Does emigration benefit the stayers? The EU enlargement as a natural experiment. Evidence from Lithuania

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Abstract

The eastern enlargement of the European Union in 2004 triggered a large flow of migrant workers from the new member states to the UK and Ireland. This paper analyzes the impact of this migration wave on the real wages in the source countries. I consider the case of Lithuania, which had the highest share of emigrants relative to its workforce among all ten new member states. Using data from the Lithuanian Household Budget Survey and the Irish Census, I find that emigration had a significant positive effect on the wages of men who stayed in the country, but no such effect is visible for women. A percentage point increase in the emigration rate increases the real wage of men on average by 1%. Several robustness checks confirm this result.

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1 Introduction

If a high number of workers emigrate from a country, this should lead to wage increases for those workers who stay behind. When in 2004 eight countries from central and eastern Europe joined the Europen Union, this triggered a wave of migration from East to West, as workers were able to earn much higher wages in Ireland and the UK than in Poland, Latvia or Lithuania. The question is, whether this emigration wave had an impact on the wages of stayers. An answer to this question can be important for other countries that might join the European Union in the future and whose workers face the same kind of incentives to emigrate. Examples are countries in the Balkan region, such as Croatia, Serbia, Montenegro, Albania, etc.

In this paper, I test empirically the hypothesis, whether emigration leads to an increase in the wages of stayers, exploiting the eastern enlargement of the European Union in 2004 as a natural experiment. I choose Lithuania for my analysis, as this country lost a high share of its workforce due to emigration after 2004. From 2004 to 2007 around 9% of Lithuanian workers registered for a work permit in Ireland and the UK. To identify the impact of emigration on the wages of stayers, I use variation in emigration rates and real wages across gender, education, experience and over time, which follows Borjas (2003) and Mishra (2007). The data come from the Lithuanian household budget survey, the Irish census, as well as the data on UK and Irish work permits.

Using a reduced-form approach, I find that an increase in emigration is associated with an increase in real wages, but this only holds for certain groups of the workforce. While we cannot see any statistically significant effect for the wages of women, I find a statistically significant positive effect of emigration on the wages of men. When interaction terms are included, it turns out that the effect is higher for unmarried men than for married men. For a percentage point increase in the emigration rate, the real wages of men increase on average by around 1%. For unmarried men, this effect is 1.5%, while for married men it is close to zero. The results are confirmed by a number of robustness checks. I also adress the question of causality. While I can show that reverse causality is unlikely, it can be the case that the results are driven by a third factor that leads to spurious correlations. In the absence of suitable instruments, an interaction of time and region dummies accounts for this problem, as they absorb factors that can have an impact on wages over time, such as FDI inflows, trade or EU strucutral funds. Given the fact that the inclusion of those fixed effects does not change the statistical significance and magnitude of the effects, this indicates a causal relationship.

This paper contributes to the scarce literature on the wage effects of emigration. Mishra (2007) analyzed in a careful empirical study the impact of emigration on wages in Mexico over a time period of 30 years and found a significant positive effect. Batista (2007) developed a dynamic macro model to analyze the contribution of capital flows and emigration to the convergence of Portuguese real wages to EU average after the country's EU accession. She only found a small contribution of emigration. Kaczmarczyk *et al.* (2009) study the migration impact on Poland and Hazans & Philips (2009) analyze descriptively the situation in Estonia, Latvia and Lithuania. They find a higher number in vacancies after 2004, lower unemployment and a higher wage growth. These developments occurred at the same time as migration, but the authors do not attempt to establish a causal relationship.

My paper differs from those papers as it exploits the EU enlargement a natural experiment to show the short-run impact of emigration on the wages of stayers. From the results we can see that this effect can be sizeable in the short run.

The paper is outlined as follows: section 2 describes the historical context of this study and explains its theoretical underpinnings. In section 3, I describe the identification strategy and the empirical framework. Section 4 presents the construction of the dataset. Section 5 contains the results of the main estimation and robustness checks. Finally, section 6 concludes.

2 Historical Overview and Theoretical Considerations

2.1 Historical Overview

On May 1^{st} 2004, the European Union was enlarged by ten new member states, of which eight were former socialist countries in Central and Eastern Europe. This enlargement posed considerable challenges to the old (EU-15) member countries. As the freedom of movement for workers is one of the core principles of the European Union,[1] workers from the new member states would have been allowed to migrate freely and work in every country of the European Union. Given the large wage differentials between the old and new member states, some of the EU-15 countries feared negative consequences from the immigration of cheap labor. Sinn (2004) calculated that around 5% of the population in Central and Eastern Europe would migrate to the West after 2004. In countries with rigid labor markets such as Germany and France, this would lead to decreasing wages of natives. Moreover, as most Western European countries have generous welfare states, Sinn (2004) expressed the fear of high fiscal burdens when migrants do not work but live on social benefits. As a consequence, the EU-15 countries agreed on transitional arrangements before the EU enlargement, allowing countries to close their borders for workers from the new member states until 2011.[2] Only Ireland, the UK and Sweden opened their labor markets immediately. While Sweden noticed a comparably small inflow from 2004 onwards[3], Ireland and the UK became the major destinations for migrants from the new member states. From 2004-2007, Ireland issued 391,618 work permits to nationals from the accession countries from Central and Eastern Europe. The number of work

[1] Art. 39 of the Treaty Establishing the European Community.

[2] See Kahanec *et al.* (2009, p.4) for a description of the transitional arrangement.

[3] Wadensjö (2007) reports around 19000 immigrants from the new EU member states to Sweden from 2004 to 2006.

permits issued in the UK in the same time was 769,530.[4] Some accession countries lost a considerable share of their workforce due to migration. Figure 1 illustrates the number of emigrants from 2004-2007 relative to the domestic workforce in 2003. Lithuania, Latvia and Poland lost the highest share of their workers, whereas Hungary and the Czech republic did not see big outflows of workers. The numbers reported in this figure reflect an upper bound to migration. The actual losses to the workforce might be smaller, as not all workers who received a work permit in Ireland and the UK, were actually part of the workforce in the source countries. However, this figure shows that emigration led to sizeable changes in labor supply in Central and Eastern Europe.

2.2 Theoretical Considerations

A standard textbook model of a labor market suggests that emigration is a negative labor supply shock that leads to labor shortages, which result in upward pressure for real wages. Considering one single labor market implicitly assumes homogeneity of the workforce or, in other words, perfect substitutability of workers with different skills. This assumption is implausible, as a labor market is usually highly fragmented and the degree of substitutability between different groups of workers depends on the proximity of skills. Workers with the same degree of education are closer substitutes than those with a different education. In a specialized economy, even within an education group, people working in different industries are not perfect substitutes. For example, a solicitor cannot easily replace a physician and vice versa, even though both have a third-level degree. If we take this heterogeneity of labor market participants and their various degrees of substitutability into account, a theoretical model, such as the one proposed by Card & Lemieux (2001), predicts that a group of workers that is affected by an emigration shock experiences a higher effect on the wages of its own workers than any other group. As

[4] Sources: CSO Ireland and UK Home Office.

emigration did not occur equally to all skill groups, this variation can be exploited to identify the effect of emigration on real wages.

In their models, Card & Lemieux (2001) and Borjas (2003) assume that capital in this economy is fixed. If capital could fully adjust, migration would lead to capital outflows, as a decrease in labor supply decreases the marginal product of capital. This was not the case in Lithuania. Figure 6 shows that the capital stock in Lithuania was actually growing from 2002 to 2006.[5] In section 3.2, I will describe, how I account for those capital flows in the empirical model.

3 Empirical Framework

3.1 Identification Strategy

To identify the impact of emigration on wages, I use variation in real wages and emigration rates across skill groups and over time. A skill group is defined by gender, education and work experience. This definition follows the works by Borjas (2003), Ottaviano & Peri (2006, 2008) and Borjas *et al.* (2008). The conjecture behind this idea is that workers belonging to the same skill group compete in the same labor market. Those skill groups in the workforce which saw large outflows of workers should have, on average, higher increases in real wages than those groups who did not experience high outflows. This is a feasible identification strategy in the case of Lithuania, as the data about educational attainment of emigrants is available from the Irish census. Their work experience is not directly observable, but it can be calculated from the age and education of the emigrants. The clustering of the workforce in education groups is based on the idea that people within one education group are close substitutes in the labor market, whereas

[5] I am aware of the possibility that capital could have increased even more in the absence of emigration. However, I consider this effect to be negligible.

people from different education groups are not. In other words, a bricklayer with lower secondary education will hardly be able to replace an engineer with a third-level degree and vice versa.

However, even within a particular education group, workers are not necessarily close substitutes if they differ in work experience, as skill formation does not end with education. Furthermore, workers acquire job-specific skills at their workplace, so that workers with the same education and a similar work experience are close substitutes on the labor market, whereas those with the same education but different levels of work experience are not. To account for those different degrees of substitutability within workers of the same education group, I cluster the workforce in three education and nine experience groups. The education groups are *lower secondary school and less*, *upper secondary school* and *third-level degree*. The experience groups are clusters of work experience intervals of five years, i.e. 0-4 years, 5-9 years, 10-14 years and so on. As the choice of those 5-year intervals is arbitrary, I will also use 2-year and 10-year clusters for robustness checks. Section A.1 explains the clustering method in detail.

Additional sources of variation commonly used in the migration literature are geography and occupations.[6] In the case of emigration, information about the distribution of emigrants across industries and cities in the source country is not available, as emigrants are usually not included in national surveys such as the census or the HBS. On the other hand, the Irish census data does not state what Lithuanian region the immigrants came from or what occupation they had prior to migration. There is information available in the Irish census about their current occupation in Ireland, but this allows no conclusion about their previous occupation in Lithuania. As Kahanec *et al.* (2009, p. 20) show, immigrants from the new EU member states after 2004 often took up jobs in the receiving countries for which they were actually over-qualified.

[6] See, for example Altonji & Card (1991) and Friedberg (2001)

3.2 Empirical Specification

The basic empirical specification essentially follows Friedberg (2001), who uses individual-level data to investigate the impact of immigration in two-digit occupation categories on real wages in Israel. Instead of occupations, I use worker skill groups as proposed by Borjas (2003). As migration was triggered by a law change, I assume that it is exogenous to changes in wages throughout the analysis.[7]

The basic empirical specification used throughout the paper is

$$\ln w^i_{ghjt} = \delta m_{ghjt} + (\boldsymbol{X^i_{ghjt}})'\boldsymbol{\beta} + \pi_t + educ_h + exp_j + (reg^i \times \pi_t) + \varepsilon^i_{ghjt}, \tag{1}$$

where $\ln w^i_{ghjt}$ denotes the log monthly real wage[8] of individual i. m_{ghjt} is the emigration rate of the skill group individual i belongs to. A skill group is composed of the following characteristics: gender g (g=male, female), education h (h= *lower secondary*, *upper secondary*, *third-level*) and experience group j (j= *0-4 years*, *5-9 years*,...,*35-39 years*, *40+ years*). t is the relevant year of the cross-section (t=2002, 2003, 2005, 2006). The emigration rate m_{ghjt} is a group variable that has the same value for all members of the group in each year. Although all members of the group may not be affected by emigration to the same extent, it is plausible that they are affected in a similar way. Hence, I expect the standard errors of the members of a particular group to be serially correlated. This can lead to biased estimates, as reported standard errors can be much lower than they in fact are.[9] To overcome this bias, I cluster the standard errors on the level of gender-education-experience-time cells.[10] Throughout the whole analysis, I only consider workers in the private sector. The argument for this is that the wage setting process in the public sector can be influenced by factors that cannot be explained by competition,

7 I will discuss potential criticisms of this assumption in section 5.2.

8 Monthly wages are deflated by the Lithuanian HCPI. See table 1g) for the HCPI.

9 Angrist & Pischke (2009, ch.8) explain the bias resulting from clustered data and propose the clustering of standard errors.

10 This makes an overall of $2 \times 3 \times 9 \times 4 = 216$ clusters

such as political considerations or seniority pay plans, family size, etc.

The coefficient of interest is δ, which measures the average percentage change in the real wage of a gender-education-experience cell, if the emigration rate of workers in this cell changes by one percentage point.

X^i_{ghjt} is a vector of individual control variables (gender, marital status, a dummy for urban areas, number of children).

$(reg^i \times \pi_t)$ is an interaction term between a vector of year dummies (π_t) and a vector of dummies for the county (reg^i) individual i lives in. The interaction accounts for unobservable changes in economic conditions across regions over time that may have an influence on real wages. Examples are the inflow of EU structural funds, interregional migration, FDI inflows or a change in the magnitude and composition of trade flows after EU accession. The inclusion of this interaction helps to diminish the endogeneity and omitted variable bias.

$educ_h$ is a dummy for each education group h. It captures unobservable characteristics that are common to the members of each education group and that do not change over time. For example, workers with a third-level degree tend to work in white-collar occupations, whereas workers with a lower secondary education rather have blue-collar jobs. The choice of those jobs influences their earnings, but we cannot observe the individual's occupation from the Lithuanian data. A similar selection pattern might occur among workers with different levels of work experience. Within an occupation, older workers might have different tasks than younger workers. This difference can affect their wages. These time-invariant unobservable characteristics of different experience groups are captured by the experience group dummies exp_j.

All regressions are weighted with sampling weights given in the HBS. A sampling weight is defined as the inverse of the probability that an observation is included in the sample. The use of those weights becomes necessary, as some groups are over- and underrepresented in the sample compared to the population. This sampling design of the survey would lead to biased estimates. The weighting of all regressions with those sampling weights eliminates this bias.

4 Data and Descriptive Statistics

The core dataset used in this study is the annual Lithuanian Household Budget Survey, which includes the characteristics and wages of stayers in Lithuania. The characteristics of emigrants are taken from the Irish census data of the years 2002 and 2006. Finally, the numbers of emigrants are extracted from the Irish "Personal and Public Service Numbers" (PPS) and the "National Insurance Numbers" (NINo) from the United Kingdom. Those data sources result in a pooled cross-sectional dataset covering the two years before EU accession 2002, 2003, and the two years afterwards, 2005 and 2006. I deliberately omitted the year 2004 from my analysis, as it is unclear, how many people actually emigrated in 2004. The registration numbers in the UK and Ireland in 2004 may reflect the fact that workers had been living and working illegally in those countries before 2004, but only applied for a work permit when Lithuania joined the EU.

The variables of interest throughout the whole study are real wages and emigration rates. The real wages can be taken from the Lithuanian HBS. The emigration rates per skill group are not directly observable and have to be calculated using information from different data sources. I take the skill distribution of Lithuanian emigrants from the Irish census data. As there is no microdata about Lithuanian emigrants to the UK available to me, I assume that the skill distribution of migrants to the UK is the same as the skill distribution of migrants to Ireland. As the total inflows of Lithuanian workers, measured from the numbers of work permits differ between Ireland and the UK, I assume that the flows to the UK per skill group are directly proportional to the flows to Ireland. The number of work permits in the UK relative to the number of work permits in Ireland in a given year describes this proportion. To obtain the emigration rates, the number of emigrants in a skill group is divided by the number of people in the Lithuanian workforce, who belong to the same skill group. In section A.2, I describe the calculation of emigration rates and discuss the necessary assumptions in detail. I also explain the cleaning of the data in section A.3.

The following sections give a description about the data sources used in this study.

Lithuanian Household Budget Survey

The Lithuanian Household Budget Survey (HBS) is an annually conducted survey of 7000-8000 households. It includes individual characteristics of household members as well as the income and expenditure of the household. The HBS is representative at the individual level.

To match the Lithuanian data with the Irish census data, I restrict the sample to all employees aged 18-64. The variables taken into consideration are *income from employment* of the household head and her personal characteristics, such as gender, marital status, the number of children, etc. Self-employed workers are dropped from the sample, as their income is decomposed in the HBS into several income categories which are not easily traceable for most observations. The data on income is self-reported and could as such be subject to misreporting. This does not seem to be the case for the Lithuanian HBS. Table 1j) compares the average self-reported income for men and women from the HBS with the average income reported by the Lithuanian statistical office, and we can conclude that misreporting should not be an issue.

Table 1a) summarizes the properties of the HBS. Table 1c) indicates that the income from employment for all groups has increased on average between 2002 and 2006.

Irish Census

The Irish census was carried out in the years 2002 and 2006 and covers all people that were present in the Republic of Ireland in the census night. The Central Statistics Office (CSO) of Ireland provided a tabulation of all Lithuanians in the census of 2002 and 2006, their educational attainment, gender and age. The Irish census data makes it possible to calculate the gender-education-experience distribution of Lithuanian migrants, which will be used to calculate the emigration rates from Lithuania for different education and experience groups.[11] Table 1b) illustrates the magnitude of the emigration wave from Lithuania after EU accession.

The difference in the magnitude of Lithuanian migrant numbers between 2002 and 2006 is noteworthy. Despite the fact that I do not have precise information about the year, in which the immigrants arrived, this difference confirms that most of the Lithuanians in the Irish census came to Ireland around or after the country's EU accession.

Tables 1d) and 1e) show the distribution of education groups in the Irish census and in the Lithuanian HBS. The share of workers with a third-level and those with upper secondary education is lower among Lithuanian immigrants in Ireland than among stayers. At the same time, the share of workers with lower secondary education is higher in among immigrants in Ireland. This difference in the educational distribution indicates a pattern of negative selection of migrants.

PPS and NINo numbers

As described above, the Irish census data can be used to determine the characteristics of Lithuanian emigrants. However, the figures of the census are only a lower bound to emigration numbers, as they are considerably lower than the figures reported by the

[11] See section A.2

worker registration schemes in the UK and Ireland. In the time from 2002 to 2007, 63,412 Lithuanians applied for a PPS number in Ireland and 90820 for a NINo number in the UK. Figure 2 shows the migration pattern over time. Obviously, the large emigration wave set in when Lithuania joined the EU in 2004.

All immigrants who wish to come to Ireland and take up legal employment are required to apply for a PPS number. Hence, the PPS numbers capture the amount of all labor migrants coming to Ireland, no matter how long they actually stay in the country and what type of job they are employed in. There is no obligation to de-register once a migrant leaves Ireland. Therefore, it cannot be concluded from the PPS numbers how long immigrants actually stay in Ireland and how many return to Lithuania. The NINo numbers in the UK are equivalent to the PPS numbers in Ireland.[12] The UK government introduced an additional registration scheme for arriving workers from the new EU member states (WRS). The data on migration flows from Lithuania to the UK are similar to those from the NINo numbers, but they only cover the period from 2004 onwards. Hence, NINo numbers are more suitable for my analysis, as they cover the whole time span from 2002. The number of immigrants can generally be overstated in the PPS and NINo numbers, as some Lithuanians might be registered in both countries. I will use the PPS and NINo numbers as weights in the calculation of emigration rates in section A.2, taking into consideration that they are an upper bound to migrant numbers and may contain double counts as well as workers who stayed abroad for a very short period in time, e.g. for a summer job.

[12] For further information about PPS and NINO numbers, see http://www.welfare.ie and http://www.direct.gov.uk

5 Estimation Results

5.1 Basic Results

I estimate the fixed-effect model in equation (1) with OLS, for which Table 3 (panel A) shows the regression results. The basic results, including all private sector workers are displayed in column (1). Controlling for observable and unobservable worker characteristics, I find a positive and statistically significant effect of emigration on real wages. In economic terms, the coefficient of the emigration rate means that an increase in the emigration rate of a certain gender-education-experience group by one percentage point, increases the wages of this group on average by 0.66%. As we can see, men have on average higher earnings than women, the same holds for people living in an agglomeration[13] and people who are married. The variable *Children* denotes the number of children under 16 living with the individual. The coefficient is negative and statistically significant, but economically negligible, as every child decreases income from employment on average by 0.036%.

Within the population, different groups of the labor force may be affected differently by emigration, for example men more than women, married people more than unmarried. To account for different wage effects for men and women, I include interaction terms of the emigration rate with the dummy for *male* (see table 3, column (2)). Furthermore, as unmarried people tend to be more mobile than married people and might differ in unobservable characteristics, the wage effect might differ for married and unmarried people. I account for this difference in table (3) column (3) with an additional interaction of the emigration rate with the dummy for *married*. This allows me to analyze the wage effects for four different groups: married women, unmarried women, married men, unmarried men.

[13] The agglomeration dummy equals 1 if the person lives in one of the five largest cities of Lithuania (Vilnius, Kaunas, Klaipeda, Siauliai, Panevezys) and zero otherwise.

Table 4 (panel A) reports the marginal effects of a 1-percentage-point increase in the emigration rate on the real wages of different groups. As we can see, there is a statistically significant positive effect for men. For every percentage point increase in their emigration rate, their real wage increases by around 1.2%. For women, we cannot see a statistically significant effect. A reason for the different effect between men and women might be the fact that emigrant women might actually not be part of the Lithuanian labor force. In case they did not emigrate *out of the workforce*, it is not surprising that we cannot find evidence for wage increases, as their outflow is not a negative labor supply shock. Another explanation can be that women work in industries that are not affected by emigration, so that no wage effect is visible.[14] The obvious gender pay gap[15] indicates such a self-selection behavior.

Considering the different effects for married and unmarried people, we can see that there is no visible effect for women. For men, we can see a sizeable difference in the effects of emigration on their real wages between unmarried and married men. At the same time, unmarried men saw their real wages increase on average by 1.4% for every percentage point increase in the emigration rate, while for married men, this effect is close to zero. Despite the fact that the effect for married men is statistically highly significant, the size of the effect is economically negligible.

The difference in the wage effect for married and unmarried men can have a number of reasons. Of course, there are no distinct labor markets for both groups. The higher wage effect for unmarried men might be driven by observable and unobservable characteristics. Unmarried men are more flexible and have lower moving costs, which gives them a higher bargaining power towards their employers. They can use the possibility of emigration as a credible threat. Moreover, unmarried men are on average younger than married men. If

14 Around 40% of all female workers are employed in the public sector, while the share of male workers is only 20%. Source: Statistics Lithuania

15 See the coefficients for the *male* dummy in table 3, column (3). Even in the absence of migration, men earn on average more than women.

younger workers have higher wage increases than older workers, this translates into higher wage increases for unmarried men.[16] Another unobservable characteristic could be the type of profession married and unmarried people choose. Married people might be more conservative and choose jobs that give them security but are not subject to high wage increases, whereas unmarried men might rather pick jobs that are riskier but experience higher wage increases.

5.2 Robustness Checks

5.2.1 Do the Results Suffer from Reverse Causality?

As the results in section 5.1 are derived using OLS, they measure a correlation between emigration and wages. However, a causal interpretation of emigration on wages is only possible, if we can exclude reverse causality. In our case, reverse causality would mean that wages drive emigration. This is certainly possible and would lead to biased estimates. As I cannot entirely exclude reverse causality, it is important to understand the direction of the bias. As it turns out, reverse causality leads to a downward bias in the estimates of the parameter δ in equation (1). As a consequence, the coefficients obtained in the regressions in section 5.1 reflect a lower bound to the actual effects, so that the effect is at least as great as δ. This can be shown as follows:
Take a simplified version of the model in equation (1),

$$\ln w = \delta m + u, \tag{2}$$

where u is an error term. In case emigration drives wages, the coefficient δ should be positive, as stayers become a more scarce resource because of higher emigration, which

[16] As the variation of emigration rates and wage changes across experience groups is central to the identification strategy, I do not test for a difference in wage increases for workers of different age.

leads to an increase in their wages. On the other hand, if we regress emigration rates on wages, the regression becomes

$$m = \gamma \ln w + v, \tag{3}$$

with v being the error term. The direction of the bias then depends on the sign of the coefficient γ. If wages were driving emigration, I would expect a negative relationship between wages and emigration, so that $\gamma < 0$: the lower the wages are, the higher the number of emigrants. If those two effects work at the same time, we can add equations 2 and 3. Solving for $\ln w$, we get

$$\ln w = \frac{\delta - 1}{1 - \gamma} m + \frac{u + v}{1 - \gamma}. \tag{4}$$

As we can see from this equation, $\delta > \frac{\delta-1}{1-\gamma}$, which is valid as $\gamma < 0$, so that the estimate of the coefficient δ in equation (1) is a lower bound to the effect of emigration on wages.

5.2.2 Are the Results Driven by a Third Factor?

Even if reverse causality is not an issue, the correlations found in table 3 may not lead to a causal interpretation, if there is a third factor that drives migration and wages at the same time. In case of the EU eastern enlargement, this situation is likely. The accession of Lithuania did not only trigger a wave of emigration, the country could also benefit from a deeper trade integration, increased FDI inflows, domestic investment and the inflows of EU structural funds. Economic theory implies that those factors, trade and capital inflows, increase labor demand, which translates into higher wages. Hence, the correlation obtained from the OLS estimates might be spurious and does not lead to any conclusion about causality. One way to overcome this problem would be the use of instrumental variables. However, in the context of the European enlargement it is difficult to find suitable instruments, which are correlated with the emigration rate and not correlated with wages, as the EU accession changed the economic conditions from one day to another, so that most variables will be correlated with wage changes.

Another problem that arises in OLS regressions when we do not control for additional variables that drive wages, is omitted variable bias. Without the use of instrumental variables, this bias cannot be entirely eliminated, but it can be reduced, either by the inclusion of appropriate fixed effects or by the inclusion of observable control variables, which have an effect on wages, such as FDI or trade. In equation (1) and in all subsequent robustness checks, I include an interaction between a set of region dummies and a set of time dummies. These interactions absorb changes in wages across regions over time and as such, they absorb the variation that is caused by changes in labor demand over time. The rationale behind this is that demand factors like inflows of FDI and EU structural funds, as well as trade flows, have a different effect on every region and on the wage level in this region.

As a robustness check, I omit the interaction *region*year* from equation (1) and include log(FDI stocks), log(Exports) and log(GDP per capita) in the regression.[17] Those three variables are measured at the county level and denominated in 2005 Litas. Panel B of table 3 reports the results for these regressions. None of the included variables (FDI, exports and GDP) is statistically significant at the 5% level. In panel B of table 4 we can see the marginal effects of emigration on wages. Compared to the results in panel A, the results in panel B have the same statistical significance and magnitude. The question arises, which method is more helpful in reducing the omitted variable bias. As the interaction terms *region*year* absorb all the developments that affect the wages differently across regions over time, this method reduces the bias more than the inclusion of the three observable variables. Because the data on some variables, such as the inflow of

[17] Source: Lithuanian statistical office.

EU strucural funds at a regional level, is not readily available, the omitted variable bias should be greater in the latter case.

5.2.3 Did the Migrants Emigrate out of Unemployment?

The increased mobility for Lithuanian workers after EU accession made it also possible for unemployed people to emigrate and look for work in Ireland and the UK. From the Irish census, I do not have any information about the previous employment status of the migrant workers. As we can see in table 1i), unemployment fell from 13.8% in 2002 to 5.6% in 2006. This decline can be due to a favourable economic climate,[18] as well as due to emigration. Emigration can affect unemployment mainly through two channels: 1) unemployed people emigrate, 2) unemployed people take up jobs of people who emigrate. I consider the first channel as unrealistic, as the skill requirements in Ireland and the UK are on average higher than in Lithuania, so that it is less likely for someone who is unemployed in Lithuania to find a job abroad. Moreover, immigrant workers from other EU member states only become eligible for social benefits in the UK and Ireland after working there for one year.[19] Thus, Lithuanian workers did not have an incentive to emigrate into unemployment and live on social benefits. The second channel could play a more important role than the first one and can as such be part of the story, why wages increase when workers emigrate. However, if unemployed workers replace workers who emigrated and receive the same wage, this would at maximum downward-bias the estimates obtained in section 5.1, so that the effect of emigration would be higher in absence of this job replacement mechanism.

[18] GDP growth from 2002-2006 was between 7 and 10%, see table 1k).
[19] Source: Irish Welfare Office, UK Department of Work and Pensions.

5.2.4 Are the Results Influenced by Immigration from Other Countries?

Wages are just one possible channel, through which the labor market can adjust to an emigration shock. Another adjustment channel is immigration from other countries. If domestic workers who emigrant are replaced by immigrant workers with the same skills, this should leave wages unchanged. As we can see in table 1h), Lithuania saw in fact an increase in migration from 2002 to 2006. However, if we break the immigration down by country, we can see that the number of immigrants from the former Soviet Union and other countries remains the same, whereas the number of Lithuanian immigrants increases. This reflects the fact that many Lithuanians emigrated for a short period in time and finally returned to their home country. Even though I cannot directly control for return migration,[20] I accounted for this fact in the calculation of emigration rates in section A.2, so that immigration from other countries and return migration should not bias the estimates.

5.2.5 Do the Emigration Rates of other Skill Groups Have an Effect?

The wages of a certain skill group do not only depend on the labor supply of this particular skill group, but also on the labor supply of other skill groups. If different skill groups enter the aggregate production function of an economy as separate labor inputs, a negative labor supply shock to one cell leads to a decreasing marginal product of all the other cells and therefore lowers wages. To account for this interdependence between different skill groups, I augment the specification in equation (1) as follows:

$$\begin{aligned} w^i_{ghjt} &= \delta m_{ghjt} + \sum_{k \neq j} \delta_{ghkt} m_{ghkt} + \sum_{l \neq h} \delta_{gljt} m_{gljt} \\ &+ (\boldsymbol{X^i_{ghjt}})'\boldsymbol{\beta} + \pi_t + educ_h + exp_j + (reg^i \times \pi_t) + \varepsilon^i_{ghjt}, \end{aligned} \tag{5}$$

[20] The HBS does not contain information about the number of return migrants by skill group.

where m_{ghkt} are the emigration rates of all other experience groups within education group j. m_{ghkt} are the emigration rates of the same experience group j but a different education group h.[21] Table 5a) reports the results for the regressions of equation (5). The sign and significance of the coefficients for the different groups are the same as in the basic model. The effect of emigration on the real wages of men comes out slightly smaller than in section 5.1, but the robustness check generally confirms the previous results.

5.2.6 Do the results depend on the calculation of skill groups?

So far, I have controlled for a worker's experience by including dummies for experience groups. In the literature, work experience often enters the econometric model as a continous variable.[22] This makes it possible to account for diminishing marginal returns to work experience by including a squared term. The empirical specification for this is

$$w^i_{ghjt} = \delta m_{ghjt} + \boldsymbol{(X^i_{ghjt})'\beta} + \pi_t + educ_h + exp^i + (exp^i)^2 + (reg^i \times \pi_t) + \varepsilon^i_{ghjt}, \qquad (6)$$

where exp^i is the work experience of individual i. The results are displayed in table 5b) and do not differ a lot from the ones in section 5.1.

In section 5.1, the workforce was clustered in 5-year work experience groups under the assumption that within an experience group, workers are perfect substitutes. The choice of those intervals, though widely used in the literature, is purely arbitrary. To check, whether the results are driven by the way the skill groups are clustered, I re-run specification (1), using 2-year and 10-year experience groups. The results can be seen in tables 5d) and 5e). In terms of sign and significance, the coefficients are equivalent to the ones obtained in section 5.1. The marginal effects of the 2-year cells are smaller than for

[21] Due to multicollinearity issues, it is not possible to include the emigration rates from all other gender-education-experience groups.

[22] See, for example, Chiswick (1978).

the 10-year cells. This difference can be due to the fact that 2-year cells allow for more variation in real wages and emigration rates across skill groups.

5.2.7 Interaction *year*education*

When Lithuania joined the EU in 2004, this accession did not only trigger an emigration wave, but the country also got access to EU structural funds and received higher FDI inflows. These factors can increase labor demand and as such have an impact on wages. In the basic specification of equation (1), I attempted to capture those factors by including time fixed effects and an interaction of region and time dummies. The time dummies capture unobservable effects on the average wages of all workers in a given year. The interaction *region*year* captures unobservable heterogeneous drivers of wage changes across regions over time. However, neither the time dummies nor the interaction accounts for heterogeneous changes in wages across education groups over time. The EU structural funds benefited particularly sectors that employ low-skilled workers, such as the construction sector. In this case, the inflow of structural funds would have a greater impact on the wages of low-skilled workers than on the ones of high-skilled workers. These unobservable heterogeneous wage changes for different education groups over time can be captured by an interaction of the time dummies with the dummies for education groups. As we can see in table 5c), the effect of emigration on the real wages is slightly smaller, but in terms of sign and significance, this robustness check confirms the findings from section 5.1.

6 Conclusion

In this paper I exploit a natural experiment to estimate the impact of emigration on stayers. I choose Lithuania for my case study, which lost a high share of its workforce due to emigration after the country's EU accession. The main result in this paper is that there is a positive effect of emigration on the wages of stayers. However, this effect is not significant for all groups of the workforce. While the wages of men increased significantly due to emigration, I cannot find such an effect for women. The use of interaction terms revealed that the increase in wages was higher for unmarried men than for married men. These results are plausible, as unmarried men are more flexible than married men, which gives them a higher likelihood to emigrate. If this translates into a higher bargaining power, their wages will increase more than the wages of other groups.

The results turn out to be robust subject to a number of robustness checks. In the absence of appropriate instruments, the question of a causal relationship between emigration and wages can only be answered indicatively. Given that the EU accession was an exogenous event and given that we control appropriately for other factors that might influence migration and wages, the causality of emigration increasing wages seems likely.

While in this study I was only able to account for capital flows using fixed effects, it would be interesting to investigate the contribution of capital flows to the changes in wages after 2004. For such a study, a structural model such as in Ottaviano & Peri (2006, 2008) is needed. This could be the subject of future research.

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errors are mine.

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A Data

A.1 Clustering: Education-Experience Groups

A.1.1 Education Groups

The Lithuanian education system offers a variety of educational tracks and degrees.[23] 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 1d) and 1e) show the distribution of the education levels in the Lithuanian HBS as well as in the Irish census.

I 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

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

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 here.

A.1.2 Experience Groups

Within each education group, I cluster the workforce by groups of work experience. Following Borjas (2003), workers of five consecutive years of work experience form one experience group: workers with 0-4 years of experience, 5-9 years, 10-14 years, etc. up to the group 40+ years. The work experience is not directly observable from the Irish census data, but can be calculated. Assuming that people enter the labor market right after completion of their education, the work experience is calculated according to the formula $exper_i = age_i - educ_i - 6$, where age_i is the age of individual i, $educ_i$ is the duration of her highest education individual i has finished and children usually enter school at the age of 6. $educ_i$ equals 10 years for workers with lower secondary school, 12 years with upper secondary school and 15 years with a third-level degree.

A.2 Calculation of Emigration Rates

Although the number of emigrants in each education-experience cell is not directly observable, the available data allows me to construct sensible measures of emigration numbers for different skill groups. The idea behind the calculation is the following: take the gender-education-experience distribution from the Irish census and weight it with the corresponding numbers of workers who applied for PPS and NINo numbers in Ireland and the UK. By dividing the calculated emigrant number of a certain gender-education-experience cell by the number of people in Lithuania with the same characteristics, we obtain the emigration rates.

The calculation of emigration rates requires three assumptions about the emigrants' gender-skill distribution: 1) the distribution is the same in the UK and in Ireland. 2) The distribution in 2002 is the same as in 2003, and 3) the distribution in 2005 is the same as in 2006.

The first assumption implicitly claims that no sorting behavior among migrants between the two destinations Ireland and the UK could be noticed. This assumption is backed by the recent literature on immigration to Ireland and the UK. When we compare the descriptive statistics of the studies by Barrett & Duffy (2008, p.605) for Ireland and Dustmann *et al.* (2009, p.23) for the UK, the educational distribution of immigrants from the A8 countries[24] who came after 2004, looks fairly similar (see table 2). Hazans & Philips (2009) analyze the occupational distribution of Lithuanians in Ireland and the UK. On the one hand, there is a difference in the sectors that employ Lithuanian immigrants in both countries. In the UK, around 30% of Lithuanian immigrants work in agriculture,

[24] A8 countries are: Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Slovakia and Slovenia.

whereas in Ireland this share is only 5%. This result could lead to the conclusion that migrants in the UK differed in their skills from those in Ireland. On the other hand, the same study shows that in both countries around 80% of Lithuanian migrants work in sectors that typically employ less-skilled workers, such as construction, health, trade, manufacturing, hotels and restaurants and agriculture. This indicates the absence of sorting behavior, so that it is reasonable to assume that the skill distribution of Lithuanian immigrants is the same in Ireland and the UK.

Assumptions 2) and 3) are reasonable as the education distribution among Lithuanian emigrants in Ireland did not change significantly from 2002 to 2006, even though the number of migrants is nine times higher in 2006. As we can see in table 1e), the share of immigrants with a third-level degree is slightly lower in 2006. At the same time, the share of those with lower secondary education is higher, but both distributions - 2002 and 2006 - do not differ a lot. Taken together, these three assumptions make it possible to extrapolate the skill distribution given in the Irish census to the UK and to the years that are not covered in the Irish census, 2003 and 2005. This allows me to present a more realistic picture of the size and impact of migration flows than we would get by only using the Irish data for 2002 and 2006 without extrapolating. In the robustness checks in section 5.2, I drop those assumptions. We will see that this has an impact on the magnitude, but not on the sign and statistical significance of the wage effects.

For the calculation of the number of emigrants for each gender-education-experience cell in the years 2002 and 2006, I use the number of Lithuanians in the Irish census of the same year and multiply it with a weighting factor, which accounts for the migration flows to the UK. For the years 2003 and 2005, I additionally weight the calculated number with the PPS and NINo numbers of those years.

Let x^t_{ghj} denote the number of people in the Irish census of gender(g)-education(h)-

experience(j) cell at time t. For $t = (2002, 2006)$, the calculated number of emigrants is

$$M_{ghj}^{t} = x_{ghj}^{t} \left(1 + \frac{NINO_t}{PPS_t}\right), \tag{7}$$

where M_{ghj}^{t} is the calculated number of emigrants in cell ghj in year t. $NINO_t$ and PPS_t are the NINo and PPS numbers issued to Lithuanians in year t. The first term in parentheses (1 in this case), accounts for the fact that I consider the raw migrant numbers in the census 2002 and 2006 for Ireland. The second term in parantheses, $\frac{NINO_t}{PPS_t}$, is a weighting factor for the extrapolation of the migrant skill distribution of the Irish census to the UK. If, for example, in 2006 the number NINo applications is twice the number of PPS applications, this factor is 2. Table 1e) displays the figures of PPS and NINo numbers issued between 2002 and 2006.

For the year 2003, I take the number of Lithuanian migrants in cell ghj of the year 2002 and weight it with the PPS and NINo numbers of 2003. This results in

$$M_{ghj}^{2003} = x_{ghj}^{2002} \left(\frac{PPS_{2003}}{PPS_{2002}} + \frac{NINO_{2003}}{PPS_{2002}}\right). \tag{8}$$

$\frac{PPS_{2003}}{PPS_{2002}}$ weights the number of migrants in the Irish census in 2002 with the change in PPS numbers from 2002 to 2003. Suppose the number of Lithuanian immigrants in Ireland was 30% higher in 2003 than in 2002. Then $\frac{PPS_{2003}}{PPS_{2002}} = 1.3$. $\frac{NINO_{2003}}{PPS_{2002}}$ accounts for the change in PPS numbers, as well as for the difference in migration flows to the UK and Ireland in 2003.[25]

The calculation of the number of emigrants in 2005 is analog the one of 2003:

$$M_{ghj}^{2005} = x_{ghj}^{2006} \left(\frac{PPS_{2005}}{PPS_{2006}} + \frac{NINO_{2005}}{PPS_{2006}}\right). \tag{9}$$

25 $\frac{NINO_{2003}}{PPS_{2002}}$ 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.

For my econometric analysis, emigration rates are more relevant than absolute emigrant numbers, as the coefficient δ in equation (1) can then be interpreted as a *quasi-elasticity*. An increase in the emigration rate of one percentage point would then increase the real wage by δ percent.

The emigration rate m_{ghjt} for cell ghj in year t is

$$m_{ghjt} = \frac{M^t_{ghj}}{\sum_i p_{ghijt}}, \tag{10}$$

where M^t_{ghj} denotes the number of emigrants calculated in equations (7) to (9). The denominator of equation 10 is the number of people in year t living in Lithuania and belonging to cell ghj. Due to the fact that I do not have data covering the entire Lithuanian population, I have to calculate the number from the HBS. The HBS is representative at the household level, so that I can calculate the total number of Lithuanians in cell ghj by summing up the sampling weights p_{ghijt}[26] over all observations i that are in cell ghj in year t.

A.3 Data Cleaning

Additional to the data cleaning mentioned in section 4, I made the following changes in the respective datasets:

Irish census

- Dropped observations if age is less than 18 years
- Calculated emigration numbers are rounded to full digits

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

Lithuanian HBS The following observations were dropped:

- Disposable income less than 0
- Socioeconomic status "pensioner" or not reported
- Less than 18 and more than 64 years old
- Workers, whose income is neither from employment nor self-employment
- Workers who own a farm or are self-employed

B Tables

Table 1: Descriptive Statistics

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

Table 2: Distribution of education among A8 immigrants after 2004 in Ireland and the UK

authors	Barrett & Duffy (2008)	Dustmann *et al.* (2009)
country	Ireland	UK
lower secondary	11.1%	11.9%
upper secondary	61%	56.1%
third-level	28.2%	32%

Table 3: OLS, weighted with sampling weights. Men and women - private sector. Dependent variable: log(real wage)

	A: interaction *region*year*			B: Controls FDI, Trade, GDP		
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	all	interaction male	interaction male*married	all	interaction male	interaction male*married
Emigration rate	0.657**	0.390	0.389	0.673**	0.406	0.411
	[0.2786]	[0.3549]	[0.3377]	[0.2752]	[0.3147]	[0.3360]
Emigration * Male		0.774**	1.115**		0.776***	1.118***
		[0.3222]	[0.3897]		[0.3191]	[0.3853]
Emigration * married			-0.336			-0.3821
			[0.4498]			[0.4443]
Emigration * married * male			-1.057*			-1.043*
			[0.5700]			[0.5698]
Male	0.168***	0.147***	0.144***	0.166***	0.146***	0.143***
	[0.0184]	[0.0197]	[0.0203]	[0.0184]	[0.0197]	[0.0206]
Married	0.522***	0.524***	0.549***	0.524***	0.527***	0.552***
	[0.0252]	[0.0251]	[0.0293]	[0.0249]	[0.0248]	[0.0290]
Children	-0.036***	-0.036***	-0.033***	-0.036***	-0.035***	-0.032***
	[0.0110]	[0.0110]	[0.0110]	[0.0109]	[0.0109]	[0.0110]
Agglomeration	0.381***	0.380***	0.381***	0.379***	0.378***	0.380***
	[0.0232]	[0.0232]	[0.0231]	[0.0228]	[0.0228]	[0.0227]
log(exports)				0.009	0.007	0.012
				[0.0821]	[0.0821]	[0.0824]
log(gdp per cap.)				0.610*	0.614*	0.622*
				[0.3160]	[0.3159]	[0.3165]
log(fdi stocks)				0.024	0.024	0.025
				[0.0164]	[0.0165]	[0.0165]
Year Dummies	yes	yes	yes	yes	yes	yes
Education Dummies	yes	yes	yes	yes	yes	yes
Experience Group FE	yes	yes	yes	yes	yes	yes
Region Dummies	no	no	no	yes	yes	yes
Interaction Region*Year	yes	yes	yes	no	no	no
Observations	9970	9970	9970	9970	9970	9970
Adjusted R^2	0.3669	0.3674	0.3681	0.3663	0.3667	0.3675

Robust standard errors in brackets

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

Table 4: Marginal effects of emigration on wages for different groups, results from table 3. P-values in brackets.

	A: interaction *region*year*	B: controls FDI, export, trade
All	**0.6568****	**0.6732****
	(0.0192)	(0.0153)
Women	0.3902	0.4061
	(0.2180)	(0.1982)
Men	**1.1647*****	**1.1182*****
	(0.0001)	(0.0001)
Women, unmarried	0.3895	0.4109
	(0.2500)	(0.2227)
Women, married	-0.0532	0.0288
	(0.4934)	(0.4411)
Men, unmarried	**1.5047*****	**1.5293*****
	(0.0000)	(0.0000)
Men, married	**0.1109*****	**0.0002*****
	(0.0006)	(0.0003)

Table 5: Robustness checks. Marginal effects of emigration on wages for different groups. P-values in brackets.

	a)	b)	c)	d)	e)
All	0.3396	0.4929*	**0.6032****	**0.4517*****	**0.8471****
	(0.3415)	(0.0827)	(0.0342)	(0.0035)	(0.0288)
Women	0.6835	0.2352	0.3572	0.2640	0.6301*
	(0.8322)	(0.4968)	(0.2630)	(0.2443)	(0.0832)
Men	**0.9910*****	**0.9420*****	**1.108*****	**0.9051*****	**1.6341*****
	(0.0006)	(0.0047)	(0.0002)	(0.0003)	(0.0003)
Women, unmarried	0.1042	0.2030	0.3509	0.2970	0.5537*
	(0.7587)	(0.5931)	(0.3071)	(0.2095)	(0.1355)
Women, married	-0.2357	0.0616	0.0297	-0.0934	0.7490
	(0.7410)	(0.8657)	(0.5674)	(0.4171)	(0.2232)
Men, unmarried	**1.3518*****	**1.2050*****	**1.4452*****	**1.0361*****	**2.1384*****
	(0.0002)	(0.0015)	(0.0001)	(0.0002)	(0.0001)
Men, married	**-0.0407*****	**0.0862*****	**-0.0471*****	**0.0524*****	**0.9438*****
	(0.0013)	(0.0064)	(0.0006)	(0.0019)	(0.0005)

a) Emigration rates of other cells included (section 5.2.5)
b) experience included as a continuous variable (section 5.2.6)
c) interaction *education group * year* (section 5.2.7)
d) 2-year experience cells (section 5.2.6)
e) 10-year experience cells (section 5.2.6)

C Figures

Figure 1: Emigrant shares after EU accession: number of work permits in the UK and Ireland from 2004-2007 divided by the number of employed people in the source country in 2003. Source: Eurostat.

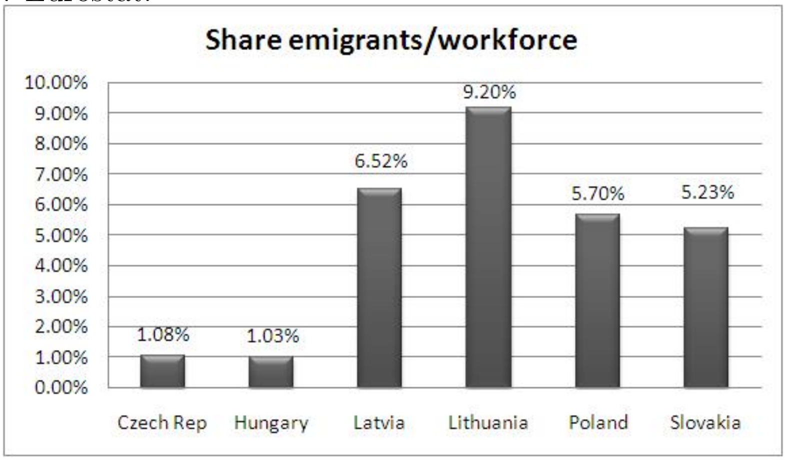

Figure 2: Number of Lithuanian emigrants to the UK and Ireland, measured by registration for work permits, i.e. PPS and NINo numbers, 2002-2007. Sources: Irish Department of Social and Family Affairs, UK Department for Work and Pensions

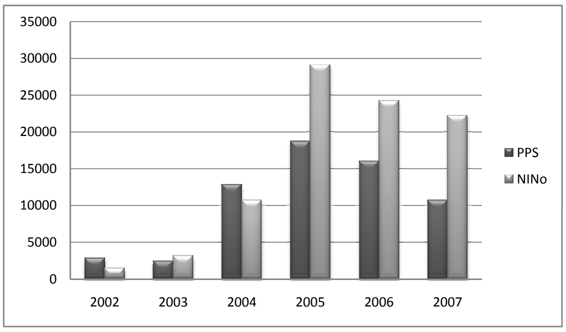

Figure 3: Lithuania: real GDP per capita, real average wages, unemployment. Source: Statistics Lithuania. 2002=100.

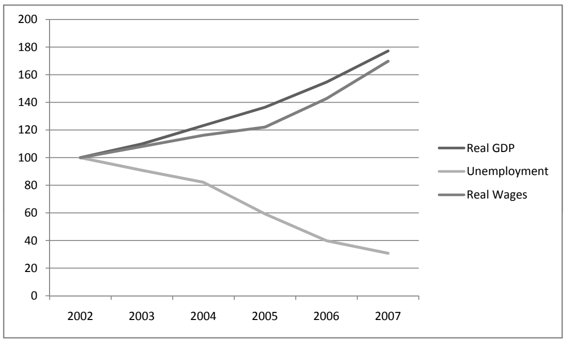

Figure 4: Scatter: wages and emigration rates for different groups (male and female, married and unmarried. Source: own calculations.)

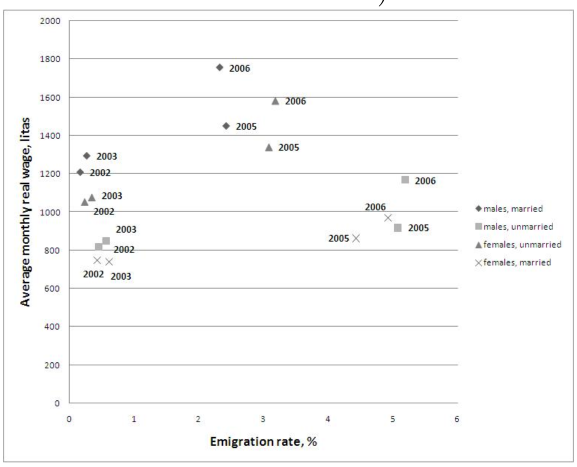

Figure 5: Wage increases for different groups, 2002-2006, 2005=100. Source: own calculations, based on the Lithuanian HBS.

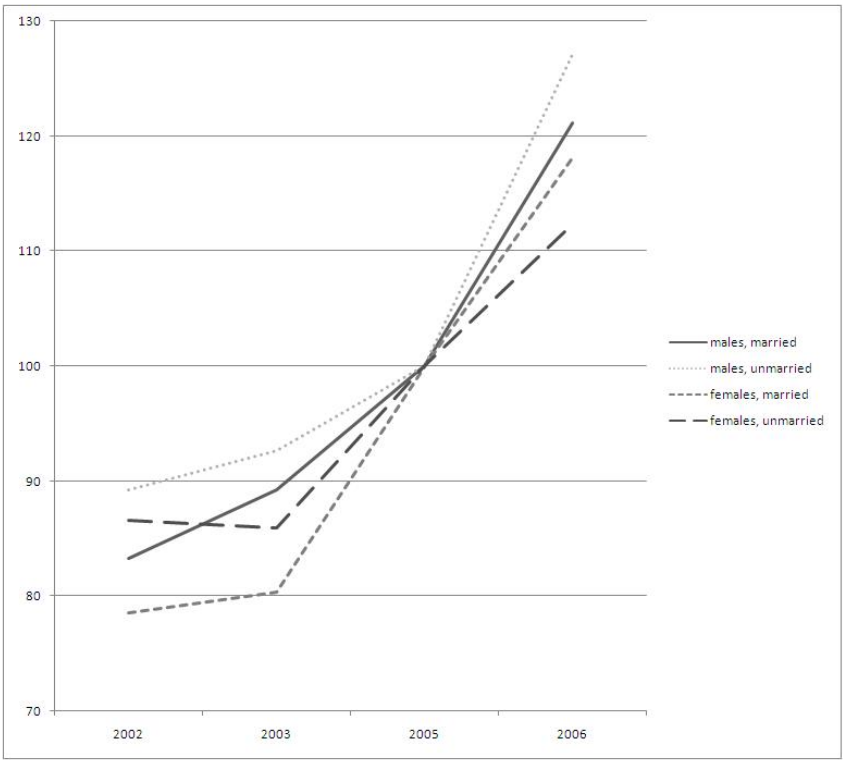

Figure 6: Gross fixed capital formation in million Litas. Sources: IMF International Financial Statistics