denver	-8,013	18%	27.1	63,812	63	45%
Houston	-7,040	19%	26.6	177,379	60	44%
Las Vegas	-8,123	23%	26.4	59,169	62	50%
Los Angeles	-6,144	23%	26.5	478,384	59	51%
New York	-6,997	14%	24.6	17,549	96	47%
Phoenix	-6,581	20%	26.8	113,476	58	47%
Washington, DC	-10,748	11%	24.6	8,845	97	42%

Note: The table displays summary statistics for Mexicans in selected US cities. For each city we chose the consistent PUMA (CONSPUMA, Public Use Microdata Area) with the largest number of Mexicans. *Losses*: losses from emigration; a negative value means that the person is better off in the US; *error*: share of Mexicans with positive losses from emigration; *Nr Mexicans*: number of Mexicans in a PUMA; *Assim.*: assimilation index (0-100); *HSD*: share of high-school dropouts (lowest education level); *College*: share of college-educated people (highest education level). Source: US and Mexican census 2000.

diffusion of Mexican immigrants in the US. In the 2000 census Mexicans were more likely to move to areas with smaller networks.

The assimilation index is the same in both periods. It has fewer observations than the other variables, as we were only able to calculate the assimilation index for metropolitan areas with more than 20 Mexicans.

Employment growth is measured as the growth from 1990 to 1995 in each metropolitan area [16] The number of observations for employment growth is smaller than for other variables, as it is not available for all metareas. Before 1990, employment data was only available at the state level, so that we only use it for the 2000 census.

Table 3.4 illustrates the variation in the key variables for selected metropolitan areas in 2000. For each metropolitan area we picked the consistent PUMA with the largest Mexican community. There is significant variation in the losses from emigration, the percentage of migrants that would be better off in Mexico, the size of the Mexican community, and the degree of assimilation. By contrast, there is a low degree of variation in the age at immigration and the share of high-skilled workers. The only exception is Boston, where both are considerably higher than in all other cities.

No obvious relation seems to exist between the size of the network and the losses

[16]Source: Bureau of Labor Statistics.

from emigration, but there is a negative relation between the degree of assimilation and the losses from emigration. The more assimilated the network was 10 years before the census, the more successful are new migrants.

3.4.3 Results

Table 3.5: Networks and the success of recent immigrants

	Dependent variable: Losses from emigration			Dependent variable: P(error)		
A: 1990	(1)	(2)	(3)	(4)	(5)	(6)
Log nr Mexicans	-16.19	-16.79	-120.26	-0.004	-0.004	-0.009*
	[57.63]	[46.08]	[88.25]	[0.003]	[0.003]	[0.005]
Share high-skilled		-36.97***			-0.079	
		[8.662]			[0.064]	
Assimilation index (1980)			-33.49***			-0.133*
			[10.63]			[0.076]
Observations	15988	15988	14561	15988	15988	14561
Clusters	272	272	141	272	272	141
R^2	0.046	0.050	0.048	0.025	0.025	0.025
B: 2000						
Log nr Mexicans	209.31***	209.27***	135.44	0.005**	0.005**	0.001
	[69.09]	[68.85]	[117.26]	[0.002]	[0.002]	[0.003]
Share high-skilled		-32.77***			-0.106**	
		[11.60]			[0.041]	
Assimilation index (1990)			-40.93***			-0.109***
			[11.06]			[0.031]
Observations	35466	35466	29031	35466	35466	29031
Clusters	438	438	197	438	438	197
R^2	0.031	0.032	0.037	0.029	0.030	0.030

Note: Columns 1)-3) show the coefficients from OLS regressions; columns 4)-6) show the marginal effects from a probit regression, evaluated at the mean. It only displays the regressors of interest. Additional controls are education, age, age squared, gender, marital status, and the number of children. The share of high-skilled and the assimilation index are scaled 0-100 in columns 1)-3), and 0-1 in columns 4)-6). The network variables are measured at the level of consistent PUMA (public use microdata level). The dependent variable in columns 4)-6) has value 1 if a person's income would be larger in Mexico than in the US. Standard errors (shown in brackets) are clustered by consistent PUMA. For the probit regressions we report the Pseudo-R^2. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Networks and the success of recent immigrants

In this section we estimate the impact of the network quality on the success of migrants. As a first measure for the success of immigrants we consider the losses from emigration — the difference between the counterfactual income in Mexico and the actual income in the US. Columns 1)-3) in Table 3.5 display results from an OLS regression of the losses from emigration on different measures for the network quality and personal characteristics. As the network measures are group variables, we cluster the standard errors at the consistent PUMA level. The effects of the network size on the losses from emigration differ considerably between 1990 and 2000. While the effect is negative and economically as well as statistically insignificant in 1990, it is positive and significant in 2000. For a 1-percent increase in the number of Mexicans, the annual losses from emigration increase on average by 209$. Migrants who moved to a larger network between 1995 and 2000 were therefore less successful.

When we add the share of high-skilled workers in Column 2), the coefficient for the network size remains unchanged. In both periods a one-percentage-point increase in the share of high-skilled Mexicans decreases the annual losses from emigration by 32 to 36$. This effect is not only statistically significant, it is also economically meaningful. Consider two different networks, one with a share of high-skilled of 40%, the other one with 50%, which are at the 25th and 75th percentile in the distribution of the share of high-skilled Mexicans. The difference in the losses from emigration between the two networks is around 360$, which is about 8% of the mean losses from emigration.

The assimilation index also has a negative and statistically significant coefficient. More assimilated networks predict a higher success for new migrants. In 2000, an increase in the assimilation index by one point decreases the losses from emigration by 41$. Again, the difference between the 25th and the 75th percentile of the assimilation index is considerably large with 480$ per year. This gain is over and above what can be explained by the network size. As we are not able to calculate the assimilation index for PUMAs with very small Mexican communities, however, these estimates can be biased. In a robustness check in Section 3.C.1 we show that we over-estimate the effect of the assimilation index to a small degree.

Our second dependent variable is in line with our theoretical model; we code all migrants who would be better off in Mexico with one and everyone else with a zero. We then run a probit regression of this error measure on the network variables as well as on personal characteristics. Columns 4)-6) in Table 3.5 display the marginal effects evaluated at the mean. Not surprisingly, the sign of all coefficients is the same as in the OLS regressions, but only in 2000 are some coefficients statistically significant.

The network size has hardly any influence on the likelihood of making an error.

Even though the coefficients in 2000, Columns 4) and 5), are statistically significant, they only predict a 0.05% increase in the likelihood of making an error for a 10% increase in the number of Mexicans. On the contrary, the proxies for the network quality, are economically significant. A 10-percentage-point increase in both the share of high-skilled workers and the assimilation index decreases the likelihood of making an error by 1%.

A potential concern with the marginal effects for the share of high-skilled Mexicans and the assimilation index is multicollinearity. If both variables had a strong positive correlation they would measure the same thing and lead to the same marginal effects. Given the construction of the assimilation index, a strong positive correlation is possible, but other patterns, like a negative or no correlation, are equally plausible. The index has a high value if Mexicans are similar to Americans in the same metropolitan area with respect to a large number of personal characteristics. In theory it is therefore not clear why high-skilled Mexicans should be much more similar to their American neighbors than low-skilled Mexicans. The data, however, reveal a moderate positive correlation of 0.36 in 1990 and 0.31 in 2000. The correlation between the assimilation index and the size of the network is stronger, with a correlation coefficient of -0.59 in 1990 and -0.52 in 2000. The negative sign indicates that larger networks are less assimilated than smaller networks. Yet a correlation of -0.59 is weak enough to rule out multicollinearity problems. The variance inflation factors, which measure the extent to which the inclusion of each variable inflates the standard errors, lie below the commonly used threshold of 5.

As described in Section 3.4.2, it is possible that the binary error measure over- or understates the number of workers that would be better off in Mexico. As an alternative, we now focus on the relative position in the distribution of the losses from emigration and code every worker as one whose losses from emigration lie above the 90th, 75th, and 50th percentile. In Table 3.6, all coefficients for the share of high-skilled workers and the assimilation index are negative, supporting the main proposition of our theory. The more assimilated the network, and the higher the share of high-skilled Mexicans, the more successful are recent immigrants, and the lower is the likelihood of being above a certain percentile of the losses from emigration.

So far, the results are consistent with the theoretical predictions. While we do not claim that the positive correlation between the network quality and the success of recent migrants is a causal relationship, we can exclude some alternative explanations. Reverse causality, often a problem in OLS regressions, is not an issue here as the network variables are predetermined; we consider as part of the network only those Mexicans who have lived in the US more than 5 years before the census, while the recent migrants have lived in the US for less than 5 years.

Table 3.6: Alternative dependent variables

	Dependent variable: P(> 90-percentile)		Dependent variable: P(> 75-percentile)		Dependent variable: P(above median)	
A: 1990	(1)	(2)	(3)	(4)	(5)	(6)
Log nr Mexicans	-0.002	-0.006*	-0.004	-0.009*	-0.006	-0.016**
	[0.002]	[0.003]	[0.003]	[0.005]	[0.004]	[0.008]
Share high-skilled	-0.030		-0.079		-0.296***	
	[0.039]		[0.064]		[0.084]	
Assimilation index (1980)		-0.086**		-0.133*		-0.282***
		[0.038]		[0.076]		[0.104]
Observations	15988	14561	15988	14561	15988	14561
Clusters	272	141	272	141	272	141
Pseudo R^2	0.033	0.035	0.025	0.025	0.028	0.028
B: 2000						
Log nr Mexicans	0.004**	0.003	0.005**	0.000	0.013***	0.006
	[0.001]	[0.002]	[0.002]	[0.004]	[0.004]	[0.007]
Share high-skilled	-0.040		-0.127***		-0.184**	
	[0.030]		[0.047]		[0.072]	
Assimilation index (1990)		-0.022		-0.134***		-0.182**
		[0.020]		[0.045]		[0.071]
Observations	35466	29031	35466	29031	35466	29031
Clusters	438	197	438	197	438	197
Pseudo R^2	0.042	0.042	0.028	0.029	0.022	0.023

Note: The table displays marginal effects of network qualitiy measures on the success of migrants. The results are derived from probit regressions, evaluated at the mean. The dependent variable equals one if the losses from emigration are above the 90th, 75th, and 50th percentile. Additional controls in each regression: gender, age, age squared, education, number of children. Standard errors are clustered by consistent PUMA. The share of high-skilled and the assimilation index are measured between 0 and 1. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

But the results can also be driven by a third factor that determines the quality of the network and the success of recent migrants at the same time. If some areas have attracted high-skilled migrants for more than 10 years, we would observe a network with a high share of high-skilled migrants at the same time as a large number of successful new migrants. To account for changes in the economic conditions across regions, we include the employment growth between 1990 and 1995 at the level of metropolitan areas as a control variable.[17] As we can see in Table 3.7, the coefficient of the size of the network becomes larger and has the same statistical significance. The effect of the assimilation index on the success of new immigrants is similar to the baseline, both in magnitude and statistical significance. By contrast, the share of high-skilled workers has a small and statistically insignificant effect. Employment growth can in fact explain the correlation between the share of high-skilled workers and the success of immigrants, but it cannot explain the effect of the assimilation index.

Table 3.7: Robustness check: including employment growth

	Dependent variable: Losses from emigration			Dependent variable: P(error)		
	(1)	(2)	(3)	(4)	(5)	(6)
Log nr Mexicans	272.32***	258.24***	55.25	0.008***	0.008***	0.003
	[67.17]	[67.84]	[112.83]	[0.002]	[0.002]	[0.003]
Share high-skilled		-23.75			-0.055	
		[15.78]			[0.048]	
Assimilation index (1990)			-30.06***			-0.105***
			[986.49]			[0.034]
Employment growth	-18.49	-21.02*	-26.79**	0.009	0.004	0.011
	[12.50]	[12.40]	[12.96]	[0.033]	[0.033]	[0.036]
Observations	28920	28920	26187	28920	28920	26187
Clusters	326	326	186	326	326	186
R^2	0.034	0.034	0.038	0.030	0.030	0.031

Note: In this table we extend the baseline regressions by including the employment growth between 1990 and 1995 as a regressor. Additional controls are age, age squared, education, gender, and the number of children. Standard errors are clustered by consistent PUMA. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

While the employment growth accounts for changes in the economic conditions across regions, the results could also be driven by long-term fundamental differences between regions. To see whether the results are affected by economic heterogeneity of regions, we include state fixed effects into the regression, so that all the variation comes from within states.[18] As shown in Table 3.8, the inclusion of fixed effects, changes the

[17]Source: Bureau of Labor Statistics. As employment at the level of metropolitan areas is only available from 1990, we limit the analysis to the 2000 census.

[18]The data has too little variation to use metropolitan area fixed effects.

size and statistical significance of the effect of the network size on the success of immigrants. In 1990 the effects are considerably larger and statistically significant, whereas in 2000 the coefficients are small and insignificant. The coefficients of the share of high-skilled workers and the assimilation index are smaller and insignificant in 1990 and of the same magnitude and significance as in the baseline in 2000. These results point at the difference between immigrant cohorts in 1990 and 2000. For immigrants arriving before 1990 the size of the network was more important, while for those arriving after 1990 the quality of the network seemed more important.

In sum, we find that more assimilated networks predict a greater success of recent migrants. This relation exists over and above the size of the network, and it is robust to controlling for employment growth and including state fixed effects. The results are less robust if we proxy for the network quality with the share of high-skilled workers, but we can exclude that the share of high-skilled workers has a negative effect on the success of recent migrants.

Networks and the timing of migration

Besides having an impact on the success of current migrants, our theory predicts that networks also affect the timing of migration. Migrants with access to a better network migrate earlier, as they need a lower number of positive signals to be convinced that migration is beneficial. In Table 3.9 we test this prediction by regressing the age at the time of immigration on the network variables, controlling for gender, education, and the number of children. The size of the network alone (Column 1) has no effect on the timing of migration. In Columns 2) and 4) we include the share of high-skilled Mexicans and the assimilation index. Both variables have positive and statistically significant coefficients, which means that Mexicans with access to a better network actually emigrate later. Yet the results are economically insignificant. Take as an example the marginal effect of the assimilation index in Panel A, column 4). The difference between the 25th and the 75th percentile of the assimilation index is 15 points, which means that a migrant with access to a network at the 25th percentile migrates 0.45 years earlier than a migrant connected to the 75th percentile.

There are two reasons why the marginal effects are not larger. First, as Table 3.4 illustrates, the average age of immigration does not vary greatly across the US. Second, the effects of the network size and network quality cancel each other out. This could especially be the case for the assimilation index and network size, which have a strong negative correlation of -0.59 in 1990 and -0.52 in 2000. Migrants with access to small, more assimilated networks may get better information, but they receive fewer signals than migrants with access to a larger but less assimilated network. The observed net

Table 3.8: Robustness check: including state fixed effects

	Dependent variable: Losses from emigration			Dependent variable: P(error)		
A: 1990	(1)	(2)	(3)	(4)	(5)	(6)
Log nr Mexicans	-168.35** [77.04]	-172.99** [68.97]	-203.16** [86.28]	-0.010** [0.005]	-0.010** [0.005]	-0.014** [0.006]
Share high-skilled		-21.23** [9.77]			0.028 [0.071]	
Assimilation index (1980)			-19.54 [14.56]			-0.011 [0.086]
Observations	15988	15988	14561	15950	15950	14545
R^2	0.062	0.065	0.064	0.035	0.035	0.034
B: 2000						
Log nr Mexicans	42.57 [93.683]	-2.48 [86.270]	110.60 [120.618]	0.001 [0.003]	0.000 [0.003]	0.004 [0.004]
Share high-skilled		-49.47*** [10.240]			-0.112*** [0.041]	
Assimilation index (1990)			-30.45*** [11.25]			-0.098*** [0.034]
Observations	35466	35466	29031	35462	35462	29030
R^2	0.039	0.042	0.046	0.035	0.035	0.035

Note: In this table we re-run the original regressions using state fixed effects. Columns 1)-3) show the coefficients from OLS regressions; columns 4)-6) show the marginal effects from a probit regression, evaluated at the mean. It only displays the regressors of interest. Additional controls are education, age, age squared, gender, marital status, and the number of children. The share of high-skilled and the assimilation index are scaled 0-100 in columns 1)-3), and 0-1 in columns 4)-6). The network variables are measured at the level of consistent PUMA (public use microdata level). The dependent variable in columns 4)-6) has value 1 if a person's income would be larger in Mexico than in the US. Standard errors (shown in brackets) are clustered by consistent PUMA. For the probit regressions we report the Pseudo-R^2. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

effect should then be close to zero. In Columns 3) and 5) we add an interaction term of the network size and network quality. For the share of high-skilled workers in 1990, the coefficients are jointly significant at the 5%-level, but the marginal effects are negligible. The coefficients in Panel A), Column 5), are jointly significant at the 1%-level, while they are insignificant in Panel B. The results in Panel A), Column 5) yield small — and for network sizes above the 5th percentile positive — marginal effects of the assimilation on the timing of migration. At a mean-sized network, the marginal effect is +0.04; at the 75th percentile it is +0.06.

In summary, the estimated effects of network size and quality on the timing of migration are small. The data on Mexican immigrants in the US do not confirm our prior that migrants with access to better networks emigrate earlier. While networks affect the success of migrants, they are unrelated to the timing of migration.

3.5 Conclusion

A large literature has examined the impact of diaspora networks on the migration decisions of future migrants. By and large, this literature explains network effects through the size of the network — the quantity. In this paper we take a different approach and focus on the quality of migrant networks and its impact on the success of future migrants.

Around the world, migrant communities differ not only in their size but also in their degree of integration in the host society. We argue that more integrated networks have a better knowledge of the labor market in the destination, and therefore give more accurate information to future migrants. Based on this reasoning, we develop a theoretical model from which we derive two propositions. First, migrants with access to a better network are more likely to make the right decision; they only migrate if they in fact are better-off abroad. Second, migrants with access to a better network migrate earlier. We test these propositions empirically, using data on Mexicans in the US. We find strong support for the first hypothesis. A more assimilated network predicts a significantly higher likelihood of succeeding in the destination. For the second hypothesis, however, we find no support in the data.

One limitation of the empirical analysis is that we only measure the economic success of migrants. Mexicans may come to the US for reasons other than a higher income, for example a better quality of life, more personal security, or a better education for their children. None of these variables can be captured by our data, but it would be generally interesting to look into these soft factors as drivers of migration flows.

Table 3.9: Networks and the timing of migration

	Dependent variable: age at immigration				
A: 1990	(1)	(2)	(3)	(4)	(5)
Log nr Mexicans	-0.079	-0.078	-0.226	0.024	-0.648**
	[0.050]	[0.051]	[0.166]	[0.074]	[0.284]
Share high-skilled		0.022**	-0.006		
		[0.011]	[0.028]		
log(Mexicans) × (share h-s)			0.004		
			[0.004]		
Assimilation index (1980)				0.030***	-0.062
				[0.011]	[0.040]
log(Mexicans) × assim. index					0.010**
					[0.004]
Observations	15988	15988	15988	14561	14561
Clusters	272	272	272	141	141
R^2	0.20	0.20	0.20	0.20	0.20
B: 2000					
Log nr Mexicans	-0.004	-0.004	-0.271	0.079	-0.331
	[0.034]	[0.032]	[0.202]	[0.057]	[0.246]
Share high-skilled		0.031***	-0.016		
		[0.009]	[0.031]		
log(Mexicans) × (share h-s)			0.006		
			[0.004]		
Assimilation index (1990)				0.012*	-0.048
				[0.007]	[0.033]
log(Mexicans) × assim. index					0.006*
					[0.004]
Observations	35466	35466	35466	29031	29031
Clusters	438	438	438	197	197
R^2	0.16	0.16	0.16	0.16	0.16

Note: The table presents results from OLS regressions of the age at the time of immigration on network variables. Additional controls are education, gender, and the number of children. Standard errors are clustered by consistent PUMAs. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

3.A Dynamic Decision Model

3.A.1 Derivation of p^*

To find a unique value for the threshold number of positive signals k^* in Equation (3.3), we determine the corresponding belief probability p^* using dynamic programming. It is possible to find p^* by looking at the optimal behavior around k^*. If $k > k^*$ the worker emigrates with certainty, which gives him the expected utility in Equation (3.1). $k < k^* - 1$ defines the continuation region, in which he will wait for further signals to arrive. In that case, even the next positive signal will not contain sufficient evidence for a positive migration prospect. The value function for the continuation region has to satisfy the Bellman equation

$$rV_1(k) = \frac{1}{dt}\mathbb{E}\left[dV_1(k)\right], \tag{3.6}$$

which is derived as follows. The value of lifetime income after migration is $V_1(k)$. In the continuation region $V_1(k)$ has to equal the expected lifetime income after an instant dt, discounted to time t, $V_1(k) = \frac{1}{1+rdt}\mathbb{E}\left[V_1(k+1)\right]$. Multiplying by $\frac{(1+rdt)}{dt}$ and noting that $\mathbb{E}\left[V_1(k+1)\right] - V_1(k) = \mathbb{E}\left[dV_1(k)\right]$, we get Equation (3.6).
To determine the value function $V_1(k)$, we use the Bellman equation and construct

$$\begin{aligned} V_1(k) = \frac{1}{1+r}&\left[p(k)\left(\lambda V_1(k+1) + (1-\lambda)V_1(k-1)\right)\right.\\ &\left.+ (1-p(k))\left(\lambda V_1(k-1) + (1-\lambda)V_1(k+1)\right)\right]. \end{aligned} \tag{3.7}$$

Equation (3.7) states that the value of the option to migrate now must equal the discounted value of the option after the next signal has arrived. It is helpful to look at the game tree in Figure 3.2 when interpreting Equation (3.7). Consider the first half of the RHS of Equation (3.7). With probability $p(k)$ he gets a good job, so that he is at the upper node of information set 1. But because the signal from the network is not entirely truthful, he ends up at the upper node of 2A with probability λ and at the upper node of 2B with probability $1-\lambda$. At 2A the value function is $V(k+1)$, at 2B it is $V(k-1)$. The interpretation of the second half of Equation (3.7) is analogous.
With some algebraic manipulation, we can write Equation (3.7) as a second-order difference equation. We first re-write Equation (3.7) as

$$\begin{aligned} (1+r)V_1(k) = V_1(k+1)&\left(2p(k)\lambda + 1 - \lambda - p(k)\right)\\ &+ V_1(k-1)\left(p(k) - 2p(k)\lambda + \lambda\right) \end{aligned} \tag{3.8}$$

Using Equation (3.2) and defining $\zeta := \frac{1-p_0}{p_0}$, the two expressions in parentheses on the RHS reduce to

$$2p(k)\lambda + 1 - \lambda - p(k) = \frac{\lambda^{k+1} + \zeta(1-\lambda)^{k+1}}{\lambda^k + \zeta(1-\lambda)^k},$$

and

$$p(k) - 2p(k)\lambda + \lambda = \frac{\lambda(1-\lambda)\left(\lambda^{k-1} + \zeta(1-\lambda)^{k-1}\right)}{\lambda^k + \zeta(1-\lambda)^k}.$$

Inserting these into equation (3.8) and defining $F(k) \equiv \left(\lambda^k + \zeta(1-\lambda)^k\right) V_1(k)$ yields

$$F(k+1) - (1+r)F(k) + \lambda(1-\lambda)F(k-1) = 0. \tag{3.9}$$

As shown in Thijssen *et al.* (2004), Equation (3.9) has the general solution $F(k) = A\beta^k$. A is a constant and β is a solution to the fundamental quadratic,[19] which is an upward pointing parabola with a global minimum at $\beta = \frac{r+\mu}{2\mu}$,

$$Q(\beta) = \beta^2 - (1+r)\beta + \lambda(1-\lambda).$$

The fundamental quadratic has two real roots

$$\beta_{1,2} = \frac{1+r}{2} \pm \frac{1}{2}\sqrt{(1+r)^2 - 4\lambda(1-\lambda)}.$$

The expression under the square root is positive due to $\frac{1}{2} < \lambda < 1$.
The general solution to Equation (3.9) is

$$F(k) = A_1\beta_1^k + A_2\beta_2^k,$$

where A_1 and A_2 are constants. A_1 will have to be determined from the dynamic optimization problem. For the value function to be well-behaved, we require $A_2 = 0$. If the number of bad signals goes to infinity, i.e. $k \to -\infty$, the value of the option to migrate should go zero, which can only be ensured if $A_2 = 0$. Hence, the value function for $k < k^*$ is

$$V_1(k) = \frac{A_1\beta_1^k}{\lambda^k + \zeta(1-\lambda)^k}.$$

The optimization problem has three unknown variables, A_1, p^* and k^*. To obtain the threshold belief probability p^* we have to consider the two threshold numbers of

[19] A second-order homogeneous linear difference Equation is of the form $y(x+2)+ay(x+1)+by(x) = 0$. The corresponding fundamental quadratic is $\beta^2 + a\beta + b = 0$.

signals $k = k^*$ and $k = k^* - 1$. At $k = k^*$ the worker is indifferent between migrating and waiting. Hence, the *value-matching condition* $V_1(k^*) = \mathbb{E}(U(k^*))$ has to be satisfied. At $k = k^* - 1$, the next good signal will either make him indifferent between migrating and staying, while in the case of a bad signal he will strictly prefer staying. Consequently, starting from a number of signals $k = k^* - 1$ he will never strictly prefer emigrating after the next signal has arrived, so that $k^* - 1$ is part of the continuation region. The *continuity condition* $V_1(k^* - 1) = \mathbb{E}(U(k^* - 1))$ states that the value of the option to postpone the migration decision has to equal the expected utility from migration now. These two conditions, together with Equation (3.3) determine a unique solution for the three unknowns. The value-matching condition yields

$$A_1 = \frac{1}{\beta_1^k}\left(\lambda^k(w^G - M) + \varsigma(1-\lambda)^k(w^B - M)\right).$$

The continuity condition is

$$A_1 = \frac{1}{\beta_1^{k-1}}\left(\lambda^{k-1}(w^G - M) + \varsigma(1-\lambda)^{k-1}(w^B - M)\right).$$

Equating the continuity condition and the value matching condition and dividing by $\lambda^k + \varsigma(1-\lambda)^k$, we have

$$p^*(w^G - M) + (1-p^*)(w^B - M) = p^*\beta_1\frac{(w^G - M)}{\lambda} + (1-p^*)\beta_1\frac{(w^B - M)}{1-\lambda}$$

$$\Leftrightarrow p^*\left(w^G - w^B - \frac{\beta_1(w^G - M)}{\lambda} + \frac{\beta_1(w^B - M)}{1-\lambda}\right) = (w^B - M)\frac{\beta_1 - (1-\lambda)}{1-\lambda}.$$

Dividing by $(w^B - M)$ and solving for p^* gives the threshold belief probability

$$p^* = \frac{\beta_1 - (1-\lambda)}{1-\lambda}\left[\frac{w^G - w^B}{w^B - M} - \frac{\beta_1(w^G - M)}{\lambda(w^B - M)} + \frac{\beta_1}{1-\lambda}\right]^{-1}. \tag{3.10}$$

In the following, we prove that p^* is a well-defined probability.

3.A.2 Proof: p^* well-defined.

Proposition 3 *p^* is a well-defined probability.*

Proof. For p^* to be well-defined, it has to be $0 < p^* \leq 1$. For p^*¿0 to hold, $\frac{\beta_1-(1-\lambda)}{1-\lambda}$ and $\left[\frac{w^G-w^B}{w^B-M} - \frac{\beta_1(w^G-M)}{\lambda(w^B-M)} + \frac{\beta_1}{1-\lambda}\right]$ have to have the same sign. Moreover, $\lambda < 1$.

$\frac{\beta_1-(1-\lambda)}{1-\lambda} > 0$ follows from $\beta_1 > 1 - \lambda$.
Note that since β_1 and β_2 are the roots of an upward-pointing parabola with mini-

mum $\frac{1+r}{2}$, it has to hold that $Q(\beta_1) = Q(\beta_2) = 0$ and $Q(\varepsilon) < 0$ for $\beta_2 < \varepsilon < \beta_1$. $Q(1-\lambda) = -r(1-\lambda) < 0$ implies $\beta_1 > 1-\lambda$.

$\left[\frac{w^G - w^B}{w^B - M} - \frac{\beta_1 (w^G - M)}{\lambda(w^B - M)} + \frac{\beta_1}{1-\lambda}\right] > 0$ holds as well. Algebraic manipulation yields $\left(1 - \frac{\beta_1}{\lambda}\right) > \left(1 - \frac{\beta_1}{1-\lambda}\right)$, which holds by the assumption $\lambda > \frac{1}{2}$. Moreover, $\lambda < 1$ by assumption. Consequently, $p^* > 0$.

Next we show that $p^* \leq 1$. This condition is equivalent to

$$
\begin{aligned}
-1 &\leq \frac{w^G - w^B}{w^B - M} - \frac{\beta_1}{\lambda}\frac{w^G - M}{w_B - M} \\
\Leftrightarrow \left(1 - \frac{\beta_1}{\lambda}\right) M &\leq \left(1 - \frac{\beta_1}{\lambda}\right) w^G,
\end{aligned}
$$

which holds by assumption $w^G > M$. Hence, p^* is a well-defined probability. ■

3.B Assimilation Index

Here we give a detailed description of the assimilation index. The index gives us a statistical measure that equals 100 if Mexicans can statistically not be distinguished from Americans, and 0 if they can be perfectly distinguished.

We first run a probit regression of the migrant status on a vector of personal characteristics $\boldsymbol{X}$ separately for each metropolitan area,

$$P(\text{Mexican}\,|\boldsymbol{X}) = F(\boldsymbol{X\beta}), \tag{3.11}$$

and obtain the coefficient vector $\hat{\boldsymbol{\beta}}$.

Based on observable characteristics and the estimated coefficients, we then predict for every Mexican i the probability that he is in fact a Mexican

$$\hat{p_i} = \Phi(\boldsymbol{X}\hat{\boldsymbol{\beta}}), \tag{3.12}$$

where Φ is the cumulative distribution function of the joint normal distribution. Let the average probability for each PUMA be $\hat{p_m}$.

Finally, we calculate the assimilation index for each PUMA as

$$\text{index}_m = 100(1 - p_m). \tag{3.13}$$

In choosing the observable characteristics, we closely follow Vigdor (2008). $\boldsymbol{X}$ contains the following variables: marital status, gender, education, employment status, number of children, wage income, age, the ability to speak English, home ownership, and veteran status. We also include the median income of the person's occupation in 1990 (variable ERSCOR90) to see whether migrants work in similar occupations compared to Americans.

The sample includes all Mexicans and Americans aged 25-64 that live in a metropolitan area with at least 20 Mexicans. We run the regression separately for each metropolitan area, but calculate the assimilation index at the PUMA level.[20] The assimilation index can be interpreted as the degree of similarity of Mexicans within a PUMA compared to all Americans living in the metropolitan area.

3.C Robustness Checks

3.C.1 Alternative specifications

Due to data constraints, it is not possible to calculate the assimilation index for areas with a small number of Mexicans. This situation leaves us with a smaller number of observations whenever the assimilation index enters the regression. The omitted observations are mostly Mexicans that live in PUMAs with very few other Mexicans, which can lead to a selection bias in our estimates, as our sample is only representative for larger Mexican communities. As the number of observations in Table 3.5, Panel B shows, we lose 6,435 observations from 241 PUMAs — in relative terms 18% of all observations from 48% of all PUMAs.

Because the assimilation index is unknown for small communities, the magnitude and direction of the selection bias cannot be directly evaluated. We can, however, get an indirect measure from dropping all observations without an assimilation index from all regressions and observing changes in the coefficients of the other measures of network quality — the size of the network and the share of high-skilled workers. The estimated coefficients, displayed in Table 3.10, are slightly larger in absolute value compared to the estimates with the full sample in Table 3.5. Therefore, by dropping migrants from small communities we over-estimate the effect of assimilation on the success of new immigrants.

[20]We also tried to estimate a separate probit regression for each PUMA, but several PUMAs had only a few Mexicans, in which case the maximum likelihood estimator did not converge.

Table 3.10: Dropped observations without assimilation index

	Dependent variable: Losses from emigration		Dependent variable: P(error)	
A: 1990	(1)	(2)	(3)	(4)
Log nr Mexicans	41.482	28.781	-0.003	-0.003
	[80.919]	[62.304]	[0.004]	[0.004]
Share high-skilled		-47.197***		-0.223***
		[11.427]		[0.079]
Observations	14561	14561	14561	14561
Clusters	141	141	141	141
R^2	0.045	0.049	0.025	0.026
B: 2000				
Log nr Mexicans	285.790***	280.815***	0.006***	0.006**
	[92.323]	[91.517]	[0.002]	[0.003]
Share high-skilled		-37.365**		-0.155***
		[16.990]		[0.054]
Observations	29031	29031	29031	29031
Clusters	197	197	197	197
R^2	0.035	0.036	0.028	0.029

Note: In this table we only consider observations for which we were able to calculate an assimilation index, i.e. metropolitan areas with more than 20 Mexicans. Columns 1) and 2) show OLS results, Columns 3) and 4) probit results. The dependent variable in the probit regressions is coded as 1 if the person would be better-off in Mexico. Additional controls in all regressions are age, age squared, education, gender, and the number of children. Standard errors are clustered by consistent PUMA. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

3.D Data Appendix

3.D.1 Education Groups

For the prediction of the counterfactual wages in Section 3.4.2 and for the regressions in Section 3.4.3 we use four broad education groups. Clustering the workers into broad education groups makes the interpretation of the estimates easier and allows us to match the Mexican and the US data. Table 3.11 shows the education groups for the Mexican and the US census. For the Mexican census we take the variable *years of schooling* (YRSCHL). The US census distinguishes between 11 education groups (variable EDUC).

Table 3.11: Education groups in the Mexican and US census

Nr	**Education group**	**Mexican census**	**US census**
1	High-school dropouts	less than 5 years of schooling	education group 1
2	Lower secondary education	5-9 years of schooling	education groups 2-4
3	Upper secondary education	10-12 years of schooling	education groups 5-7
4	Third-level education	13 or more years of schooling	education groups 8-11

Part IV

Conclusions

In this thesis I present three essays on the causes and consequences of international migration. The first two papers study the consequences of migration for the migrant sending countries. Compared to the wage effects in the receiving countries, the sending countries are vastly understudied. The first essay presents a result that is consistent with a simple supply-and-demand framework: emigration decreases labor supply and causes an increase in wages. The effect found in the first chapter is larger than the wage effects of migration that are typically found in the receiving countries. This indicates that the labor markets of sending and receiving countries have a different structure, which means that that the labor markets in the sending countries deserve special attention in the literature.

The second essay goes beyond an average wage effect of emigration, and studies the distributional impacts of emigration. The effect on the wage distribution depends on the characteristics of migrants and stayers. Stayers that are close substitutes to emigrants should see an increase in their wages, while the wages of those that are complements should decrease. Furthermore, if a significant share of the workforce emigrates, general equilibrium effects become important. For example, fewer workers translate into lower aggregate demand, which has a negative impact on wages. When all these first- and second-order effects are added up, I find that only the youngest cohort experiences wage increases, while for the positive and negative effects add up to zero for older workers.

In contrast to the first two chapters, the third chapter studies one of the determinants of migration: migrant networks and the information they provide to future migrants. Based on the observation that migrant networks have different degrees of integration in the society of their host country, we argue that more integrated networks provide more accurate information about the labor markets abroad. We hypothesize that migrants who receive information from a more integrated network will make a more accurate decision — they only migrate if they are in fact better off doing so — and migrate earlier. Based on data on recent Mexican immigrants in the US we test these hypotheses and find that migrants with access to more integrated networks are indeed more successful, and they are less likely to be better off in Mexico. For our second hypothesis we find no support, however; the quality of the network has no impact on the timing of migration.

These three essays open several avenues for future research. Inspired by the first two chapters, one important direction is extending the analysis to more countries. The first two chapters, together with works of other researchers on Mexico, Honduras, and Moldova, indicate that emigration has a significant impact on the wage structure in the sending countries. The effects found in these studies are consistently larger than the ones found in receiving countries. Cross-country studies, or at least case studies on more sending countries, can help to evaluate whether the results of the previous studies are generalizable, or whether they are specific to certain countries. The biggest obstacle to research on the sending countries is data availability. A survey that tracks migrants in their sending and receiving country could lead to a significant improvement in data quality, and hopefully to promising insights.

As EU enlargement triggered a large migration wave within a very short time, it could shed light on other interesting aspects related to migration. After the enlargement, Eastern European workers emigrated in large numbers because they could easily find well-paid work in the booming economies of the UK and Ireland. With the economic crisis hitting both economies in 2008, many migrants subsequently returned to their home countries. From this sequence of boom and bust it would be possible to study selection dynamics of migration. It would be interesting to see which workers emigrated first, which ones followed after some time, and the same for workers who returned.

A key finding of the second paper is that young and old workers in a transition country like Lithuania are less substitutable than in countries with a longer tradition of a market economy, such as the US or the UK. One explanation for the low degree of substitutability in transition countries is that the old generation was educated under socializm, and therefore their skills are less adaptable to a market economy, so that they face a wage penalty. One interesting research area would be to analyze the evolution of this wage penalty as transition goes along, and to see whether the substitutability between old and young workers has changed over time, and what the determinants of this change are.

As for the third chapter, there is certainly more scope for research on the role of information in migration decisions. First of all, while our empirical results are consistent with the theory, it would be helpful to find some exogenous variation in the network quality and to obtain credible causal estimates for the impact of the quality of networks on the success of migrants. Besides networks, migrants potentially use many more information sources, such as TV, the internet, or newspapers. An interesting project would be to disentangle the effect of each of these sources on migration decisions and on the success of migrants in the receiving country. Due to the limited availability of data, and the difficulty to find a quasi-experimental setting, it would be promising to combine a survey with some experimental evidence.

Bibliography

ACEMOGLU, DARON, OZDAGLAR, ASUMAN, & GHEIBI, ALI PARANDEH. 2010. Spread of (Mis)Information in Social Networks. *Games and Economic Behavior*, **70**, 194–227.

ALGAN, YANN, DUSTMANN, CHRISTIAN, GLITZ, ALBRECHT, & MANNING, ALAN. 2010. The Economic Situation of First and Second-Generation Immigrants in France, Germany and the United Kingdom. *The Economic Journal*, **120**, F4–F30.

AMBROSINI, J. WILLIAM, & PERI, GIOVANNI. 2012. The Determinants and the Selection of Mexico-US Migrants. *The World Economy*, **35**(2), 111–151.

AMUEDO-DORANTES, CATALINA, & MUNDRA, KUSUM. 2007. Social Networks and their Impact on the Earnings of Mexican Migrants. *Demography*, **44**(4), 849–863.

ANDERSSON, FREDRIK, BURGESS, SIMON, & LANE, JULIA. 2009. Do as the Neighbors Do: The Impact of Social Networks on Immigrant Employment. *IZA Discussion Paper*, **4423**.

ANGRIST, JOSHUA, & PISCHKE, JÖRN-STEFFEN. 2009. *Mostly Harmless Econometrics - An Empiricist's Companion*. Princeton University Press.

AYDEMIR, ABDURRAHMAN, & BORJAS, GEORGE. 2007. Cross-Country Variation in the Impact of International Migration: Canada, Mexico and the United States. *Journal of the European Economic Association*, **5**(4), 663–708.

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. 2009. EU Enlargement and Ireland's Labour Market. *Pages 145–161 of:* KAHANEC, MARTIN, & ZIMMERMANN, KLAUS F. (eds), *EU Labor Markets after Post-Enlargement Migration*. Berlin: Springer-Verlag.

BARRETT, ALAN, & DUFFY, DAVID. 2008. Are Ireland's Immigrants Integrating into its Labour Market? *International Migration Review*, **42**(3), 597–619.

BAUER, THOMAS, EPSTEIN, GIL S., & GANG, IRA N. 2005. Enclaves, Language, and the Location Choice of Migrants. *Journal of Population Economics*, **18**, 649–662.

BAUER, THOMAS, EPSTEIN, GIL S., & GANG, IRA N. 2007. Herd Effects or Migration Networks? The Location Choice of Mexican Immigrants in the U.S. *Research in Labor Economics*, **26**, 199–229.

BAUER, THOMAS K., & ZIMMERMANN, KLAUS F. 1999. Assessment of Possible Migration Pressure and its Labour Market Impact Following EU Enlargement to Central and Eastern Europe. *IZA Research Report*, **3**.

BEAN, FRANK D., CORONA, RODOLFO, TUIRAN, RODOLFO, WOODROW-LAFIELD, KAREN A., & VAN HOOK, JENNIFER. 2001. Circular, Invisible, and Ambiguous Migrants: Components of Difference in Estimates of the Number of Unauthorized Mexican Migrants in the United States. *Demography*, **38**(3), 411–422.

BECKHUSEN, JULIA, FLORAX, RAYMOND J.G.M., DE GRAAFF, THOMAS, POOT, JACQUES, & WALDORF, BRIGITTE. 2012. Living and Working in Ethnic Enclaves: Language Proficiency of Immigrants in U.S. Metropolitan Areas. *IZA Discussion Paper*, **6363**.

BEINE, MICHEL, DOCQUIER, FRÉDÉRIC, & ÖZDEN, ÇAĞLAR. 2010. Diasporas. *Journal of Development Economics*, **95**(1), 30–41.

BEINE, MICHEL, DOCQUIER, FRÉDÉRIC, & ÖZDEN, ÇAĞLAR. 2011. Dissecting Network Externalities in International Migration. *CESifo Discussion Paper*, **3333**.

BIKCHANDANI, SUSHIL, HIRSHLEIFER, DAVID, & WELCH, IVO. 1992. A Theory of Fads, Fashion, Custom and Cultural Change as Informational Cascades. *Journal of Political Economy*, **100**(5), 992–1027.

BLANCHFLOWER, DAVID G., & SHADFORTH, CHRIS. 2009. Fear, Unemployment and Migration. *The Economic Journal*, **119**, 136–182.

BOERI, TITO, & BRÜCKER, HERBERT. 2001. Eastern Enlargement and EU-Labour-Markets. *World Economics*, **2**(1), 49–68.

BORJAS, GEORGE J. 1995. Ethnicity, Neighborhoods and Human-Capital Externalities. *The American Economic Review*, **85**(3), 365–390.

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.

Borjas, George J., Freeman, Richard B., & Lang, Kevin. 1991. Undocumented Mexican-born Workers in the United States: How Many, How Permanent? *Chap. 2, pages 77–100 of:* Abowd, John M., & Freeman, Richard B. (eds), *Immigration, Trade and the Labor Market*. University of Chicago Press.

Bouton, Lawrence, Paul, Saumik, & Tiongson, Erwin R. 2011. The Impact of Emigration on Source Country Wages: Evidence from the Republic of Moldova. *Worldbank Policy Research Working Paper*, **5764**.

Brücker, Herbert, & Jahn, Elke J. 2011. Migration and Wage Setting: Reassessing the Labor Market Effects of Migration. *Scandinavian Journal of Economics*, **forthcoming**.

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**.

Burda, Michael C. 1995. Migration and the Option Value of Waiting. *The Economic and Social Review*, **27**(1), 1–19.

Card, David. 2001. Immigrant Inflows, Native Outflows and the Labor Market Impact of Higher Immigration. *Journal of Labor Economics*, **19**(1), 22–64.

Card, David, & Lemieux, Thomas. 2001. Can Falling Supply Explain the Rising Return to College For Younger Men? A Cohort-Based Analysis. *The Quarterly Journal of Economics*, **116**(2), 705–46.

Card, David, & Lewis, Ethan G. 2007. The Diffusion of Mexican Immigrants During the 1990s: Explanations and Impacts. *Chap. 6, pages 193–228 of:* Borjas, George J. (ed), *Mexican Immigration to the United States*. University Of Chicago Press.

Carrington, William J., Detragiache, Enrica, & Vishwanath, Tara. 1996. Migration with Endogenous Moving Costs. *The American Economic Review*, **86**(4), 909–930.

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

Chiquiar, Daniel, & Hanson, Gordon H. 2005. International Migration, Self-Selection and the Distribution of Wages: Evidence from Mexico and the United States. *Journal of Political Economy*, **113**(2).

CHISWICK, BARRY R. 1978. The Effect of Americanization on the Earnings of Foreign-born Men. *The Journal of Political Economy*, **86**(5), 897–921.

CICCONE, ANTONIO, & PERI, GIOVANNI. 2005. Long-Run Substitutability between More and Less Educated Workers: Evidence from US States, 1950-1990. *The Review of Economics and Statistics*, **85**(4), 652–663.

CLEMENS, MICHAEL A. 2011. Economics and Emigration: Trillion-Dollar Bills on the Sidewalk? *Journal of Economic Perspectives*, **25**(3), 83–106.

CONSTANT, AMELIE F. 2011. Sizing it up: Labor Migration Lessons of the EU Enlargement to 27. *IZA Discussion Paper*, **6119**.

COSTANZO, JOSEPH M., DAVIS, CYNTHIA, IRAZI, CARIBERT, GOODKIND, DANIEL, & RAMIREZ, ROBERTO. 2002. Evaluating Components of International Migration: The Residual Foreign Born. *US Census Bureau Population Division Working Paper*, **61**.

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.

DELANEY, LAURA, & THIJSSEN, JACCO J. J. 2011. Valuing Voluntary Disclosure using a Real Options Approach. *University of York Discussion Paper*, **11/13**.

DEUTSCHER BUNDESTAG. 2004. Entwurf eines Gesetzes ber den Arbeitsmarktzugang im Rahmen der EU-Erweiterung. *Drucksache 15/2672*.

DOCQUIER, FRÉDÉRIC, & RAPOPORT, HILLEL. 2011. Globalization, Brain Drain and Development. *Journal of Economic Literature*, **forthcoming**.

DOCQUIER, FRÉDÉRIC, ÖZDEN, ÇAĞLAR, & PERI, GIOVANNI. 2011. The Wage Effects of Immigration and Emigration. *NBER Working Paper*, **16646**.

DRINKWATER, STEPHEN, EADE, JOHN, & GARAPICH, MICHAL. 2009. Poles Apart? EU Enlargement and the Labour Market Outcomes of Immigrants in the UK. *International Migration*, **47**(1), 161–190.

DUSTMANN, CHRISTIAN, FRATTINI, TOMMASO, & HALLS, CAROLINE. 2010. Assessing the Fiscal Costs and Benefits of A8 Migration to the UK. *Fiscal Studies*, **31**(1), 1–41.

EDIN, PER-ANDERS, FREDERIKSSON, PETER, & ASLUND, OLOF. 2003. Ethnic Enclaves and the Economic Success if Immigrants - Evidence from a Natural Experiment. *The Quarterly Journal of Economics*, **118**(1), 329–357.

ELSNER, BENJAMIN. 2010. Does Emigration Benefit the Stayers? The EU Enlargement as a Natural Experiment. Evidence from Lithuania. *FEEM Nota di Lavoro*, **151**.

ELSNER, BENJAMIN. 2011. Emigration and Wages: The EU Enlargement Experiment. *IZA Discussion Paper*, **6111**.

EPSTEIN, GIL S. 2010. Informational Cascades and the Decision to Migrate. *Chap. 2, pages 25–44 of:* EPSTEIN, GIL. S., & GANG, IRA N. (eds), *Migration and Culture*. Emerald Group Publishing Limited.

EUROPEAN COMMISSION. 2007. The European Structural Funds (2004-2006), Lietuva.

FARRÉ, LIDIA, & FASANI, FRANCESCO. 2011. Media Exposure and Internal Migration: Evidence from Indonesia. *IZA Discussion Paper*, **6012**.

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

FRIEDBERG, RACHEL M., & HUNT, JENNIFER. 1995. The Impact of Immigration on Host Country Wages, Employment and Growth. *Journal of Economic Perspectives*, **9**(2), 23–44.

GAGNON, JASON. 2011. "Stay with Us?" The Impact of Emigration on Wages in Honduras. *OECD Working Paper*, **300**.

GIBSON, JOHN, & MCKENZIE, DAVID. 2011. Eight Questions about Brain Drain. *Journal of Economic Perspectives*, **25**(3), 107–128.

HANSON, GORDON, & MCINTOSH, CRAIG. 2010. The Great Mexican Emigration. *The Review of Economics and Statistics*, **92**(4), 798–810. Download: working paper.

HANSON, GORDON H. 2006. Illegal Migration from Mexico to the United States. *Journal of Economic Literature*, **44**(4), 869–924.

HAZANS, MIHAILS, & PHILIPS, KAIA. 2009. The Post-Enlargement Migration Experience in the Baltic Labor Markets. *Pages 255–304 of:* KAHANEC, MARTIN, & ZIMMERMANN, KLAUS F. (eds), *EU Labor Markets after Post-Enlargement Migration*. Berlin: Springer-Verlag.

HOME OFFICE. 2009. Accession Monitoring Report, May 2004-December 2008, A8 Countries. *Home Office Report*.

IBARRARAN, PABLO, & LUBOTSKY, DARREN. 2007. Mexican Immigration and Self-Selection: New Evidence from the 2000 Mexican Census. *Chap. 5, pages 159 – 192* *of:* BORJAS, GEORGE J. (ed), *Mexican Immigration to the United States*. University Of Chicago Press.

KACZMARCZYK, PAWEL, MIODUSZEWSKA, MARTA, & ZYLICZ, ANNA. 2009. Impact of the Post-Accession Migration on the Polish Labor Market. *Pages 219–253 of:* KAHANEC, MARTIN, & ZIMMERMANN, KLAUS F. (eds), *EU Labor Markets after Post-Enlargement Migration*. Berlin: Springer-Verlag.

KAHANEC, MARTIN, & ZIMMERMANN, KLAUS F. (eds). 2009. *EU Labor Markets After Post-Enlargement Migration*. Berlin: Springer-Verlag.

KAHANEC, MARTIN, ZAICEVA, ANZELIKA, & ZIMMERMANN, KLAUS F. 2009. Lessons from Migration after EU Enlargement. *Pages 3–45 of:* KAHANEC, MARTIN, & ZIMMERMANN, KLAUS F. (eds), *EU Labor Markets after Post-Enlargement Migration*. Berlin: Springer-Verlag.

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

KERR, SARI PEKKALA, & KERR, WILLIAM R. 2011. Economic Impacts of Immigration: A Survey. *Finnish Economics Papers*, **24**(1), 1–32.

KRUSELL, PER, OHANIAN, LEE E., RÍOS-RULL, JOSÉ-VÍCTOR, & VIOLANTE, GIOVANNI L. 2000. Capital-Skill Complementarity and Inequality: A Macroeconomic Analysis. *Econometrica*, **68**(5), 1029–1053.

LAZEAR, EDWARD P. 1999. Culture and Language. *The Journal of Political Economy*, **107**(6), S95–S126.

LONGHI, SIMONETTA, NIJKAMP, PETER, & POOT, JACQUES. 2010. Joint impacts of Immigration on Wages and Employment: Review and Meta-Analysis. *Journal of Geographical Systems*, **12**, 355–387.

LUBOTSKY, DARREN. 2007. Chutes or Ladders? A Longitudinal Analysis of Immigrant Earnings. *Journal of Political Economy*, **115**(5), 820–867.

MANACORDA, MARCO, MANNING, ALAN, & WADSWORTH, JONATHAN. 2011. The Impact of Immigration on the Structure of Male Wages: Theory and Evidence from Britain. *Journal of the European Economic Association*, **forthcoming**.

MASSEY, DOUGLAS S., & MALONE, NOLAN. 2002. Pathways to Legal Immigration. *Population Research and Policy Review*, **21**(6), 473–504.

MASSEY, DOUGLAS S., & ZENTENO, RENÉ. 2000. A Validation of the Ethnosurvey: The Case of Mexico-U.S. Migration. *International Migration Review*, **34**(3), 766–793.

MCKENZIE, DAVID, & RAPOPORT, HILLEL. 2007. Network Effects and the Dynamics of Migration and Inequality: Theory and Evidence from Mexico. *Journal of Development Economics*, **84**, 1–24.

MCKENZIE, DAVID, & RAPOPORT, HILLEL. 2010. Self-Selection Patterns in Mexico-U.S. Migration: The Role of Migration Networks. *Review of Economics and Statistics*, **92**(4), 811–821.

MCKENZIE, DAVID, GIBSON, JOHN, & STILLMAN, STEVEN. 2007. A Land of Milk and Honey with Streets Paved with Gold: Do Emigrants Have Over-Optimistic Expectations about Incomes Abroad? *IZA Discussion Paper*, **2788**.

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

MORAGA, JESÚS FERNÁNDEZ-HUERTAS. 2011. New Evidence on Emigrant Selection. *The Review of Economics and Statistics*, **93**(1), 72–96.

MORETTO, MICHELE, & VERGALLI, SERGIO. 2008. Migration Dynamics. *Journal of Economics*, **93**(3), 223–265.

MUNSHI, KAIVAN. 2003. Networks in the Modern Economy: Mexican Migrants in the U.S. Labor Market. *The Quarterly Journal of Economics*.

ORRENIUS, PIA M., & ZAVODNY, MADELINE. 2005. Self-Selection among Undocumented Immigrants from Mexico. *Journal of Development Economics*, **78**, 215–240.

OTTAVIANO, GIANMARCO, & PERI, GIOVANNI. 2011. Immigration and National Wages: Clarifying the Theory and the Empirics. *Journal of the European Economic Association*, **forthcoming**.

PEDERSEN, PEDER J., PYTLIKOVA, MARIOLA, & SMITH, NINA. 2008. Selection or Network Effects? Migration Flows into 27 OECD Countries, 1990-2000. *European Economic Review*, **52**, 1160–1186.

REDSTONE, ILANA, & MASSEY, DOUGLAS S. 2004. Coming to Stay: An Analysis of the U.S. Census Question on Immigrants' Year of Arrival. *Demography*, **41**(4), 721–738.

SALEHEEN, JUMANA, & SHADFORTH, CHRIS. 2006. The Economic Characteristics of Immigrants and Their Impact on Supply. *Bank of England Quarterly Bullettin*, **Q4**, 373–385.

SINN, HANS-WERNER. 2004. EU Enlargement, Migration, and the New Constitution. *CESifo Working Paper*, **1367**.

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

THIJSSEN, JACCO J. J., HUISMAN, KUNO J. M., & KORT, PETER M. 2004. The Effect of Information Streams on Capital Budgeting Decisions. *European Journal of Operational Research*, **157**, 759–774.

UMBLIJS, JANIS. 2012. The Effect of Networks and Risk Attitudes on the Dynamics of Migration. *International Migration Institute Working Paper*, **54**.

VERGALLI, SERGIO. 2008. The Role of Communities in Migration Decisions. *Labour*, **22**(3), 547–567.

VIGDOR, JACOB L. 2008. Measuring Immigrant Assimilation in the United States. *Center for Civic Innovation, Civic Report*, **53**.

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

WINTERS, PAUL, DE JANVRY, ALAIN, & SADOULET, ELISABETH. 2001. Family and Community Networks in Mexico-U.S. Migration. *Journal of Human Resources*, **36**(1), 159–184.

ZAICEVA, ANZELIKA, & ZIMMERMANN, KLAUS F. 2008. Scale, Diversity and Determinants of Labour Migration in Europe. *Oxford Review of Economic Policy*, **24**(3), 428–452.