Essays on the economic determinants and impacts of migration: the roles of broadband connectivity, industry-level productivity and human capital

by

Cansu UNVER

Department of Economics
Birmingham Business School
College of Social Sciences
University of Birmingham

Abstract

This thesis investigates various aspects of e/migration. Its focus is on examining the motivation behind individuals' decision to migrate, the impact of migration on the host countries' economies, and finally the impact of high skilled emigration on the human capital level in origin countries. In our analyses, wherever possible, we attempt to distinguish among origin countries in terms of OECD and non-OECD origins, EU and non-EU origins, the skill level of e/migrants as well as the level of well-being of the origin countries.

To begin with, Chapter 1 investigates whether ICT facilitates migration flows from OECD to OECD countries, as well as non-OECD to OECD countries based on the magnitude of the flows, examining those with a thresholds 0.1, 0.3 and 0.5 flows that are more than an equal to 100, 300 and 500 people, respectively. Our non-linear instrumental approach to broadband penetration rates find a positive and strong effect on migration flows. This effect appears to be even stronger for non-OECD to OECD flows in comparison to OECD to OECD flows. The results improve above the larger (that is 0.5) constraint.

Chapter 2 concludes that the results for the UK showed that migration has a positive and significant effect on the productivity of industries in the long run, particularly those who are highly educated non-EU migrants. For Spain, the effect of migration on the productivity of firms both in the short run and long run seems to be positive in most cases. As to the Netherlands, the effect of migration on productivity in the short run is positive and significant for EU migrants only. Due, mainly, to limited observations, the results for Germany do not show any significant changes in productivity with migration, although the direction of change is positive. Various findings are presented in order to distinguish between EU and non-EU origins as well as the skill level of migrants.

Chapter 3 contributes an insightful panel data analysis of human capital and high skilled emigration for 74 origin countries from 1980 to 2000 with a five-year frequency. In contrast to Beine *et al*.'s (2011) first panel data analysis of the same dataset, we find a significant negative brain drain impact of high skilled emigration across countries sampled. This is due, mainly, to the fact that the origin countries sampled and the additional control variables used in our analysis.

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LIST OF ABBREVATIONS

EU	European Union
EU-15	European Union of the first 15 countries
GDP	Gross Domestic Product
RGDP	Real Gross Domestic Product
OECD	Organization for Economic Co-operation and Development
OtO	Flows from OECD countries to OECD countries
non-OtO	Flows from non-OECD countries to OECD countries
ICT	Information and Communication Technology
IT	Information Technology
LFS	Labour Force Survey
TFP	Total Factor Productivity
VA	Value added
GO	Gross output
MFP	Multi Factor Productivity
G7	Group of seven major advanced economies
BE	Belgium
CZ	Czech Republic
DK	Denmark
EE	Estonia
FI	Finland
FR	France
DE	Germany
HU	Hungary
IT	Italy
NL	Netherlands
NO	Norway
PL	Poland
SK	Slovakia
ES	Spain
SE	Sweden
TR	Turkey
UK	United Kingdom
LU	Luxembourg
DZ	Algeria
AM	Armenia
BA	Bosnia and Herzegovina
BG	Bulgaria
CN	China
EG	Egypt
MA	Morocco
NG	Nigeria
PK	Pakistan
RO	Romania
RU	Russian Federation
TN	Tunisia
UA	Ukraine
LU	Luxembourg

INTRODUCTION

Chapter-1 investigates whether ICT facilitates migration flows from OECD to OECD (hereafter OtO) countries, as well as from non-OECD to OECD (hereafter non-OtO) countries. Within ICT tools, we primarily focused on broadband. The main host countries here are Austria, Belgium, the Czech Republic, Denmark, Finland, France, Germany, Hungary, Italy, Luxembourg, Netherlands, Norway, Poland, Spain, Sweden and the UK. The selection of both OECD and non-OECD origin countries are based on the magnitude of the flows, examining those with a minimum number of 100 people (threshold 0.1) who are migrating from source to host, followed by 300 (threshold 0.3) and 500 (threshold 0.5) people. We do not consider migration flows of less than 100 people The main reason why we focused on threshholds such as the number of people that are less than or equal to 100, 300 and 500 is the fact that there are too many missing variables where there are less than a 100 people migration from origin to host (OECD, migration database). For example, the flows data from Turkey (TR) to Slovakia (SK) is missing from 1995 to 2002. From Norway (NO) to Belgium (BE) the data available only after 2007, or to Slovakia and Slovenia only after 2003 and 2007, respectively. Thus, we had to focus on the flows where we can gain the most data in terms of time. In Chapter 1, we explore the role of ICT connections as a potential determinant of a person's decision to migrate while controlling for a number of economic variables. Since the data captures both time series and cross-sectional components, panel data analysis will be progressed. By looking at the efficacy of ICT connections, we intend to fill the gap in the literature on the relationship between communication facilities and migration decisions.

We find strong and positive effect of broadband on migration flows between 1995 and 2009. This supports the fact that ICT connections between origin and host affect migration flows from origin to host country by improving the flow of information about the host which affects migration decisions from the origin.

This effect is more prominent for non-OECD to OECD country pairs. Results improve for larger thresholds. This is due to the fact that we believe higher frequency of moving - although capturing fewer country pairs - will produce more accurate results.

Chapter 2 focuses on the productivity effects of migration in four European Union (EU) countries: the UK, Spain and the Netherlands for 1995-2008 and Germany for 2002-2008. This analysis was carried out using EU Labour Force Survey (LFS) and EU-KLEMS data.

In Chapter 2, the large range of productivity variables provided by the EU KLEMS database is combined with the EU LFS, so that detailed information on the share of migrants in each industry is calculated.

The productivity implications of migration are more likely to be seen in the long run than in the short-run. Using a Cobb Douglas production function, we provide both the short-run and long-run effects of migration across industries for the four EU countries. While doing so, we desegregate migrants into high, medium and low skill groups as described by the International Standard Classification of Education (ISCED) (5-6), ISCED (3-4), ISCED (1-2) codes within the EU LFS database. This allows us to pay attention to the different effects of migration by different skill groups.

In order to investigate the long-run impact of migration on firm productivity, we apply the Pooled Mean Group (PMG) variant for the autoregressive distributed-lag (ARDL) estimator. The PMG estimator constrains the long-run coefficients to be identical across firms but allows short-run coefficients and error variances to vary across units. The PMG estimator has been shown to deliver consistent results if the lag order is specified correctly (Pesaran *et al*., 2012). We use the Akaike information criterion (AIC) to determine the optimal lag length.

According to our results, high and low skilled EU and non-EU migrants contribute to productivity significantly while medium skilled migrants affect productivity negatively and significantly in the UK. For Spain, we observed significant contribution of non-EU migrants but negative effect of EU migrants. We also find that low skilled migrants always affect the productivity positively without distinction of EU and non-EU origins. We find that only the Netherlands experienced increase in productivity in the short run. Apart from low and medium skilled EU immigrants, we observed positive and significant productivity effect of migration. Due to limited data, we fail to observe any significant link between migration share and productivity in Germany both in the short run and long run, although we observed positive effect at all times. However, we believe that if we have had more data available for Germany, we would have found significant link between migration share and productivity, due particularly to the long history of migration in Germany.

Chapter 3 examines the impact of high skilled emigration on human capital in 74 origin countries. To do this, we use a panel of data constructed by the World Bank Development Research Group, and collected by Cécily Defoort (Beine *et al*., 2011). In this dataset, most data for migration stocks and their educational attainments are based on six major OECD countries acting as host countries: Australia, Canada, France, Germany, the UK and the USA. The data is available from 1975 to 2000 with a 5-year frequency.

We apply the $\beta - convergence$ empirical model and set the difference between log of human capital in year t (ex-*post emigration*) and $t-5$ (*ex-ante emigration*) as the dependent variable. We regress the dependent variable on the log of *ex-ante* human capital, the log of the high skilled emigration rate at the beginning of the period (i.e. at time $t-5$) and an interaction variable for possible non-linearity in the relationship between emigration rate and human capital. In order to control for this possible non-linearity that is based on the well-being of the origin countries, such that an interaction variable is measured as $\log p_{t-5} x \log GDPpc_{t-5}$ where $\log p$ is the log of high skilled emigration rate and the log of $\log GDPpc$ is GDP per capita. We carry out our estimations with sub-sample of origin countries. Such that, we set two dummies - $D15$ and $D10$ - that are equal to 1 if an origin country's GDP per capita is less than 15% and 10% lower than the average GDP per capita of the G7 countries, (Canada, France, Germany, Italy, Japan, UK and USA). In doing this, we are able to distinguish two country groups with two different GDP per capita frontiers. We expect to find robust results based on these two specifications, although perhaps better results may be expected for countries with $D10$ as the deviation of GDP per capita across countries will be smoother in comparison to the countries with $D15$.

Additionally, we control the dependent variable by a variable remittance at time $t-5$, because this eases the constraints on human capital investment for individuals in the origin and for potential return migrants. We also consider that public expenditure on education may have a direct effect on the human capital level of a country. Thus, we use it as a control variable. As a proxy for the cost of acquiring education, we use population density at time $t-5$, and we also include population density in our model. Finally, we have regional dummies for sub-Saharan and Latin American countries.

The selection of origin countries is mostly based on the availability of data. We attempt to include as many origin countries as possible and end up with 74 origin countries from 1980 to 2000 with a 5-year frequency.

We apply OLS, IV-fixed effects and IV-first difference on the $\beta - convergence$ model. Our findings for countries with $D15$ and $D10$ specification are not so different in terms of the signs of the coefficients, but the significance improves much more for sub-sample of countries with $D10$. In general, we find a divergence in natives' human capital among the origin countries sampled. We observe a negative brain drain effect, suggesting that there is a loss of skilled population in origin countries rather than a brain gain *ex-post* emigration. This could be explained by the fact that high skilled emigrants do not come back to origin countries with additional skills acquired in the host countries. Nor do individuals left behind in origin countries become more skilled, or, assuming they do, they also choose to emigrate rather than stay and level off the skill level difference after emigration. A negative and significant result for the interaction variables of high skilled emigrants with $D15$ and $D10$ suggests a weak incentive effect in origin countries. In fact, this effect is stronger for sub-sample of countries with $D10$. As expected, remittance and public expenditure are found to be positively related with the change in human capital level. Population density is also found to be positive and significant, suggesting that the higher the population density (less cost of acquiring education), the larger the increase in the human capital level.

CHAPTER 1

Does ICT Facilitate Immigration Flows?
A non-Non-linear Instrumental Variable Approach

1.1 Introduction

The history of migration encompasses a large period of time affecting different countries at different levels, from different perspectives and in different time periods. A massive influx of migration occurred from all over Europe to the USA in the 1600s, and this pattern reached a peak between 1820 and 1920. After World War II there was a substantial wave of immigration across the world. In recent years, the rate of international migration has increased noticeably. Currently 232 million individuals, who represent approximately 3.6 per cent of the world population, are living outside their country of origin. According to the International Organization for Migration (IOM) Report (2013), the growth in the number of immigrants between 2000 and 2010 was double in comparison to the previous decade. This figure is slightly higher in Europe compared to the USA.

Evidently, the USA has received the largest influx of migrants, specifically from Europe, since the 1600s, and is currently hosting 44,183,643 migrants (which represent approximately 14.3 per cent of the USA population) (US Census, 2010). Nevertheless, persons within Europe have had more intention to stay within Europe than move to the USA for the last couple of decades. Due to the onset of the recession, the European countries paved the way for new inflows after the first oil crisis in the 1970s, in the late 1980s and early 1990s, the situation settled owing to the fact that the fall of the Iron Curtain enabled persons to travel within Europe with fewer or no restrictions (Beets and Willekens, 2009).

With such a significant number of individuals choosing to live outside their country of origin our attention is drawn to the reasons behind individuals' decision to migrate. In this regard, we intend to investigate flows from OECD to OECD (hereafter OtO) countries, as well as non-OECD to OECD (hereafter non-OtO) countries. The main host countries here are Austria, Belgium, the Czech Republic, Denmark, Finland, France, Germany, Hungary, Italy, Luxembourg, Netherlands, Norway, Poland, Spain, Sweden and the UK, and the selection of the host countries are based on the availability of the data. The selection of both OECD and non-OECD origin countries are based on the magnitude of the flows, examining those with a minimum number of 100 people who are migration from origin to host, followed by 300 and 500 people. Country pairs based on these three thresholds are listed in ***Tables 1.11*** to ***1.16*** in ***Appendix A.***

Throughout the literature, multiple economic, political and social aspects have been pointed out as reasons behind individuals' decision to migrate, chiefly, wages, employment and unemployment rates, inequality, GDP per capita/GDP level, population/population density, trade, immigration law, and education attainments. We find it surprising that ICT facilities between origin and host have not been considered as a determinant, especially considering how this plays a crucial role in the life of a person who is away from their home country in terms of information exchange, etc. Also and more importantly, we believe that ICT connections affect migration flows from origin to host country by improving the flow of information about the host which affects migration decisions from the origin.

In this chapter, we look at the role of ICT connections as a potential determinant of migration as well as a number of economic aspects as reasons behind a person's decision to migrate. In order to do this, we will use the number of people aged 15-64 from the origin to receiving country, obtained from the OECD; controlled for employment rate in the host country and unemployment rate in the origin country (EUROSTAT); real gross domestic product per capita (GDP); broadband, cable TV and voice telephony subscription penetration rate (International Telecommunication Union, ITU); average wage across industries (OECD-Occupational wages around the world (OWW)) in the host; and the distance between origin and host country; (CEPII, Mayer and Zignago, 2011). A dummy variable to capture institutional features, FREE, is equal to 1 if there is no legal restriction on travelling/staying/working from the origin to host country (EUROSTAT, EEA). Since the data captures both time series and cross-sectional components, a panel data analysis will be progressed. By including ICT connections, we intend to fill the gap on the relation between communication facilities and migration decisions, and we expect to find a significant effect of communication facilities on a person's decision to migrate for OtO and non-OtO flows between 1995 and 2009.

This chapter examines reasons behind individuals' decision to migrate. Section 1.2 represents a literature review. Section 1.3 presents the data analysis and estimated model. Section 1.4 discusses endogenous variables, non-linear instrumental variables, validity of instruments, some robustness checks and analysis result. Finally, Section 1.5 presents the conclusion. ***Appendix A*** presents the country pairs for 0.1, 0.3 and 0.5 thresholds. ***Appendix B*** provides empirical results with additional methods. ***Appendix C*** provides descriptive statistics for actual and predicted broadband , ***Appendix D*** illustrates the curves for the actual and predicted broadband penetration rates. ***Appendix E*** presents the results for the validity of instruments. Finally, ***Appendix F*** provides some additional robustness checks.

1.2 Literature Review

From prehistoric to modern times, human beings have always been on the move. This means that the history of migration coincides with the history of humanity. By and large it may be seen that individuals move to better and safer places, but what is a better and safer place? Are these criteria sufficient to encompass the reasons behind individuals' decisions to migrate?

Before investigating the reasons behind individuals' decision to migrate, it is beneficial to explain what it is to be a migrant and what migration is. Any occupant who was born in a foreign country can be defined as an immigrant (Rowthorn, 2008; Gonzáles and Ortega, 2008). A more comprehensive description given by Gott and Johnson (2002) is that an immigrant is a person who was born abroad or who is an offspring that is not older than 16 with at least one foreign-born parent. Apart from these studies, there are many different opinions for classifying immigrants. When it comes to immigration, it is rather an event than a person(s). In the literature, migration is generally defined as a replacement of location. In these terms, a person who leaves their country of origin between the ages of 15 and 74 without any distinction of gender, marital status or occupational status is referred to as an immigrant.

Lewis (1954) pointed out that a necessary condition for an individual to migrate is the availability of sufficient earnings in the host country. However, the important question to ask in this context is how an individual decides where to go for the purpose of working. In Lewis' (1954) neoclassical approach it is assumed that the modern sector attracts those who are in the traditional agricultural sectors until wages in the two sectors are equalised (Zanker-Hagen, 2008). Todaro (1969) and Todaro and Harris (1970) enhanced this approach by paying attention to the urban labour market which attracts rural workers in less developed countries. Their papers questioned whether an unskilled rural worker can find a standard urban job with a better salary as a process of labour transfer from rural to urban environments. A change from low skill jobs to high skill jobs is expected and it is shown that although it is possible not to get a job upon arrival in the city, an individual tends to migrate due to an expectation of better income. More generally, the direction of movement is from low earning to high earning countries (Massey *et al*., 1994).

Moreover, Lee (1966) proposed a 'push and pull' migration theory under the supply and demand side of the migration framework. He pointed out that there are factors that hold individuals in the home country or impel them to move from their home country. He essentially grouped the factors that may trigger migration by taking individuals' characteristics into account. This approach suggests that individuals tend to move to places where they believe they will gain maximum benefit. In order to predict where this greatest benefit may be gained, all positive, negative and neutral factors as well as obstacles, such as migration laws, and personal factors are taken into consideration. Thus, Lee's push and pull theory puts together almost all possible components of the migration process rather than looking at the more specific causal mechanisms.

Sjaastad (1962) was the first to model migration under Human Capital Theory. The theory depends upon the maximum benefit to the individual's self-improvement that is to be gained by staying or moving. Considering the skill they have, individuals calculate the net present value of the returns by staying home and the expected net present value of the returns in the host, and choose to migrate if the latter is relatively greater. Chiswick (1999) claimed that the relative wage difference between the host and origin countries to both direct and indirect migration cost (i.e. $\frac{W_i - W_j}{C_{direct} + C_{indirect}}$) determines the approximate rate of return from migration, and the greater this rate, the more probability the person will migrate. According to this theory, the more educated and/or the younger the individual, the more likely they are to migrate; as well as the longer the distance, the greater the risk that needs to be taken, and the less likely they are to migrate; in other words, a higher cost of migration leads to less migration. However, the theory only applies for individual perspectives on immigration rather than general aspects of migration.

An increased demand on the labour market in developed countries attracts those who are in need of a job or better earnings, even for a temporary period. This would be described as complementary changes in the labour markets within different countries in which the purpose of both the employers' need for labour and the employees' need for a good job will be served. The approach known as The Dual Labour Market Theory is a result of such changes in the labour market (Piore, 1972; Piore, 1979; Harrison and Sum, 1979). For instance, a massive labour demand in Germany in the 1960s opened its doors to Italian, Portuguese, Greek and mostly Turkish migrants until the demand met its capacity later in the 1970s. Demand in the labour market arises as natives refuse to do less skilled and/or unimportant jobs in the host country (Hagen-Zanker, 2008). Thus, migrants here play a complementary role and consequently do not pose a threat to natives.

Another popular approach is the Network Migration Model. People with the same cultural, religious and/or linguistic background are more compatible with each other and Network Migration theory relies upon these factors. A person who decides to migrate to a certain country is more likely to follow a previous migrant that they know (Massey, 1990). Epstein (2008) emphasised the importance of network as an essential component of the utility function of a new immigrant in the host country and claimed that the greater the network size (i.e. of individuals who have previous migration experience from the same origin as the new arrivals) the more probable migration is to occur. If one questions why capital cities are more diverse than other cities in the host, networks could be an explanation. Individuals tend to move to capitals as a starting point as they are considered to be a less unknown location. The cycle starts by attracting other immigrants and eventually capitals become the centre of the host country for immigrants. The main assumption of this theory is that the stronger the network of an individual, the higher their tendency to migrate. Thus, networking is assumed to be positively related to migration.

Furthermore, Greenwood (1975) surveyed the literature until the 1970s, and showed that certain aspects were considered by individuals before making a decision to migrate, such as distance, earnings of immigrants, networking, cost of migration, and characteristics of an immigrant. Greenwood (1985) conducted another survey to cover the period until the 1980s, and found that, in addition to the factors listed in his first survey, labour market conditions, taxation conditions and environmental features in the host country, personal job skill, and personal circumstances such as education, age, gender, marital status, are essential determinants of migration. On the sociological side, 'networks' are quite intensive features in decisions on where to move as they reduce the risk (Haug, 2008).

Migration is an issue of self-selection. In this regard, the majority of labour economists follow Roy's (1951) self-selection model, which is based on the assumption that individuals' decisions on participating in job markets depends upon the ability that they have, the technology that is to be applied and the correlation amongst these skills in a community, where there are only two occupations available. Although Roy's model captures a simple case, it provides a basis for decision-making problems such as job, location and education. Borjas (1987), for instance, launched the first extension to Roy's model to point out how earnings of immigrants across multiple skill groups are important in terms of deciding whether to move from or stay in the origin country. The basis of the theory lies in:

$$\ln w_i = \mu_i + \varepsilon_i \qquad \textbf{(1.1)}$$

$$\ln w_j = \mu_j + \varepsilon_j \qquad \textbf{(1.2)}$$

where; w_i, w_j are wages in the origin and host countries; μ_i , μ_j are observable socioeconomic variables in the origin and host countries, and ε_i , ε_j are characteristics of immigrants which are unobservable and normally distributed with a zero mean and $\sigma_i{}^2$, $\sigma_j{}^2$ standard errors respectively. According to this theory, migration occurs if:

$$I \approx (\mu_j - \mu_0 - \pi) + (\varepsilon_j - \varepsilon_i) > 0 \qquad \textbf{(1.3)}$$

where π is the time equivalent measure of the cost of migration. In other words, migration occurs if the value of logged wages in the host outweighs the logged value of wages in the origin country plus migration cost.

The earnings of individuals are decisive in the decision-making process, and are perhaps the most fundamental determinant. However, it would be too easy to assume that there is only one factor that influences individuals' decision to migrate. Therefore, Borjas (1989) modified his previous theory and presented a more comprehensive approach by taking individuals' skill into account as follows:

$$\log w_i = X\delta_i + \varepsilon_i \qquad \textbf{(1.4)}$$

$$\log w_j = X\delta_j + \varepsilon_j \qquad \textbf{(1.5)}$$

where, w_i , w_j are wages in the origin and host countries respectively, $X\delta_i$, $X\delta_j$ indicate the expected earnings of an individual determined by the observable vector of skill of immigrant (X) and ε_i , ε_j are unobservable variables that are normally distributed with a zero mean and σ_i^2 , σ_j^2 variance respectively. Hence, immigration occurs if:

$$I \approx [X(\delta_j - \delta_i) - \pi] + (\varepsilon_j - \varepsilon_i) > 0 \qquad \textbf{(1.6)}$$

Thus, according to Borjas (1989), the decision to migrate depends upon expected earnings that are relative to the skill that an immigrant has and the relative cost of migration (e.g. travel costs, relocation in the host country, foregone salary in the home country, sufficient amount of money to survive in the host country until having a job).

Clark (2002, 2007), however, modified Borjas(1987, 1989) theory by expanding the meaning of migration cost; that is, based on an individual k with skill s they decide to migrate if:

$$I \approx [w_j(s_k) - w_i(s_k)] - (z_k - c_1 + c_2(q) - \gamma(\delta - s_k)) > 0 \qquad \textbf{(1.7)}$$

where, for an individual s_k, z_k is individual-specific costs based on expected income from the host country; c_1 is the direct cost , as defined above, considered as the necessary amount of money used before securing a job in the host country after arrival; $\gamma(\delta - s_k)$ is the skill-related cost (in here δ is a benchmark skill level in the host, and γ is the skill selectivity of immigration policy), relative to the average skill level in the host country, and finally $c_2(q)$ is quota-related costs based on the status of a migrant under the quota. The term *quota* was first used as a migration policy term in America in order to avoid mass migration from all around the world. By dividing immigration costs into four sections, Clark *et al*., (2002, 2007) provided an insightful approach to Borjas'(1987, 1989) theory as well as shedding light on political restriction as a migration cost.

Following this, Mayda (2008) argued that political restrictions are essential factors that must be included in migration theories. That is, although the host country may potentially meet most of the expectations of those immigrants, the immigration policy itself should be considered as an essential deterrent factor, as initial entrance to this country - work permission - being able to work for intended hours - being able to claim some benefit while working at the same time - being exempt from taxation are designated by immigration policy. Thus it may be claimed that decision-making on migration depends fundamentally on the combination of the net benefit to an individual, political restriction and characteristics of immigrants. In fact, the characteristics of immigrants - in regard to how much risk they are willing to take - have more impact on the decision-making process than first appears. According to Arcand and Mbaye (2013), for instance, those who migrate illegally do not seem to consider net benefit of migration or policy restrictions before they migrate: they only appear to be willing to escape from the home country without considering what the consequences will be.

Niedercorn and Bechdolt (1969) looked at the gravity model using the framework of utility theory. Variables included in this theory are the population of the host country, the finite number of journeys planned, the period of time that will be spent in the host, and the sum of money that will be needed for this journey from a single origin country to multiple host countries.

The most general form of the gravity model was given by Vanderkaup (1977). The level of immigration flows depends upon the relative population in the origin and host countries and the distance between those countries (i.e. $Flows_{ij} = \frac{P_i^{\alpha} P_j^{b}}{D_{ij}^{\ c}}$ where $Flows_{ij}$ indicates the flow rate from i to j , $P_i^a \, and \, P_j^b$ indicates the population of the origin and host countries respectively, D_{ij}^c indicates the distance between the origin and host countries; *a* and *b* are to be estimated, *c* is the distance elasticity).

Rodrigue *et al*. (2009), however, approached the gravity model of migration, which is described as a physical science (also known as Newton's law), and explained that if the importance of one location increases across any two locations, there will also be an increase in movement between those two locations. Here, the importance of the location is measured by *population, GDP level, employment, unemployment, poverty* or other appropriate variables, and the model is set up as: $Flows_{ij} = k\frac{P_i^a P_j^b}{D_{ij}^c}$,where P_i^a *and* P_j^b indicates the importance of the origin and the host country, and *k* is related to the temporal rate of the event that is measured by the time of the migration. This gravity model is different from Niedercorn & Bechdolt's (1969) gravity model in that the importance of a country is not constrained by population only, but captures GDP, labour market conditions and other relevant factors. Thus, it would be appropriate to state that a general assumption of the gravity model of migration is that the greater the relative importance of the origin and host countries, the more the migration. A gravity model mainly focuses on the importance of the country within country pairs and can be adjusted using other migration theories depending upon the expectation of what aspects of decision-making are to be analysed. Thus, this paper will use the gravity approach.

Hypothetically, a number of economic factors, such as economic hardship, poverty, low standard of living, low wages, wage differences, infrastructure and social factors, such as wars, famine, drought and natural disasters trigger people to seek other countries to live in. This paper intends to focus on economic reasons.

The history of migration encounters several aspects of immigration intentions at the macro and micro levels (Hagen-Zanker, 2008). Whilst individual expectations motivate individuals to migrate, social ties, affiliation or more generally the expectation of a better economic structure trigger people to move from their country of origin (Jong, 2010).

Employment opportunity is deemed to be an essential incentive to migrate, as well as a high level of income (Daniels and Ruhr, 2003; Sorhun, 2011). Individuals consider moving to places with a high potential of finding a job so that they can start earning money for survival after arrival. A high level of unemployment, and low level and/or share of GDP per capita in the home country are also considered motivations for people to seek other places (Feridun, 2007). That is, failure to find a job in a certain period of time pushes individuals to seek locations with lower unemployment rates. On the other hand, the distance between the origin and receiving countries is deemed to be an essential deterrent (Mayda, 2008; Sorhun 2011), meaning that greater distance requires more cost of travel as well as more risks. As such, with the on-going turmoil in some Middle East countries such as Egypt, Libya, Yemen and most recently Syria, multiple nationalities from those countries are attracted by Turkey, which does not have the desired level of economic growth compared to more developed countries but is chosen by neighbouring countries that have a close border (Sirkeci and Esipova, 2013).

Additionally, Greenwood (1985) indicated that housing markets and the taxation system, both local and state, might be vital issues for potential migrants. Bilaterally, if house prices are costly in the host country, this influences the person's decision to move there, and if house prices are high in the origin country this also affects individuals seeking places with low/lower house prices.

What is more, Coulon and Wadsworth (2010) showed that purchasing power parity in the host country is as important a factor as wage differentials across skill groups during decision-making on migration. Ogilvy (1979) showed using National Health Service data within England and Wales that individuals with previous migration experience are more likely to migrate. Thus, individuals with previous migration experience gain substantial information on how to find a place to stay, how to find a job, how to search networks and how to settle down. In other words, there is less risk in comparison with first-time immigration.

Unemployment rate and earnings differentials play a significant role in deciding to move to another region, as they show the tendency to migrate to places with a low unemployment ratio and less wage disparity in not only cross-national migration but also inter-regional migration (Pissarides and McMaster, 1990).

What is more, Ivlevs and King (2012) pointed out that immigration is an incentive for further immigration, which they call the 'snowball effect' of immigration. Furthermore, Sorhun (2011) examined the economic size of the receiving country as another motivation to migrate, as well as the association of income level with the migration decision in the case of Turkey's internal/external migration. In other words, people tend to choose places to move to that are economically approximately 20% better. Additionally, people tend to move to countries where they feel happier, more secure and comfortable (Borjas, 1989).

Furthermore, migrants also take into account the skills they have when deciding where to move (Greenwood, 1985). In that regard, it is unrealistic to expect a farmer to choose to go to a place where there is no agricultural industry. On the other side, skill composition is also a vital concern from the perspective of the host country. Geis *et al*., (2011) for instance, found substantial differences within the skill composition of immigrants in France, Germany, the UK and the USA: the UK and the USA host highly skilled immigrants compared to France and Germany, the two large EU member states. Thus, those with high skills are expected to choose places where they are provided with more convenient conditions, such as a less restrictive immigration policy, better social rights, or jobs with better wages. Immigration policy is taken into account not only by highly skilled migrants but also by unskilled ones, because less restrictive migration policies are considered to be a motivation to migrate (Hatton, 2010; Mayda 2008) and restrictive migration policies are counted as an obstacle. , it would be more desirable to migrate to places with no or lower limits. Even in internal migration, different policies within states affect the individual's decision to choose a location. Zavodny (1999) investigated location choices within six states of the USA, and found that people desired states where they could benefit more.

Living in a hugely populated country, poverty and unpleasant environments are encountered as reasons to leave the home country (Amacher *et al*., 1998). Indeed, living under such conditions inevitably pushes individuals to move not to the best but at least better places. Deciding on a host country is also done under the consideration of gaining the greatest return in terms of human capital (Stark and Taylor, 1991). GDP per capita both in the origin and receiving country are found to be another aspect that is considered in terms of deciding whether to go and/or where to go (Marques, 2010).

Generally, the decision to migrate depends both upon an immigrant's characteristics and the labour market conditions in the host country (Pissarides and Wadsworth, 1989) and it can both be an individual level or a more general level decision-making process. If considered at the macro level, in general, the economic structure of the origin country is a huge push factor. Tsuda (1999), for instance, drew attention to the Brazilian-Japanese migration case. Brazil hosted a massive migration influx from Japan in the early 20th century to deal with a labour shortage. However, the extensive recession in Brazil accounted for a massive inflation rate followed by a decrease in real personal income and job security, and Japanese migrants returned to their home country in the late 1980s. Indeed, a long-lasting economic handicap produces an uneasy community that pushes people to return to their home country.

Considering that people move towards living in better conditions, it is unlikely to expect a flow from powerful countries into powerless or impoverished countries. Portes and Böröcz (1989), for instance, noted that in the light of push and pull theories the advanced European counties are likely to be attracted by equatorial African immigrants as well as those from other undeveloped countries.

Historically more migration occurs amongst single men in comparison to single women. However, some countries, such as Thailand, have the opposite case. Because Thai women have to repay their parents for raising them, migration is more frequent among Thai women (Jong, 2010). This suggests that migration is linked to individual expectations.

Although it is emphasised that individuals expect better living standards in the host places, this may become problematic if having high living standards in the host country costs more than the salaries that an individual is earning. Champion (1999), for instance, showed that within the UK's regions, London experiences more out-migration than in-migration compared to the rest of the UK between 1990 and 1991. The expense of living in London is the highest among the UK's regions, although it provides better salaries and a higher standard of living, thus individuals choose to move to places where their living standards and earnings are balanced.

So far, the majority of the motivations to migration have been captured. Having considered the characteristics of an immigrant, it is now safe to generalise that a person decides to migrate if the benefit of moving outweighs the benefit of staying. Considering we are living in the 21st century and telecommunication has an essential role in individuals' life in respect of keeping in touch with the families and friends in origin countries, exchanging information between origin and host countries, one should consider that, in addition to other factors, telecommunication may trigger migration flows as well. Thus, this chapter will investigate whether there is such relationship between migration flows and telecommunication, and if so, fill in the gap in the migration literature.

As this paper is to adapt the Gravity Model of Migration, the gravity model literature is kept separate and shown in ***Table 1.1***. As can be seen from the table, to the best of our knowledge, no gravity model includes telecommunications facilities as a determinant of migration. Telecommunications facilities are considered as a tool to measure a country's wealth in relation to GDP, but not as a tool that improves the flow of information about host countries which may as a result affect decisions to move from the origin country. Our gravity model will allow us to see such mobility in flows from origin to host in relation to telecommunications facilities.

Table1.1 Gravity Model through the literature

Author(s)	Geographical units and sample period	Methodology	Dependant variable	Significant explanatory variables
Karamera. et al. (2000)	19 European, 16 African, 16 Asian, 2 North American, 3 Central American, 3 Caribbean, 12 South American countries to North America; 1976-1986	Panel with time and country pair fixed effects and origin region dummies	Total migration inflows	(+): Population (origin), income (origin+host), unemployment (host), business credit ratings (origin), relative freedom (origin), common border, population density. (-): Distance, population (host), inflation (origin), political instability (origin), political rights (origin), civil liberty (origin), immigration policy
Mayda (2008)	Migration to 14 OECD countries: Australia, Belgium, Canada, Denmark, France, Germany, Japan, Luxembourg, Netherlands, Norway, Sweden, Switzerland, UK, USA;1980-1995	Panel OLS with individual country dummies	Emigration rate	(+): Per worker GDP (host), Young population (origin). (-): Distance
Beine et al. (2006)	Migration to OECD countries; 1990 and 2000	Panel OLS with dummy for 2000	Skilled migrant inflows	(+): Distance, GDP per capita ratio, social expenditure (host), democracy index (origin), public education expenditure (origin) (-): Linguistic proximity, education expenditures (host), openness to immigration.
Shen (1999)	Chinese provinces; 1985-1990	Panel OLS	Total migration flows	(+): Population (origin), GNP growth rate (origin+host) (-): Distance, illiteracy (host), agricultural employment (origin+host), population growth (origin), population density (origin+host)
Pedersen et al. (2008)	Migration to OECD countries; 1990-2000	Panel fixed effects for host, WLS and GEE with host or country pairs dummy	Total migration inflows	(+): Stock of immigrants, common border, common language, colony dummy, trade volume, relative population (host\origin), social expenditure (host), (-): Distance, GDP per capita (origin+host), unemployment (host), illiteracy (origin), freedom house index (origin)
Helliwell (1997)	From USA to Canada, within Canada ; 1991	Cross section OLS	Total migration inflows	(+): Population (origin+host), real personal income (host) (-): Distance, real personal income (origin)
Kumo (2007)	Flows within Russian regions; 2003	Cross section OLS	Total migration flows	(+): Population (origin+host), gender ratio, paved roads, common border, some regional dummies (-): Distance, below working age ration, some regional dummies
Ashby (2007)	Interregional flows within 48 USA states; 2000	Cross section with spatial dependency	Migration rate	(+): Relative economic freedom, relative population, relative income, relative employment growth, relative retired, relative heating days, distance squared, (-): Distance, relative precipitation, relative density, dummy for movers
Fertig (2001)	Flows from 17 OECD countries into Germany; 1960-1994	Panel GLS with origin country dummies	Migration rate	(+): Per capita income ratio, employment (host), free movement dummy (-): Lagged migration rate, employment (origin).
Marques (2010)	Flows from Central and Eastern Europe to EU-15 countries; 1986-2006	Panel fixed effects for host with region dummies	Total migration flows	(+): GDP (origin+host), GDP per capita (origin), current migration stock, contiguity, common language, liberal policy reform (host), some regional dummies (-): GDP per capita (host), unemployment (origin), political environment (host), distance, some regional dummies
Andrienco & Guriev (2004)	Interregional migration in Russia; 1992-1999	Panel OLS with time dummies and region-pairs fixed effects	Number of people who migrate	(+): Income per capita (host), unemployment rate (origin), poverty (origin), public goods provision (host) (-): Distance, income per capita (origin), unemployment rate (host), poverty(host), public goods provision (origin)
Lewer & den Berg(2008)	General	Join hypothesis of cross-section	Level of immigration	(+):population(origin) x population(host), common language, colonial link between host and origin, relative distance to income per capita in the origin, immigrants in the host (-) distance

As can be seen from the table, in almost all cases distance is found to be a significant demotivating factor, as the higher the distance, the higher the risk and the higher the migration cost. Higher wages, high GDP per capita, and a low unemployment rate/high employment rate in the host country are found to be the main motivating factors in deciding where to migrate. Our results in Section 1.3 will also confirm how these factors play an essential role in deciding where to move.

1.3 Data and Empirical Model

The empirical analysis employs a panel of data from a sample of inflows in thousands from origin country i to host country j at time t .As an international telecommunications channel, we expect broadband to be the most convenient communication tool, as it is cheaper and allows for job applications and job interviews from overseas. Even so, we also analysed whether other telecommunications channels, such as mobile phones or fixed landline phones affect flows between origin and host, but found no strong evidence.

In order to capture both ICT connections and a number of economic aspects as reasons behind individuals' decision to migrate, the following gravity model will be applied:

$$\begin{aligned} \log FLOWS_{ij,t} &= \log \beta_1 ICT_i + \log \beta_2 ICT_{j,t} + \beta_3 \log DIST_{ij} + \beta_4 \log RGDP_{ij,t} \\ &+ \beta_5 \log WAGE_{j,t} + \beta_6 UNEMPR_{i,t} + \beta_7 EMPR_{j,t} + \varepsilon_{ij,t} \end{aligned} \qquad \textbf{(1.8)}$$

where $FLOWS_{ij}$ is the flow of immigrants in thousands. Here, we grouped migration flows into three thresholds that are equal to and greater than 0.1, 0.3 and 0.5 (i.e. 10, 30 and 50 per 1,000 population), both for OtO country pairs and non-OtO; ICT_i, ICT_j are ICT connections in the origin and host respectively; $DIST_{ij}$ is the distance between the origin and host country;

$RGDP_{ij}$ is the relative real GDP (i.e. $\frac{RGDP_i}{RGDP_j}$ both real GDP in the origin- $RGDP_i$ and real GDP in the host- $RGDP_j$ are constant at 2000 US$); $WAGE_j$ is the average wage across industries in the host country all adjusted to 2000 US$; $UNEMPR_i$ is the unemployment rate in the origin; $EMPR_j$ is the employment rate in the host and finally, ε_{ij} is the error term. Throughout the literature, technology is assumed to evolve along an exponential growth curve (Griliches, 1957; Geroski, 2000; Gruber and Verboven, 2001; Comin *et al*., 2006; Czernich *et al*., 2011), thus, ICT connections in origin and host can be written as:

$$ICT_{it} = \alpha_1 e^{\lambda_{it}} \text{ and } ICT_{jt} = \alpha_2 e^{\lambda_{jt}} \qquad \textbf{(1.9)}$$

where λ_{it} *and* λ_{jt} are the growth parameters of the rate of the ICT tool in the origin and host country, respectively. In our analysis, we primarily focus on broadband as an ICT tool for the reasons we explain in Section 1.4. Broadband here is counted as from 256kbit/s to under 2Mbit/s. Since migration occurs between specific country pairs, we focus on the relative broadband penetration rate within those country pairs. Thus, it can be written as:

$$BROAD_{ij,t} = BROAD_{it} x BROAD_{jt} \qquad \textbf{(1.10)}$$

Based on equation (1.9), $BROAD_{ij,t}$ takes the exponential form as:

$$BROAD_{ij,t} = \alpha^* e^{\lambda^*_{it}} \qquad \textbf{(1.11)}$$

Here, $BROAD_{ij}$ is defined as the multiplication of broadband penetration rate in the origin and host country at time t. There is no previous literature as to how to set up country pair specific variable such that. However, since communication is a concept of information exchange, and broadband is our communication variable, we needed to work on such interaction variables. Because, for example broadband may have been introduced country A(origin) two years later than country B(host), and if so, such interaction variable will enable us to observe what happens after A and B have broadband at the same time. We cannot have them the form of fractions because there is a possibility that either of the broadband variable can be zero (e.g. broadband has not been introduced yet). Since the sample has a mix of core EU countries and recent 2004 (Czech Republic, Hungary, Poland, Slovakia) as well as 2007 accession countries (Bulgaria and Romania), we control for legal restriction of travelling/staying and working in the host country by setting a dummy variable $FREE_{ij}$ that is equal to 1 if there is no such restriction on moving from the origin to host country, 0 otherwise.

In order to see the different effects of broadband penetration rate across country pairs, we also control for catching-up in broadband diffusion by including the years since broadband introduction in country pairs, $T^{B}_{ij,t}$ (Gruber and Verboven, 2001; Czernich et al., 2011) where B represents the broadband penetration rate between country pairs (i.e. $BROAD_{ij}$). The calculation of $T^{B}_{ij,t}$ is made based on broadband penetration rate, and it is the number of years that country pairs both have been introduced to broadband. Having added time and country pair subscriptions, the complete estimation equation will be as follows:

$$\begin{aligned} \log FLOWS_{ij,t} &= \beta_0 + \beta_1 BROAD_{ij,t} + \beta_2 \log DIST_{ijt} + \beta_3 \log RGDP_{ijt} + \beta_4 \log WAGE_{jt} \\ &+ \beta_5 UNEMPR_{i,t} + \beta_6 EMPR_{j,t} + \beta_7 FREE_{ij,t} + \beta_8 T^{B}_{ij,t} + \delta_{ij} + \theta_t + \varepsilon_{ij,t} \end{aligned} \tag{1.12}$$

where δ_{ij} and θ_t are the country pair effects and time fixed effect respectively. When the independence of irrelevant alternatives fails to characterise the reasons behind individuals' decision to migrate, it then purely depends upon the benefits of migrating to destination places- which is called multilateral resistance to migration (Bertoli and Moraga, 2013). In the presence of multilateral resistance to migration, some of the studies adopt the Common Correlated Effects (Pesaran, 2006), or used *ad hoc* controls for time varying benefits of migration, or provide more restricted assumptions when specifying the estimated model. Considering that in any gravity model, there are more than one origin and similarly more than one destination country; one must deal with the relationship amongst specific country pairs (Anderson, 2010). In this chapter, the specification of our main independent variable is in an interaction form (i.e. $BROAD_{ij,t} = BROAD_{it} x BROAD_{jt}$). By doing so, we believe we account for the relative attractiveness of country pairs sampled. However, additional methods could be adopted for a follow up robustness checks for this chapter in the future.

See ***Table 1.2*** below for a detailed description of the data:

Table1.2 Data and origins

Notation	Variable	Unit	Origin
$FLOWS_{ij}$	Inflows of foreign population by nationality	Thousands	OECD
$BROAD_i$	Broadband penetration rate in origin	256 kbit/s to less than 2Mbit/s Share of the population that has subscribed to broadband	ITU (International Telecommunication Union) ICT Database
$BROAD_j$	Broadband penetration rate in host	256 kbit/s to less than 2Mbit/s Share of the population that has subscribed to broadband	ITU (International Telecommunication Union) ICT Database
TEL_i	Fixed telephone subscriptions in origin	Per 100 inhabitants	ITU (International Telecommunication Union) ICT Database
TEL_j	Fixed telephone subscriptions in host	Per 100 inhabitants	ITU (International Telecommunication Union) ICT Database
$CABLE_i$	Cable TV subscribers in origin	Per 100 inhabitants	ITU (International Telecommunication Union) ICT Database
$CABLE_j$	Cable TV subscribers in host	Per 100 inhabitants	ITU (International Telecommunication Union) ICT Database
$DIST_{ij}$	Distance between origin and host	Km	CEPII
$RGDP_i$	Real GDP in origin	Constant 2000 US$	WORLDBANK, World Development Indicators
$RGDP_j$	Real GDP in host	Constant 2000 US$	WORLDBANK, World Development Indicators
$WAGE_j$	Average wage across industries in the host	Total wage across industries divided by number of total employees in the industries (All LCU adjusted to 2000 US$ dollar)	OECD STAN Database, OWW Database for the UK, (ECB) European Central Bank Statistical Data Warehouse for US dollar exchange rate
$UNEMPR_i$	Unemployment rate (origin)	Total, % of total labour force, in million	IMF
$EMPR_j$	Employment rate (host)	Percentage (Total gender, aged:20-64)	EUROSTAT
$FREE_{ij}$	=1 if no legal restriction on living, working in host	0,1	Author calculation based on EUROSTAT-EEA
$T^{B}_{ij,t}$	Years since country pairs both first introduced broadband	Varies from 0 to 10 for OtO Varies from 0 to 8 for non-OtO	Author calculation based on ITU (International Telecommunication Union) ICT Database

1.3.1 Causality of Broadband and Migration Flows

The basic gravity model may suffer from different origins of endogeneity. One concern is reverse causality, in that, considering the origin and host country we might imagine that the greater the flows of people from origin to host the greater the communication flows between host and origin as migrants talk to family and friends: we will discuss this in more detail in ***Section 1.4.1***. Another concern is that broadband penetration rate is endogenous to RGDP, employment rate and unemployment rate. Furthermore, considering that migration is a dynamic event, treating natives in the host country as fixed simplifies the fact that they can also migrate within those countries.

We first attempt to correct for the endogeneity in the model by applying the Arello-Bond GMM estimator (Blackburne and Frank, 2007). The GMM results for OtO and non-OtO flows for the 0.1, 0.3 and 0.5 (100, 300 and 500 or more people) thresholds is presented in ***Model* (4)** in ***Tables 1.18*** to ***Table 1.23*** in ***Appendix D*.** However, GMM does not seem to address multiple origins of endogeneity problems well. Firstly because, autocorrelation results for first order autocorrelation fails in most cases, and only improved in few cases in the second order autocorrelation as can be seen from ***Tables 1.18-1.23***. Secondly, the Sargan test of over-identification appears to fail. Finally, the presence of decreasing numbers of observations for different flow thresholds creates more trouble with GMM.

Thus, in order to address several source of endogeneity bias in the model, we adopted Czernich et. al.'s (2011) instruments for the IV approach. Since broadband platforms rely on either the copper wire of voice telephony or the coaxial cable of cable TV between households and the main distribution frame, we instrumented the ceiling of broadband penetration η_{ij} with voice telephony and cable TV for the year 1997, which is the year before broadband was first introduced to both countries amongst country pairs at the same instant:

$$\eta_{ij} = \eta_0 + \eta_1 VOICE_{ij,1997} + \eta_2 CABLE_{ij,1997} \qquad \textbf{(1.13)}$$

Here we use the number of non-digital telecommunication access lines in 1997 ($VOICE_{ij,\,1997}$) and the number of cable TV subscribers in 1997 ($CABLE_{ij,\,1997}$) to measure the spread of the traditional telecommunication and cable networks in country pairs, calculated as:

$$VOICE_{ij,1997} = VOICE_{i,1997} \times VOICE_{j,1997} \qquad \textbf{(1.14)}$$

$$CABLE_{ij,1997} = CABLE_{i,1997} \times CABLE_{j,1997} \qquad \textbf{(1.15)}$$

where $\mathrm{VOICE}_{i,1997}$ and $\mathrm{VOICE}_{j,1997}$ are the number of non-digital telecommunications access lines per 100 inhabitants in 1997 in the origin and host countries respectively; $\mathrm{CABLE}_{i,1997}$ and $\mathrm{CABLE}_{j,1997}$ are the number of cable TV subscribers per 100 inhabitants in 1997 in the origin and host countries respectively. These variables were obtained from the World Telecommunication/ICT Indicators Database- International Telecommunication Union (ITO).

Although $VOICE_{ij,1997}$ and $CABLE_{ij,1997}$ are time invariant variables, Stata 13's *nl* (i.e. non-linear) command provides time invariant coefficients for each of these variables.

The majority of researchers have followed the logistical growth curve for a new technology defined by Griliches (1957) (Gruber and Verboven, 2001; Comin et al., 2006; Geroski, 2000; Czernich et al., 2011; Stoneman, 2002; Beck et al. et al., 2005; Michal and Tobias, 2006):

$$BROAD_{ij} = \frac{\eta_{ij}}{1 + e^{-[\beta(t-\tau)]}} \qquad \textbf{(1.16)}$$

Again, $BROAD_{ij}$ is the broadband penetration rate measured as the multiplication of the share of the population that has subscribed to broadband in the origin and the share of the population that has subscribed to broadband in the host (i.e. $BROAD_i \times BROAD_j$), whereas,

η_{ij} determines the maximum broadband penetration rate, β is the diffusion speed, and finally τ is the inflexion point. Inserting equation **(1.13)** into equation **(1.16),** we obtain the following non-linear first stage equation:

$$BROAD_{ij,t} = \frac{\eta_0 + \eta_1 VOICE_{ij,1997} + \eta_2 CABLE_{j,1997}}{1 + e^{-[\beta(t-\tau)]}} \qquad \textbf{(1.17)}$$

By applying such non-linear least squares estimation, we compute the predicted broadband penetration rate with absolute exogenous factors. In order to receive consistent estimates from the second stage of the nonlinear equation, first-stage estimation must be specified correctly (Angrist and Imbens, 1995; Angrist and Kruger, 2001a;, 2001b).

In order to see the fit of the first stage of the diffusion curve of the instrumental model, we plot the graphs of actual and predicted broadband for OtO and non-OtO country pairs for each threshold, but we only present 10 country pairs for each thresholds as there are 366 OtO country pairs (148+118+100) and 269 non-OtO country pairs (101+92+76) in total and it would take up generous space. ***Figures 1.1 to Figure 1.6 are*** presenting the actual and predicted broadband penetration rate. (please see ***Appendix B***). For OtO country pairs with 0.1 thresholds, Poland-UK and Germany-Austria appears to have a perfect fit of actual and predicted broadband penetration rate. Whereas, predicted broadband penetration rate for Netherlands-Belgium, Sweden-Norway, Belgium-Luxembourg country pairs seem to be a little below the actual rates. The actual and predicted values for the rest of country pairs, on average, seem to fit all right. Same pattern holds for OtO country pairs with 0.3 and 0.5 thresholds. When it comes to non-OtO country pairs with 0.1 thresholds, Algeria-France, Russia-Germany, Bosnia and Herzegovina-Austria, and Bulgaria-Spain seem to have a good fit, whereas for the rest of the country pairs predicted values stays a little below the actual rates. In all, we can see a diffusion curve shape for all country pairs as expected which confirms the fit of first stage of the diffusion curve, which corresponds to the majority of literature on technology diffusion (Griliches, 1957; Geroski, 2000; Gruber and Verboven, 2001; Comin et al., 2006; Czernich et al., 2011). Also, we find consistent inflexion points for both OtO and non-OtO flows for each threshold. Hence, we believe that the first-stage estimation is specified adequately. As can be noticed from ***Figures 1.1-1.3*** the same country pairs look like identical, this is same with ***Figures 1.4-1.6.*** We additionally provide descriptive statistics for actual and predicted broadband penetration rate in ***Table 1.17*** in ***Appendix C***. The starting and finishing point for each graph is very close to each other thus they look identical.

In order to establish valid fitted values for broadband penetration rate, we attempt to use purely exogenous instrumental variables. Therefore, we use voice telephony and cable TV subscribers per 100 inhabitants in 1997, the year before the first emergence of broadband in the country pairs at the same time. Even though the instruments are time invariant, this produces time variant fitted values.

The first stage of the non-linear instrumental variable is estimated by ***Equation (1.17)*** using a non-linear least square. Column (I), (II) and (III) of ***Table 1.3*** presents 148, 118 and 101 OtO country pairs respectively, whereas ***Table 1.4*** presents 101, 92, 76 non-OtO country pairs respectively, for 1995- 2009 .

Table1.3 OECD to OECD flows: diffusion curve of the Instrumental Model first stage

Dependent variable: Broadband penetration rate($BROAD_{ij,t}$)	**(I)**	**(II)**	**(III)**
Voice telephony penetration rate ($VOICE_{ij,1997}$)	0.274*** (0.006)	0.276*** (0.007)	0.277*** (0.008)
Cable TV penetration rate ($CABLE_{ij,1997}$)	0.334*** (0.018)	0.347*** (0.018)	0.302*** (0.017)
Diffusion speed (β)	0.917*** (0.025)	0.903*** (0.027)	0.890*** (0.028)
Inflexion point (τ)	2005.662*** (0.057)	2005.668*** (0.064)	2005.720*** (0.068)
Constant	0.003** (0.001)	-0.004*** (0.001)	-0.004** (0.001)
R^2	0.97	0.97	0.97
N	1981	1580	1342
F-test (p-values in parenthesis)	121.90 (0.000)	99.41 (0.000)	88.10 (0.000)

(I), (II), (III) present the first stage results of the diffusion curve for flows with 0.1, 0.3 and 0.5 thresholds respectively. For each threshold, we control the first stage model with more control variables, namely distance, real GDP, wage, unemployment rate, employment rate. The results are quite significant but the coefficients are very small, so we do not present them. They are available upon request.

Table1.4 Non-OECD to OECD flows: diffusion curve of the Instrumental Model first stage

Dependent variable: Broadband penetration rate($BROAD_{ij,t}$)	**(I)**	**(II)**	**(III)**
Voice telephony penetration rate ($VOICE_{ij,1997}$)	0.152*** (0.020)	0.154*** (0.021)	0.145*** (0.024)
Cable TV penetration rate ($CABLE_{ij,1997}$)	0.107*** (0.014)	0.106*** (0.014)	0.105*** (0.017)
Diffusion speed (β)	0.997*** (0.104)	0.995*** (0.106)	0.954*** (0.113)
Inflexion point (τ)	2007.308*** (0.271)	2007.308*** (0.277)	2007.437*** (0.343)
Constant	0.005*** (0.001)	0.005*** (0.001)	0.005*** (0.001)
R^2	0.84	0.85	0.83
N	1359	1233	1015
F-test(p-values in parenthesis)	44.70 (0.000)	43.23 (0.000)	28.13 (0.000)

(I), (II), (III) present the first stage results of the diffusion curve for flows with 0.1, 0.3 and 0.5 thresholds respectively. For each threshold, we control the first stage model with more control variables, namely distance, real GDP, wage, unemployment rate, employment rate. The results are quite significant but the coefficients are very small, so we do not present them. They are available upon request.

For OtO flows, ***Table 1.3*** shows that voice telephony penetration rate, cable TV penetration rate, diffusion speed and inflexion point are quite significant in determining broadband penetration rate. In fact, they are still very significant even after we control our first-stage model with more control variables. However, we do not present them here, as the coefficients are very small (they are available upon request). The inflexion point is estimated at around 2005 for OtO flows, and it does not vary much for different thresholds of flows.

For non-OtO flows, ***Table 1.4*** also confirms the significance of voice telephony penetration rate, cable TV penetration rate, diffusion speed and inflexion point in determining broadband penetration rate. The inflexion point for non-OtO flows is estimated at around 2007 and does not vary much for different thresholds of flows. Considering the different aspects of adopting technology, it is reasonable to find different inflexion points for OtO and non-OtO flows.

Both voice telephony penetration rate and cable TV penetration rate appear to have positive and significant effects on the ceiling of the broadband penetration rate η_{ij} . The F-test of joint significance for voice telephony and cable TV suggest that the null hypothesis that the estimated coefficients for both are different from zero at a 99% confidence interval.

1.4 Empirical Results

Our empirical results are based on Equation ***(1.12)*** in ***Section 1.3***. The results shown in ***Tables 1.18*** to ***Table 1.23*** in ***Appendix D*** present the OtO and non-OtO migration flows with 0.1, 0.3 and 0.5 thresholds. In all tables, ***Model (1)*** presents the OLS, ***Model (2)*** the random effect, ***Model (3)*** the country pair and time fixed effect, and finally ***Model (4)*** presents the GMM results. As discussed in ***Section 1.3.1,*** the GMM results do not seem to fix the endogeneity problem of either flow (OtO and non-OtO) under any thresholds as explained in ***Section 1.3.1.*** In all six cases (OtO flows with 0.1, 0.3 and 0.5 thresholds, and non-OtO flows with 0.1, 0.3 and 0.5 thresholds) second order autocorrelation is found to have no evidence of autocorrelation. However, apart from for OtO flows with 0.1 thresholds, the Sargan test of over-identification fails. The fixed effect results are presented in ***Model (3)*** for six cases, and as a time invariant variable the log of distance is dropped from the model.

Table.1.18 in ***Appendix D*** presents the results for OtO flows with a 0.1 rate threshold. Broadband penetration rate does not seem to have a significant effect in any of the models, and the coefficients are very small, especially in the fixed effect model. The dummy variable $FREE_{ij,t}$ which is equal to 1 if there is no restriction on travelling/staying/working from the origin country to the host appears to have a positive and significant effect on migration flows, which confirms that less restriction will result in more migration. The coefficients for control variables are consistent from ***Model (2)*** to ***Model (4),*** but the significance does not hold across all of these models.

Table 1.19 in ***Appendix D*** presents the results for OtO migration with a 0.3 threshold. Broadband penetration rate seems to have no effect on migration flows in any of the models, while the dummy variable $FREE_{ij,t}$ has a positive and significant effect. Wages in the host country are found to be always positive and significant as a determinant of migration flows only in the random effect and fixed effect model. Generally, both relative RGP and distance are found to be negative and significant. To the extent that the more distance the more risk and the higher the migration cost, it is considered as a demotivating factor.

Table 1.20 in ***Appendix D*** shows the results for OtO migration with a 0.5 threshold. Broadband penetration rate here also does not seem to have any effect on migration flows. The coefficient is very small in the GMM model in particular. The majority of the signs of the coefficients and their significance hold similar to the OtO flows with 0.1 and 0.3 thresholds. Interestingly, neither unemployment rate in the origin, nor employment rate in the host show much evidence of significant effect on migration for OtO flows with any thresholds.

Table 1.21 in ***Appendix D*** gives the non-OtO flows with a 0.1 threshold. Apart from in the random effect model, broadband penetration rate is found to have no significant effect on migration flows. This also is the case for non-OtO flows with 0.3 and 0.5 thresholds in ***Table 1.22*** and ***Table 1.23***. Generally, for all thresholds, dummy $FREE_{ij}$ is found to have a positive and significant effect on migration flows. Based on the fixed effect models, the coefficient of dummy variable of $FREE_{ij}$ is much larger for non-OtO flows. Considering the legal issue that migration cost increases when distance increases, legal issues might be a more important factor for those who are migrating from outside the OECD into the OECD. Furthermore, we do not have much evidence that unemployment rate in the origin and employment rate have an effect on the migration flows for OtO and non-OtO flows under any thresholds. Years since broadband was introduced to the country pairs seem to have a positive and significant effect, unlike what was expected. As we believe that broadband penetration rate facilitates migration flows, we expect the migration flows to be relatively lower in the years before broadband was introduced to country pairs.

Thus, the overall results confirm the several origins of endogeneity that are causing inconsistency across different models. We believe that our non-linear IV approach will address the problem sufficiently. Based on the first stage of the diffusion curve, we calculate the predicted broadband penetration rate and plug this variable in equation **(1.12).** The second stage results are shown in ***Tables 1.5 and 1.6*** for OtO and non-OtO migration flows, respectively. Besides this, we also calculate the predicted years since broadband was introduced to the country pairs at the same time and plug this in equation **(1.12).**

Models with odd numbers are all second stage of the instrumental variable model with OLS; whereas models with even number are second stage instrumental variable model with the country pair fixed effect. To account for the fact that broadband penetration rate is predicted by the first stage of the non-linear model, standard errors are bootstrapped (200 repetitions) in the second stage of the non-linear models. Broadband penetration rate seems to have a positive and significant effect on both OtO and non-OtO migration flows. The significance improves greatly in fixed effect models. The coefficient of broadband penetration rate is much higher for the non-OtO country pairs. This suggests that broadband connections between non-OECD and OECD countries affect migration flows from origin to home country more that between OECD and OECD countries by improving the flow of information about the host that affects migration decisions from the origin. This can be explained by the fact that the inflexion point is around 2007 for non-OtO country pairs - approximately two years later than the inflexion point for OtO country pairs. Broadband usage has been a more important communication tool between non-OECD and OECD than OECD and OECD countries between 1995 to 2009, therefore it is sensible that broadband penetration rate has more effect on migration flow for non-OtO than OtO flows. Consistent with the gravity literature, distance and relative RGDP are found to be a significant deterrent both for OtO and non-OtO migration flows for all thresholds. When it comes to wages in the host country, we observe a positive and significant relation with migration flows as expected. It is only negative in OtO flows with 0.3 and 0.5 thresholds and non-OtO with 0.3 thresholds and second-stage OLS, but is not significant. Unemployment in the origin country has a positive and significant effect on migration flows for fixed effect models of OtO and non-OtO flows with all thresholds. To some extent, higher unemployment in the country of origin will trigger individuals to seek for a job in other places. This also confirms the finding that employment rate in the host country is a decisive factor that facilitates migration flows in all fixed effect models for OtO and non-OtO migration flows. In other words, individuals tend to move to where the employment rate is higher. The dummy variable $FREE_{ij}$ is again found to be positive and significant in all cases. Predicted years since broadband introduced is found to be significant and negatively related to migration flows in fixed effect models. The coefficients of the predicted years since broadband was introduced seem to be much higher for the non-OtO country pairs. This confirms the consistent idea that the effect of broadband penetration rate is much higher for non-OtO country pairs.

Table1.5 The effect of broadband penetration rate on OtO migration flows: second stage results

Dependant variable: Log of migration flows	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Predicted penetration rate ($BROAD_{ij,t}\_hat$)	0.007(0.017)	0.048***(0.012)	0.034**(0.017)	0.044***(0.012)	0.044**(0.018)	0.045**(0.014)
Log of distance ($\log DIST_{ij}$)	-0.540***(0.046)		-0.367***(0.047)		-0.172***(0.048)	
Log of relative real GDP ($\log RGDP_{ij,t}$)	-0.249***(0.018)	-0.869**(0.407)	-0.257***(0.017)	-1.585***(0.419)	-0.212***(0.018)	-1.663***(0.450)
Log of wage in the host country ($\log wage_{j,t}$)	0.114**(0.037)	0.056**(0.024)	-0.033(0.033)	0.046*(0.025)	-0.020(0.031)	0.045*(0.025)
Unemployment rate in the origin ($Unempr_{i,t}$)	0.032(0.009)	0.002**(0.009)	0.039(0.009)	0.001***(0.010)	0.034 (0.009)	0.002***(0.010)
Employment rate in the host ($Empr_{i,t}$)	-0.011(0.003)	0.024*(0.014)	-0.007(0.003)	0.025**(0.013)	0.001(0.003)	0.029**(0.014)
Dummy=1if no restriction ($FREE_{ij,t}$)	0.614***(0.088)	0.707***(0.138)	0.349***(0.092)	0.992***(0.158)	0.450***(0.094)	1.024***(0.166)
Predicted years $T^{\beta}_{ij,t}\_hat$)	0.061(0.024)	-0.003*(0.015)	0.048(0.023)	-0.006*(0.013)	0.030(0.024)	-0.014*(0.014)
Constant	3.034***(4.478)	-1.063(0.983)	3.452***(0.462)	-1.010(0.883)	1.665(0.478)	-1.143(0.979)
R^2	0.17	0.27	0.15	0.37	0.12	0.36
N	2064	2064	1644	1644	1409	1409
Country pairs	148	148	118	118	100	100

Table1.6 The effect of broadband penetration rate on non-OtO migration flows: Second Stage results

Dependant variable: Log of migration flows	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Predicted penetration rate ($BROAD_{ij,t}\_hat$)	0.078***(0.012)	0.103***(0.021)	0.089***(0.012)	0.101***(0.023)	0.072***(0.012)	0.109**(0.030)
Log of distance ($\log DIST_{ij}$)	-0.071(0.066)		-0.179**(0.063)		-0.466***(0.054)	
Log of relative real GDP ($\log RGDP_{ij,t}$)	-0.287***(0.021)	-0.923**(0.371)	-0.249***(0.021)	-0.950**(0.382)	-0.196***(0.019)	-0.928**(0.440)
Log of wage in the host country ($\log wage_{j,t}$)	0.080**(0.041)	0.062*(0.037)	0.053(0.041)	0.082**(0.036)	0.200***(0.038)	0.089**(0.037)
Unemployment rate in the origin ($Unempr_{i,t}$)	-0.062(0.007)	0.016*(0.013)	-0.058(0.007)	0.015*(0.014)	-0.060(0.006)	0.013*(0.015)
Employment rate in the host ($Empr_{i,t}$)	0.030*(0.003)	0.039*(0.002)	0.022*(0.003)	0.042*(0.023)	0.022(0.003)	0.049*(0.033)
Dummy=1if no restriction ($FREE_{ij,t}$)	0.062(0.299)	0.709***(0.153)	0.158(0.298)	0.725***(0.161)	0.961***(0.264)	0.739***(0.199)
Predicted years ($T^{\beta}_{ij,t}\_hat$)	0.030(0.073)	-0.025*(0.048)	-0.088(0.072)	-0.032*(0.050)	-0.219(0.081)	-0.062*(0.061)
Constant	3.289***(0.609)	-3.470**(1.695)	4.152***(0.562)	-3.607(1.747)	5.475***(0.496)	-3.732(2.398)
R^2	0.20	0.34	0.19	0.36	0.28	0.36
N	1397	1397	1277	1277	1049	1049
Country pairs	101	101	92	92	76	76

Models (1)-(3)-(5) and Models (2)-(4)-(6) of Table 0.11 and Table0.12 present the second stage of instrumental variable and second stage of instrumental variable with country pair and time fixed effect, respectively. Models (1)-(2), Models (3)-(4), and Models (5)-(6) are for 0.1, 0.3 and 0.5 rate thresholds for OtO and non-OtO migration flows, respectively. Bootstrapped standard errors are in parenthesis.

1.4.1 Validity of Instruments

In order to see whether our instruments, the voice telephony and cable networks, might have an independent direct effect on migration flows, or affect migration flows through other channels than broadband, we consider whether other communication technologies such as mobile phones and number of subscriptions to the integrated services digital network (ISDN) which enables voice or data transmission might also affect the migration flows. In order to estimate the diffusion curves for mobile telephones and ISDN, we apply the same ceiling $\eta_{ij} = \eta_0 + \eta_1 TEL_{ij,1997} + \eta_2 CABLE_{ij,1997}$ based on voice telephony and cable TV penetration rate per 100 individuals for each flow rate threshold for both OtO and non-OtO flows. Then we follow the logistic curve ($\frac{\eta_{ij}}{1+e^{-[\beta(t-\tau)]}}$) for both mobile phones and ISDN. The use of broadband comes considerably later than the use of voice telephony and cable TV. The fact that we measure the predicted broadband penetration rate based on these two variables at year 1997- that is before broadband introduced to country pairs sampled- it is safe to say our instruments are predetermined when considering broadband diffusion. Yet, predetermination may be necessary but not sufficient condition for exogeneity in an econometric sense Czernich *et al*. (2011). Thus, first of all, we analyse whether our instruments- TEL and CABLE might have an indirect effect on migration flows, or they affect migration flows through other channels then broadband. Our instruments, TEL and CABLE may not only effect the deployment of broadband network but also the diffusion of other technologies which may also trigger migration flows. For that, we pick one of the most common communication tool- mobile phones in which the adoption and diffusion has started since the 1980s (Kalba, 2008) and the oldest telecommunication tool - ISDN which has being used since 1970s (https://www.nfon.com/gb/solutions/resources/glossary/isdn/) (4) To test our claim, we estimate diffusion curves with the same ceiling (Please see *Model 1.16*) for MOB and ISDN. We presented the results from ***Table 1.24- 1.29*** in ***Appendix E*** and as can be seen from these tables there is no significant effect is found. Thus, we found no significance of penetration of the traditional networks – TEL and CABLE- on the diffusion of MOB and ISDN. We conclude that our instruments, TEL and CABLE only determine broadband diffusion and not the diffusion of other potential telecommunication tools that might have an impact on migration flows, underlying the validity of our instruments. TEL and CABLE could also have a direct impact on migration flows. To see whether our instruments have direct impact on migration flows, we inserted them in the same model as broadband but find no significance. (Please see ***Table 1.30*** and ***1.31*** in ***Appendix F***)

As can be seen from ***Table 1.24- Table 1.29*** in ***Appendix E***, we observe no significant effect of voice telephony and cable TV on either of the alternative communication channels, mobile telephony and ISDN at a conventional level. This confirms the validity of our instruments. Here, we obtained both mobile telephone subscribers per 100 inhabitants and ISDN subscriber per 100 inhabitants from the ITU World telecommunication –ICT database. The F-test of joint significance for voice telephony and cable TV suggest that the null hypothesis that is the estimated coefficients for both are different from zero at a 99% confidence interval.

1.4.2 Robustness Checks

Our first stage results are based on voice telephony penetration rate and cable TV penetration rate per 100 inhabitants in the population. This is to estimate the predicted broadband penetration rate per 100 inhabitants in the population. However, such a measurement may cause a correlation in the first stage result, as both the endogenous and instrumental variables have common denominator. Thus we estimate the first stage diffusion curve with voice telephony penetration rate per 100 inhabitants and cable TV penetration rate per 100 inhabitants to estimate broadband penetration rate at household level as in ***Table 1.7*** for OtO migration flows with 0.1, 0.3 and 0.5 rate thresholds and ***Table 1.8*** for non-OtO migration flows with 0.1, 0.3 and 0.5 thresholds. The levels of both instruments, voice telephony penetration rate per 100 inhabitants and cable TV penetration rate per 100 inhabitants, remain positive and significant for both OtO and non-OtO cases. In fact, the coefficients are much higher, suggesting that both instrumental variables determine broadband penetration rate to be higher if measured at the household level. The inflexion point remains around 2005 for OtO flows, and 2007 for non-OtO flows.

Table1.7 Diffusion Curve: first stage of the Instrumental Variables for OtO flows

Dependent variable: $BROADHH_{ij}$	**(1)**	**(2)**	**(3)**
Voice telephony penetration rate $VOICE_{ij,1997}$)	1.251*** (0.047)	1.236*** (0.052)	1.221*** (0.056)
Cable TV penetration rate $CABLE_{ij,1997}$)	0.926*** (0.144)	1.059*** (0.143)	0.835*** (0.184)
Diffusion speed (β)	0.905*** (0.030)	0.893*** (0.033)	0.891*** (0.035)
Inflexion point (τ)	2005.783*** (0.070)	2005.785*** (0.080)	2005.840*** (0.087)
Constant	0.084*** (0.008)	0.081*** (0.000)	0.088*** (0.009)
R^2	0.96	0.96	0.96
N	1981	1580	1342
F-test (p-values in parenthesis)	459.54(0.000)	375.74(0.000)	312.76(0.000)

$BROADHH_{ij}$ is measured as a multiplication of broadband subscribers per household in the population in origin and host

Table1.8 Diffusion Curve: first stage of the Instrumental Variables for non-OtO flows

Dependent variable: $BROADHH_{ij}$	**(1)**	**(2)**	**(3)**
Voice telephony penetration rate ($VOICE_{ij,1997}$)	0.709*** (0.141)	0.662*** (0.113)	0.006*** (0.002)
Cable TV penetration rate ($CABLE_{ij,1997}$)	0.708*** (0.265)	0.684*** (0.154)	0.671*** (0.100)
Diffusion speed (β)	0.961*** (0.103)	0.962*** (0.106)	0.918*** (0.112)
Inflexion point (τ)	2007.347*** (0.298)	2007.348*** (0.306)	2007.477*** (0.381)
Constant	0.065*** (0.010)	0.063*** (0.010)	0.069*** (0.012)
R^2	0.80	0.80	0.78
N	1359	0.85	1015
F-test (p-values in parenthesis)	35.26(0.000)	34.10(0.000)	22.82(0.000)

$BROADHH_{ij}$ is measured as a multiplication of broadband subscribers per household in the population in origin and host

Following the first stage results based on household level of broadband subscription, the second stage of the estimation results are presented in ***Table 1.9*** for OtO flows with 0.1, 0.3, and 0.5 thresholds, and ***Table 1.10***. for non-OtO flows with 0.1, 0.3 and 0.5 thresholds. As can be seen from both tables, the significance and the sign of the coefficients remain the same. The pattern of how coefficients change across different thresholds also remains the same. The F-test of joint significance for voice telephony and cable TV suggests that the null hypothesis that the estimated coefficients for both are different from zero at a 99% confidence interval for both OtO and non-OtO country pairs.

Table1.9 Second stage of the Instrumental Variables Model for OtO flows

Dependant variable: Log of migration flows	**(1)**	**(2)**	**(3)**
Predicted penetration rate ($BROAD_{ij,t}\_hat$)	0.052(0.018)	0.056**(0.017)	0.049**(0.018)
Log of distance ($\log DIST_{ij}$)	-0.543***(0.047)	-0.371***(0.047)	-0.175***(0.049)
Log of relative real GDP ($\log RGDP_{ij,t}$)	-0.251***(0.018)	-0.257***(0.017)	-0.212***(0.018)
Log of wage in the host country ($\log wage_{j,t}$)	0.098**(0.037)	-0.043(0.033)	-0.024(0.031)
Unemployment rate in the origin ($Unempr_{i,t}$)	0.028**(0.009)	0.037***(0.009)	0.034***(0.009)
Employment rate in the host ($Empr_{j,t}$)	-0.009(0.003)	-0.006(0.003)	0.002(0.003)
Dummy=1if no restriction $(FREE_{ij,t})$	0.634***(0.087)	0.353***(0.093)	0.451***(0.095)
Predicted years $(T^{\beta}_{ij,t}\_hat)$	-0.033(0.023)	0.004(0.021)	0.019(0.022)
Constant	3.392(0.476)	3.587***(0.455)	1.628**(0.470)
R^2	0.16	0.15	0.12
N	2064	1644	1409

(I), (II), (III) present the OLS estimation of the second stage results of instrumental variables for OtO flows with 0.1, 0.3 and 0.5 rate thresholds, respectively. We also obtained a fixed effect estimation of the second stage results, but do not present it here as the time invariant variable is dropped from the model. The sign and significance of the coefficients remain the same in the fixed effect model. They are available upon request.

Table1.10 Second stage of the Instrumental Variables Model for non-OtO flows

Dependant variable: Log of migration flows	**(1)**	**(2)**	**(3)**
Predicted penetration rate ($BROAD_{ij,t}\_hat$)	0.082***(0.013)	0.094**(0.013)	0.077***(0.012)
Log of distance ($\log DIST_{ij}$)	-0.080(0.066)	-0.187**(0.062)	-0.452***(0.054)
Log of relative real GDP ($\log RGDP_{ij,t}$)	-0.286***(0.021)	-0.247***(0.021)	-0.195***(0.019)
Log of wage in the host country ($\log wage_{j,t}$)	0.078*(0.041)	0.049(0.041)	0.196*(0.038)
Unemployment rate in the origin ($Unempr_{i,t}$)	-0.062(0.007)	-0.058(0.007)	-0.060(0.006)
Employment rate in the host ($Empr_{j,t}$)	0.029(0.003)	0.022(0.003)	0.022(0.003)
Dummy=1if no restriction $(FREE_{ij,t})$	0.064(0.230)	0.159(0.298)	0.961***(0.264)
Predicted years $(T^{\beta}_{ij,t}\_hat)$	0.032(0.073)	-0.090(0.071)	-0.221**(0.081)
Constant	3.208***(0.606)	4.080***(0.558)	5.414***(0.491)
R^2	0.20	0.20	0.28
N	1397	1277	1015

(I), (II), (III) present the OLS estimation of the second stage results of instrumental variables for non-OtO flows with 0.1, 0.3 and 0.5 rate thresholds, respectively. We also obtained a fixed effect estimation of the second stage results, but do not present it here as the time invariant variable is dropped from the model. The sign and significance of the coefficients remain the same in the fixed effect model. They are available upon request

Additional robustness checks have been presented in ***Table 32-37 in Appendix G*** .One can argue that, apart from broadband, digital landline phones might have an effect on migration flows. In order to check this, we controlled the second stage results with an extra variable of landline phone penetration rate per 100 inhabitants in the population, obtained from the ITU (International Telecommunication Union) ICT Database. ***Table 32 and Table 33*** in ***Appendix G*** present the results for OtO and non-OtO flows with 0.1, 0.3 and 0.5 thresholds. As can be seen from the tables, we observe no significant effect of landline phone penetration rate in either case under any thresholds, while broadband penetration rate still remains positive and significant.

However, high or low landline phone penetration might not be the factor that affects individuals' decision to migrate, it may be international phone traffic between origin and host. Thus, we calculated the variable:

$$phntraffic_{ij} = phntraffic_i \times phntraffic_j \tag{1.18}$$

where $phntraffic_i$ stands for international incoming phone traffic to the origin, and $phntraffic_j$ is international outgoing phone traffic from the host country. This variable will give the approximate international phone traffic between country i and country j at time t. ***Table 34 and Table 35*** in ***Appendix G*** present the results for OtO and non-OtO countries with 0.1, 0.3 and 0.5 thresholds under Models (I), (II) and (III) respectively. Indeed, phone traffic within country pairs is found to have a positive and significant effect on OtO migration flows, whereas there is not much evidence that this holds for non-OtO flows. All in all, broadband penetration rate is still positive and significant; also the sign of the remainder of the control variables remains the same.

The different effect of phone traffic for OtO and non-OtO country pairs attracts our attention. Thus, this time, we intend to see the individual effect of international incoming phone traffic in the origin county and international outgoing phone traffic in the host. ***Table 36*** and ***Table 37*** in ***Appendix G*** present the OtO and non-OtO migration flows with 0.1, 0.3 and 0.5 thresholds with Models (I), (II), and (III) respectively. Both the OtO and non-OtO flows suggest that international outgoing phone traffic in the host has a positive and significant effect on migration flows, while international incoming phone traffic in the origin shows no significant effect on the flows of migration. This may in a sense suggest that the direction of information flows is from host to origin, which in return results in migration flows from origin to host. Broadband penetration rates is still found to be positive and significant for both OtO and non-OtO country pairs.

1.5 Conclusion

Our non-linear instrumental approach to broadband penetration rates find a positive and strong effect on migration flows. This effect appears to be even stronger for non-OtO flows in comparison to OtO flows.

Our results are robust to a number of different specifications. For instance, measuring broadband penetration rate at household level while keeping instrumental variables - voice telephony and cable TV penetration rate - at per 100 inhabitants level did not affect the second stage results in terms of the sign of coefficients nor significance: in fact, the significance improved. Additionally, we checked whether landline phone traffic between country pairs, or international calling-in or out phone traffic also have a similar effect along with broadband, controlling for them all in the models. Broadband penetration rate is still the main determinant of migration decisions, while the sign of other variables remains the same for all three thresholds.

The effect of broadband penetration rate is higher in non-OtO migration flows. This maybe is likely not only for information exchange purposes, but also job applications and interviews are more likely to take place online, whereas, job-orientated travelling can be undertaken more easily within closer countries. In other words, migrants of non-OtO flows make more use of broadband in terms of ensuring a place to work or place to stay, while migrants of OtO flows can interact with the host country not only through broadband but also in person.

We have different thresholds, namely 0.1, 0.3 and 0.5 (100, 300 and 500 people or more people), as we want to capture the relationship between broadband penetration rate and migration flows at different levels. The lowest threshold we focus on is 0.1 (100 and more people as we believe that the flows should be at a countable level in order to analyse the effect of broadband penetration rates on migration flows. To give even more accountability, we chose the other thresholds of 0.3 and 0.5. The results for each threshold, particularly 0.3 and 0.5, are quite similar, and they are all consistent. The results improve above the larger (that is 0.5) constraint. This is due to the fact that we believe higher frequency of moving - although capturing fewer country pairs.

The different thresholds for OtO flows give consistent results with each other, and the results improving from the 0.1 to 0.5 rate thresholds. This holds the same for non-OtO flows, where the significance of the right-hand side variables improves from the 0.1 to 0.5 rate threshold. We found inflexion points for OtO and non-OtO flows as 2005 and 2007 respectively. This could be explained by the way in which more developed countries (OECD ones) adopt technology versus developing or undeveloped countries (non-OECD ones). The inflexion point of 2007 for non-OECD countries suggests that they adopt technology and reach saturation point around two years later.

What is more, having no legal restriction is always found to be positively and significantly correlated with migration flows, both OtO and non-OtO migration flows; this relationship is stronger for the latter. In this regard, considering legal restriction as a migration cost, flows from more distant countries will take legal restrictions more into account. That is also consistent with the result for distance which is found to be consistent with the gravity models of migration across the literature, as one of the essential demotivating factors in deciding where to move.

Overall, we found that broadband penetration rate has a significant and positive effect on migration flows. This effect is stronger for non-OtO migration flows. Broadband appears to be preferred in comparison to landline phones amongst migrant candidates between 1995 and

2009. Further research is needed to investigate whether smart phones facilitate migration flow, which we believe to be true, as mobile phones also provides cheaper and easier communications overseas, and so may be preferred by migrant candidates. However, we were unable to investigate whether such an effect exists due to lack of data. The ITU World telecommunications ICT indicators have only few years of data available on smart phone subscriptions, but more data will be available in several years’ time which will enable researchers to investigate this in more detail.

APPENDIX A

Table1.11 Country Pairs for OtO Flows at Threshold 0.1 (100 and more people)

Origin	Host	No of pairs
1.AT	DE, HU ,NL, ES, PL,	5
2.BE	AT, DE, LU, NL, ES	5
3.CZ	AT, DE, NL, ES.	4
4.DK	AT, BE , DE, LU, NO, ES ,SE	7
5.EE	DK ,FI, DE, ES,	4
6.FI	AT, DK, DE, NL , NO, ES, SE	7
7.FR	BE , DK, DE, HU, IT, LU, NL, NO, PL, ES, SE ,UK	12
8.DE	AT, BE, CZ, DK, FI, HU, IT, LU, NL, NO, PL, ES, SE, UK	14
9.HU	AT, FR, DE, NL, ES	5
10.IT	AT, BE, DK, DE, LU, NL, NO, PL, ES, UK, HU	11
11.NL	AT, BE, DK, DE, LU, NO, PL, ES, SE,	9
12.NO	DK, DE, ES, SE,	4
13.PL	AT, BE, CZ, DK, FR, DE, HU, IT, NL, NO, ES, SE, UK.	13
14.SK	AT, CZ, DE, HU, NO, ES	6
15.ES	AT, BE, DK, FI, DE, LU, NL, , NO, PL, SE	10
16.SE	AT, BE, DK, FI, DE, LU, NO, ES.	8
17.TR	AT, BE, DK, FI, FR, DE, HU, NL, NO, ES, SE,	11
18. UK	AT, BE, DK, FI, DE, HU, IT, LU, NL, NO, PL, ES, , SE	13
18 Origin	**16 Different host countries**	**148 Pairs**
	AT, BE, CZ, DK, FI, FR, DE, HU, IT, LU, NL, NO, PL, ES, SE, UK	

Table1.12 Country Pairs for OtO Flows at Threshold 0.3 (300 and more people)

Origin	Host	No of pairs
1.AT	DE, NL, ES,	3
2.BE	DE, LU, NL, ES	4
3.CZ	AT, DE, NL, ES.	4
4.DK	BE, DE, NO, ES ,SE	5
5.FI	DE, NL , NO, ES, SE	5
6.FR	BE, DK, DE, IT, LU, NL, NO, PL, ES, SE, UK	11
7.DE	AT, BE, CZ, DK, HU, IT, LU, NL, NO, PL, ES, SE, UK	13
8.HU	AT, DE, NL, ES	4
9.IT	AT, BE, DK, DE, LU, NL, PL, ES, UK	9
10.NL	AT, BE, DK, DE, NO, ES, SE,	7
11.NO	DK, DE, ES, SE,	4
12.PL	AT, BE, CZ, DK, FR, DE, IT, NL, NO, ES, SE, UK.	12
13.SK	AT, CZ, DE, HU, ES	5
14.ES	AT, BE, DK, DE, NL, ,SE	6
15.SE	AT, BE, DK, FI, DE, NO, ES.	7
16.TR	AT, BE, DK, FR, DE, NL, NO, SE,	8
17. UK	AT, BE, DK, DE, IT, LU, NL, NO, PL, ES, SE	11
17 Origin	**16 Different host countries**	**118 Pairs**
	AT, BE, CZ, DK, FI, FR, DE, HU, IT, LU, NL, NO, PL, ES, SE, UK	

Table1.13 Country Pairs for OtO Flows at Threshold 0.5(500 and more people)

Origin	Host	No of pairs
1.BE	DE, LU, NL, ES	4
2.CZ	AT, DE, ES.	3
3.DK	DE, NO, ES ,SE	4
4.FI	DE, NO, ES, SE	4
5.FR	BE, DE, IT, LU, NL, PL, ES, SE, UK	9
6.DE	AT, BE, CZ, DK, HU, IT, LU, NL, NO, PL, ES, SE, UK	13
7.HU	AT, DE, NL, ES	4
8.IT	AT, BE, DE, LU, NL, ES, UK,	7
9.NL	AT, BE, DE, ES, SE,	5
10.NO	DK, DE, ES, SE,	4
11.PL	AT, BE, CZ, DK, FR, DE, IT, NL, NO, ES, SE, UK.	12
12.SK	AT, CZ, DE, HU, ES	5
13.ES	BE, DE, NL,	3
14.SE	BE, DK, FI, DE, NO, ES.	6
15.TR	AT, BE, DK, FR, DE, NL, SE,	7
16.UK	AT, BE, DK, DE, IT, NL, NO, PL, ES, , SE	10
16 Origin	**16 Different host countries**	**100 Pairs**
	AT, BE, CZ, DK, FI, FR, DE, HU, IT, LU, NL, NO, PL, ES, SE, UK	

Table1.14 Country Pairs for non-OtO Flows at Threshold 0.1 (100 and more people)

Origin	Host	*No of pairs*
1.DZ	AT, BE, FR, DE, ES	5
2.AM	FR, DE, PL, ES	4
3.BA	AT, DK, FR, DE, NO, SE	6
4.BG	AT, CZ, FR, DE, PL, ES,	6
5.CN	AT, BE, DK, FI, FR, DE, HU, IT, LU, NL, NO, PL, ES, SE, UK	15
6.EG	AT, FR, DE, IT, ES	5
7.MA	AT, BE, FR, DE, IT, NL, NO, ES	8
8.NG	AT, FR, DE, ES, UK	5
9.PK	AT, DK, FR, DE, IT, NO, ES, UK	8
10.RO	AT, BE, CZ, DK, FR, DE, HU, IT, NO, PL, ES, SE.	12
11.RU	AT, BE, CZ DK, FI, FR, DE, HU, IT, NO, PL, ES, SE	13
12.TN	AT, BE, FR, DE, IT	5
13.UA	AT, CZ, DK, FI, FR, DE, HU, IT, PL	9
13 origin	**16 Different host countries**	**101 pairs**
	AT, BE, CZ, DK, FI, FR, DE, HU, IT, LU, NL, NO, PL, ES, SE, UK	

Table1.15 Country Pairs for non-OtO Flows at Threshold 0.3 (300 and more people)

Origin	Host	*No of pairs*
1.DZ	BE, FR, DE, ES	4
2.AM	FR, DE, PL, ES	4
3.BA	AT, FR, DE, NO, SE	5
4.BG	AT, CZ, FR, DE, PL, ES,	6
5.CN	AT, BE, DK, FI, FR, DE, HU, IT, NL, NO, PL, ES, SE, UK	14
6.EG	AT, FR, DE, IT, ES	5
7.MA	BE, FR, DE, IT, NL, ES	6
8.NG	AT, DE, ES, UK	4
9.PK	AT, DK, FR, DE, IT, NO, ES, UK	8
10.RO	AT, BE, CZ, DK, FR, DE, HU, IT, NO, ES, SE.	11
11.RU	AT, BE, CZ DK, FI, FR, DE, HU, IT, NO, PL, ES, SE	13
12.TN	BE, FR, DE, IT	4
13.UA,	AT, CZ, DK, FR, DE, HU, IT, PL	8
13 origin	**16 Different host countries**	**92 pairs**
	AT, BE, CZ, DK, FI, FR, DE, HU, IT, LU, NL, NO, PL, ES, SE, UK	

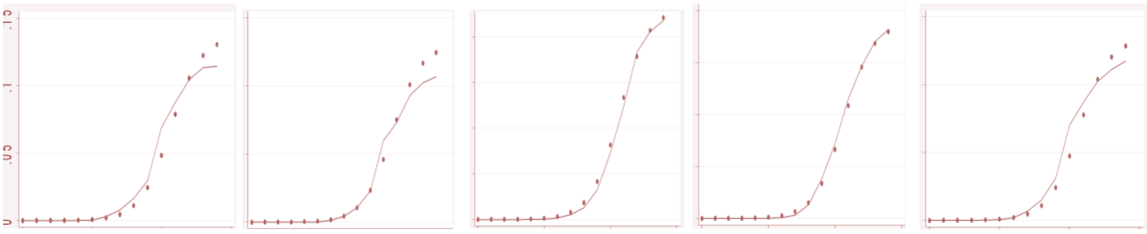
Table1.16 Country Pairs for non-OtO Flows at Threshold 0.5(500 and more people)

Origin	Host	*No of pairs*
1.DZ	BE, FR, DE, ES	4
2.AM	FR, DE, PL, ES	4
3.BA	AT, DE, SE	3
4.BG	AT, DE, ES,	3
5.CN	AT, BE, DK, FR, DE, HU, IT, NL, PL, ES, SE, UK	12
6.EG	AT, FR, DE, IT,	4
7.MA	BE, FR, DE, IT, NL, ES	6
8.NG	AT, DE, ES, UK	4
9.PK	FR, DE, IT, NO, ES, UK	6
10.RO	AT, BE, FR, DE, HU, IT, ES, SE.	8
11.RU	AT, BE, CZ FI, FR, DE, IT, NO, PL, ES, SE	11
12.TN	FR, DE, IT	3
13.UA	AT, CZ, DK, FR, DE, HU, IT, PL	8
13 origin	**16 Different host countries**	**76 pairs**
	AT, BE, CZ, DK, FI, FR, DE, HU, IT, LU, NL, NO, PL, ES, SE, UK	

APPENDIX B

Figure1.1 Actual and Predicted broadband penetration rates for country pairs OtO Flows at Threshold 0.1 (100 and more people)

Poland-Germany | Turkey-Germany | Poland-UK | Germany-Austria | Italy-Germany



Netherlands-Belgium | Sweden-Norway | Belgium-Luxembourg | Turkey-Netherlands | Denmark-Sweden

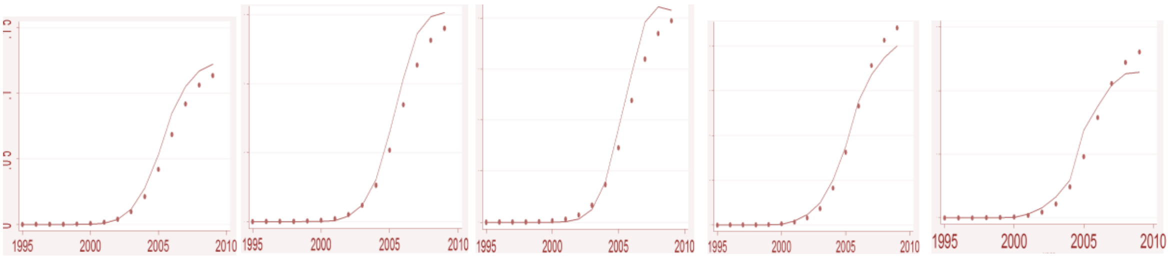
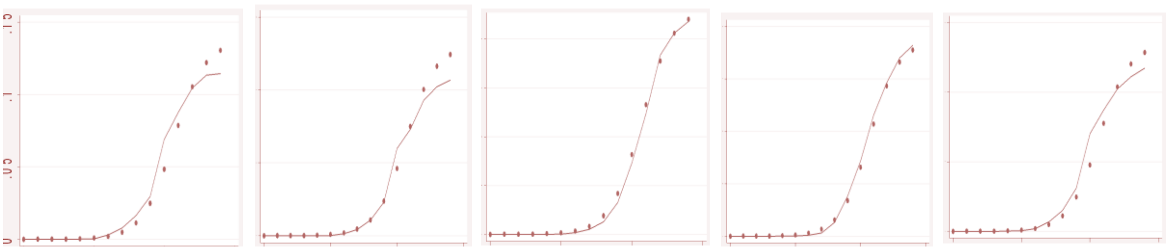
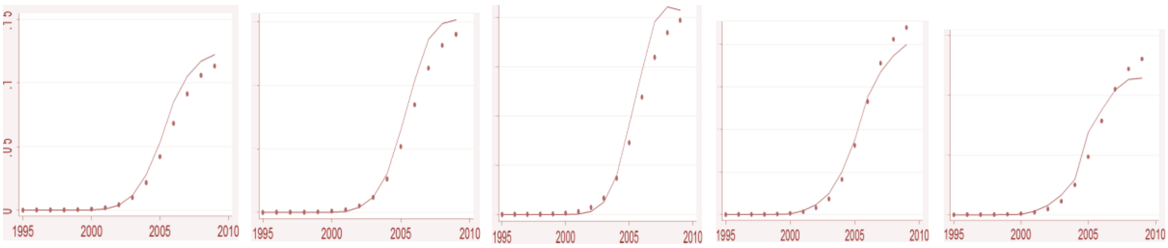


Figure1.2 Actual and Predicted broadband penetration rates for country pairs OtO Flows at Threshold 0.3 (300 and more people)

Poland-Germany | Turkey-Germany | Poland-UK | Germany-Austria | Italy-Germany



Netherlands-Belgium | Sweden-Norway | Belgium-Luxembourg | Turkey-Netherlands | Denmark-Sweden



Actual broadband penetration rate———————— Predicted broadband penetration rate- - - - - - - -

Figure1.3 Actual and Predicted broadband penetration rates for country pairs OtO Flows at Threshold 0.5(500 and more people)

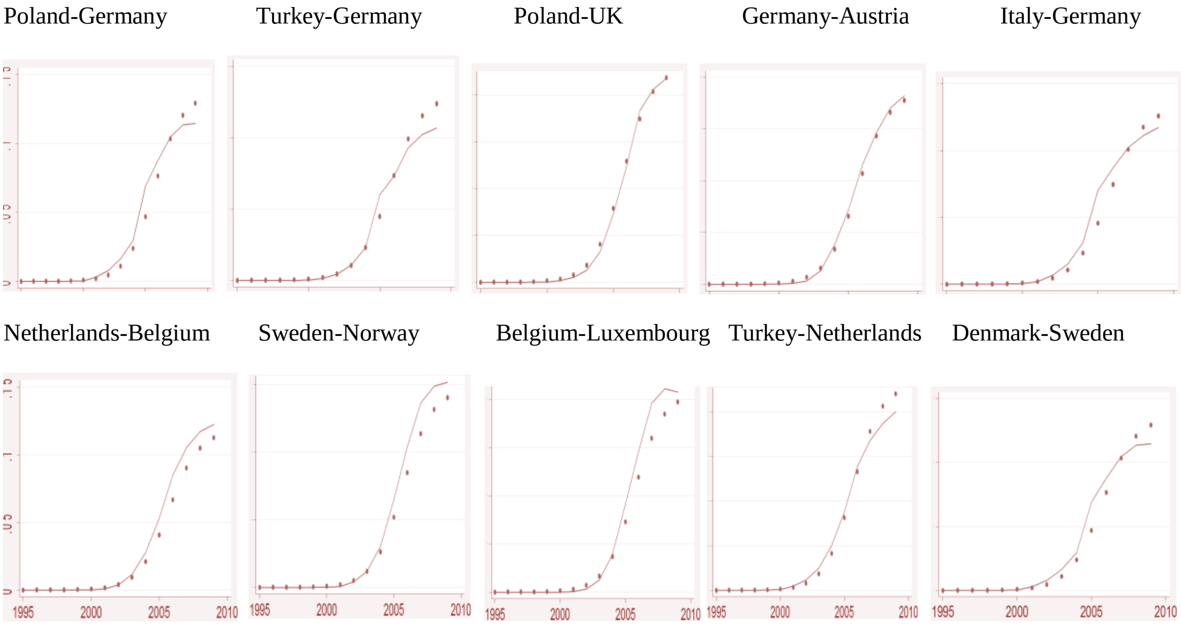
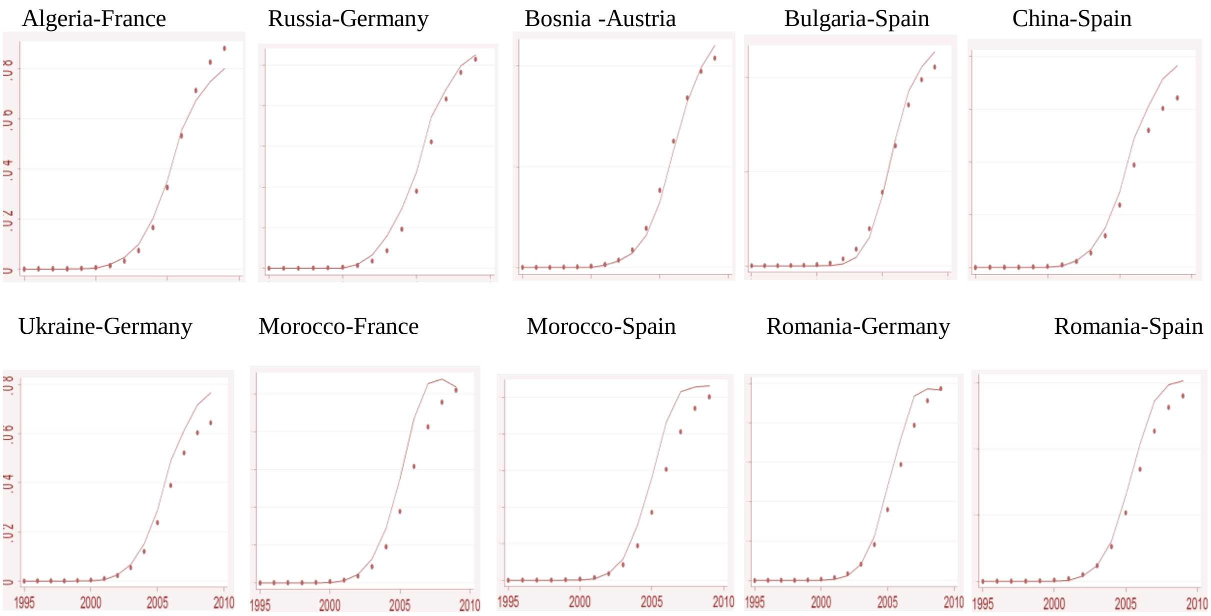


Figure1.4 Actual and Predicted broadband penetration rates for country pairs non-OtO Flows at Threshold 0.1 (100 and more people)



Actual broadband penetration rate———— Predicted broadband penetration rate- - - - - - - -

Figure1. 5 Actual and Predicted broadband penetration rates for country pairs non-OtO Flows at Threshold 0.3 (300 and more people)

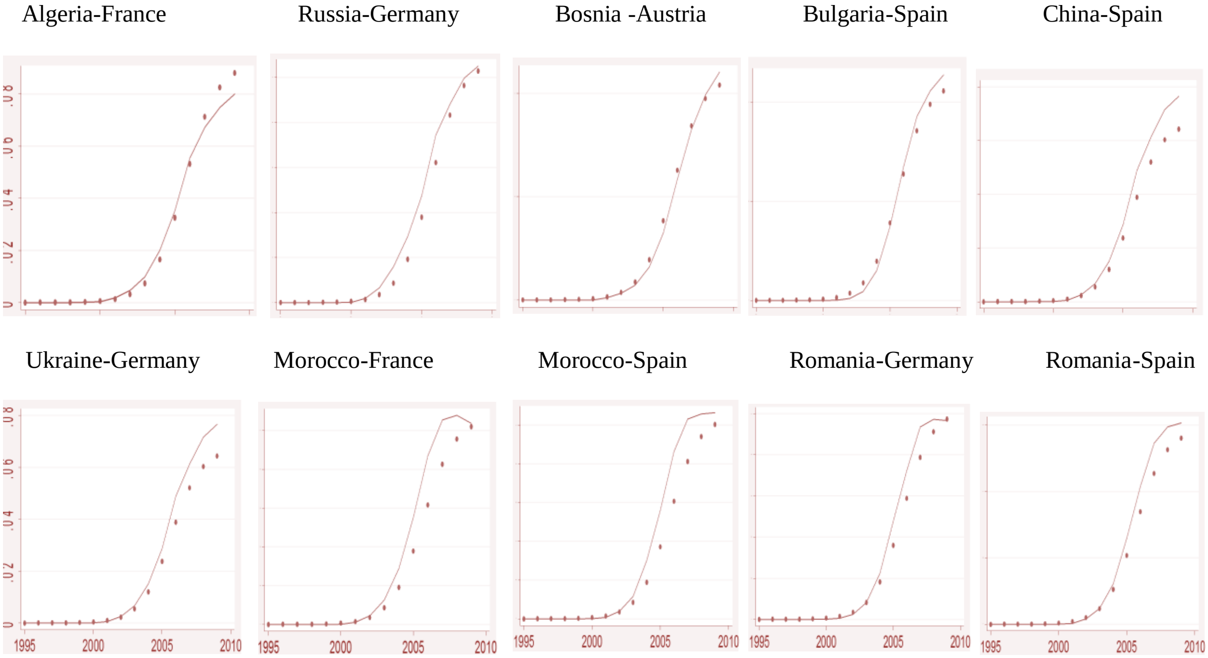
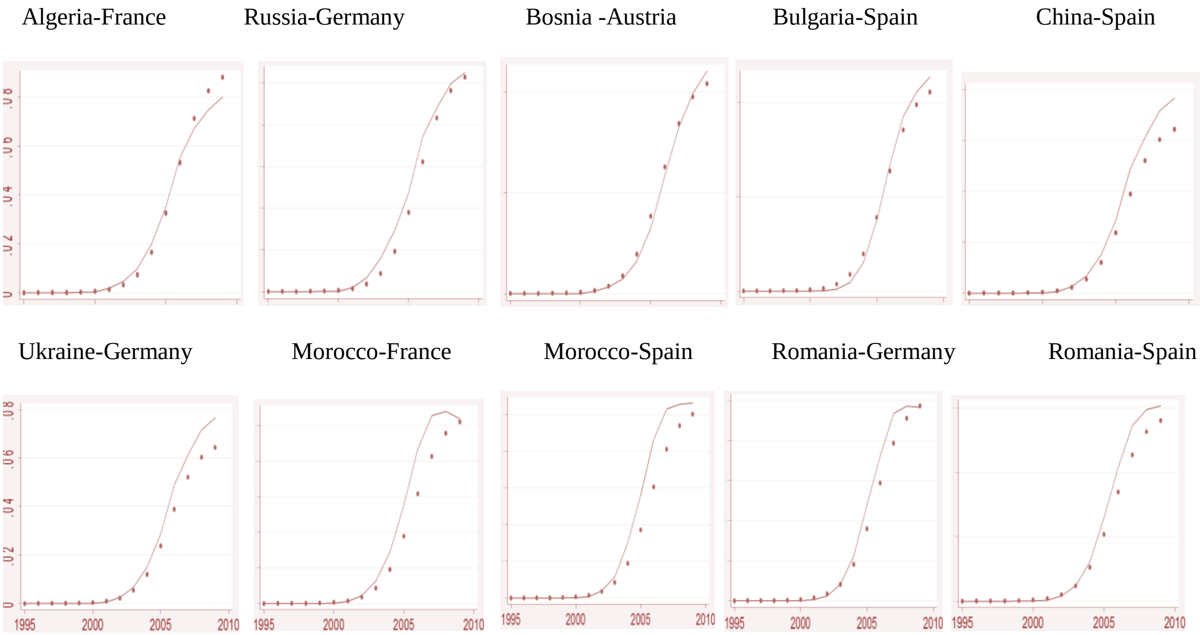


Figure1.6 Actual and Predicted broadband penetration rates for country pairs non-OtO Flows at Threshold 0.5(500 and more people)



Actual broadband penetration rate——————— Predicted broadband penetration rate- - - - - - - -

APPENDIX C

Table1. 17 Descriptive Statistics for Actual and Predicted Broadband

	Obs	**Mean**	**Std Dev.**	**Min**	**Max**
OTO 0.1 Threshold					
$BROAD_{ij}$	2220	0.0176976	0.02768	8.89e-0.7	0.1304825
$BROAD\_hat_{ij}$	1981	0.0194699	0.0293502	0	0.1342842
OTO 0.3 Threshold					
$BROAD_{ij}$	1770	0.0182054	0.0282747	9.46e-07	0.1304609
$BROAD\_hat_{ij}$	1580	0.0200022	0.0300073	0	0.1342842
OTO 0.5 Threshold					
$BROAD_{ij}$	1500	0.0175877	0.0275892	9.87e-07	0.1291897
$BROAD\_hat_{ij}$	1342	0.019256	0.029271	0	0.122237
Non-OTO 0.1 Threshold					
$BROAD_{ij}$	1515	0.0026988	0.0058787	2.35e-08	0.0504853
$BROAD\_hat_{ij}$	1359	0.0029813	0.0068128	0	0.0470337
Non-OTO 0.3 Threshold					
$BROAD_{ij}$	1380	0.0027747	0.0060423	2.31e-0.8	0.0501948
$BROAD\_hat_{ij}$	1233	0.0030777	0.0069958	0	0.0470337
Non-OTO 0.5 Threshold					
$BROAD_{ij}$	1140	0.0025518	0.0055387	3.68e-08	0.0480635
$BROAD\_hat_{ij}$	1015	0.0028398	0.0064991	0	0.0410672

APPENDIX D

Table1.18 Migration flows from OECD to OECD countries and broadband penetration rate Threshold 0.1 (100 and more people)

Dependant variable: Log of migration flows	(1)	(2)	(3)	(4)
Broadband penetration rate ($BROAD_{ij,t}$)	-0.031(0.024)	0.007(0.009)	0.004(0.008)	0.024*(0.013)
Log of distance ($\log DIST_{ij}$)	-0.507***(0.054)	-0.461**(0.158)		-0.702*(0.390)
Log of relative real GDP ($\log RGDP_{ij,t}$)	-0.236***(0.022)	-0.241**(0.067)	-0.167(0.441)	-0.340*(0.132)
Log of wage in the host country ($\log wage_{j,t}$)	0.344***(0.077)	0.205**(0.084)	0.205**(0.087)	0.348(0.244)
Unemployment rate in the origin ($Unempr_{i,t}$)	0.049***(0.012)	-0.020(0.015)	-0.021(0.015)	-0.001(0.019)
Employment rate in the host ($Empr_{j,t}$)	-0.017***(0.003)	0.011(0.009)	0.026**(0.013)	0.015(0.018)
Dummy=1if no restriction ($FREE_{ij,t}$)	0.420**(0.132)	0.319**(0.111)	0.315**(0.113)	0.008(0.140)
Years since broadband introduced ($T^B_{ij,t}$)	0.277**(0.127)	0.116**(0.040)	0.095**(0.042)	0.139**(0.041)
Constant	1.233(0.750)	0.991(1.489)	-3.221**(1.213)	3.552(2.692)
R^2	0.16	0.17	0.17	
N	1413	1413	1413	1403
Country pairs	148	148	148	148

Notes: A panel of data for 148 country pairs for OtO flows estimations for 1995-2009. Model (1)-Model (4) present the OLS, random effect, fixed effect, dynamic GMM, respectively. Robust t-statistics in parentheses. Significance at *10%, **5%, ***1%. AR (1) and AR(2) Arellano-Bond autocorrelation test for GMM are, -2.556(0.011) and 1.108(0.268) respectively and AR(2) shows no evidence of autocorrelation at a conventional level of significance.

Table1.19 Migration flows from OECD to OECD countries and broadband penetration rate Threshold 0.3 (300 and more people)

Dependant variable: Log of migration flows	(1)	(2)	(3)	(4)
Broadband penetration rate ($BROAD_{ij,t}$)	-0.007(0.024)	-0.003(0.009)	-0.005(0.008)	0.003(0.016)
Log of distance ($\log DIST_{ij}$)	-0.389***(0.057)	-0.302*(0.166)		-0.733(0.579)
Log of relative real GDP ($\log RGDP_{ij,t}$)	-0.233***(0.020)	-0.316***(0.066)	-0.917*(0.472)	-0.306(0.198)
Log of wage in the host country ($\log wage_{j,t}$)	0.053(0.082)	0.219**(0.090)	0.206**(0.091)	0.139(0.188)
Unemployment rate in the origin ($Unempr_{i,t}$)	0.054***(0.011)	-0.013(0.016)	-0.021(0.016)	0.021(0.059)
Employment rate in the host ($Empr_{j,t}$)	-0.013***(0.003)	0.014(0.010)	0.029**(0.013)	0.011(0.017)
Dummy=1if no restriction ($FREE_{ij,t}$)	0.240*(0.136)	0.560***(0.124)	0.574***(0.127)	0.117(0.190)
Years since broadband introduced ($T^B_{ij,t}$)	0.218*(0.122)	0.118**(0.039)	0.093**(0.041)	0.156***(0.037)
Constant	3.114***(0.857)	-0.265(1.602)	-3.125**(1.247)	4.751(3.554)
R^2	0.15	0.24	0.25	
N	1130	1130	1130	1121
Country pairs	118	118	118	118

Notes: A panel of data for 118 country pairs for OtO flows estimations for 1995-2009. Model (1)-Model (6) present the OLS, random effect, fixed effect, dynamic GMM, 2nd stage of Instrumental variable, second stage of instrumental variable with fixed effect, respectively. Robust t-statistics in parentheses. Significance at *10%, **5%, ***1%. AR (1) and AR (2) Arellano-Bond autocorrelation test for GMM are, --1.664(0.096) and 0.717(0.473) respectively and AR(2) shows no evidence of autocorrelation at a conventional level of significance.

Table1.20 Migration flows from OECD to OECD countries and broadband penetration rate Threshold 0.5(500 and more people)

Dependant variable: Log of migration flows	**(1)**	**(2)**	**(3)**	**(4)**
Broadband penetration rate ($BROAD_{ij,t}$)	-0.015(0.024)	-0.003(0.009)	-0.001(0.009)	0.000(0.014)
Log of distance ($\log DIST_{ij}$)	-0.155**(0.059)	-0.108(0.170)		-0.641*(0.379)
Log of relative real GDP ($\log RGDP_{ij,t}$)	-0.188**(0.022)	-0.271***(0.068)	-1.263**(0.508)	-0.286*(0.149)
Log of wage in the host country ($\log wage_{j,t}$)	0.119*(0.069)	0.128*(0.076)	0.095(0.069)	0.095(0.141)
Unemployment rate in the origin ($Unempr_{i,t}$)	0.046***(0.012)	0.015(0.018)	0.027(0.018)	0.019(0.092)
Employment rate in the host ($Empr_{j,t}$)	-0.004(0.003)	0.015(0.010)	0.024(0.015)	0.005(0.020)
Dummy=1if no restriction ($FREE_{ij,t}$)	0.374**(0.139)	0.582***(0.131)	0.603***(0.133)	0.193(0.136)
Years since broadband introduced ($T^{B}_{ij,t}$)	0.215*(0.125)	0.107*(0.043)	0.083*(0.046)	0.136*(0.071)
Constant	0.475(0.796)	-0.702(1.545)	-1.642(1.238)	4.128(2.679)
R^2	0.10	0.23	0.25	
N	953	953	953	948
Country pairs	100	100	100	100

Notes. A panel of data for 100 country pairs for OtO flows estimations for 1995-2009. Model (1)-Model (6) present the OLS, random effect, fixed effect, dynamic GMM, second stage of Instrumental variable, second stage of instrumental variable with fixed effect, respectively. Robust t-statistics in parentheses. Significance at *10%, **5%, ***1%. AR (1) and AR (2) Arellano-Bond autocorrelation test for GMM are, -1.637(0.102) and 0.807(0.420) respectively and both results show no evidence of autocorrelation at a conventional level of significance.

Table1.21 Migration flows from non-OECD to OECD countries and broadband penetration rate Threshold 0.1 (100 and more people)

Dependant variable: Log of migration flows	**(1)**	**(2)**	**(3)**	**(4)**
Broadband penetration rate ($BROAD_{ij,t}$)	0.025(0.019)	0.026**(0.009)	-0.011(0.012)	0.007(0.008)
Log of distance ($\log DIST_{ij}$)	0.050(0.090)	-0.116(0.243)		0.211(0.197)
Log of relative real GDP ($\log RGDP_{ij,t}$)	-0.354***(0.031)	0.039(0.074)	1.090**(0.309)	-0.074(0.057)
Log of wage in the host country ($\log wage_{j,t}$)	0.028(0.101)	0.035(0.153)	0.047(0.149)	0.104(0.233)
Unemployment rate in the origin ($Unempr_{i,t}$)	-0.087***(0.009)	0.015(0.011)	0.021*(0.012)	0.030**(0.010)
Employment rate in the host ($Empr_{j,t}$)	-0.036***(0.004)	-0.008(0.012)	0.019(0.017)	-0.029(0.018)
Dummy=1if no restriction ($FREE_{ij,t}$)	-0.200(0.279)	0.705***(0.163)	0.801***(0.154)	0.361**(0.139)
Years since broadband introduced ($T^{B}_{ij,t}$)	0.343**(0.162)	-0.011(0.052)	-0.160**(0.056)	-0.037(0.086)
Constant	3.031**(1.052)	2.461(2.196)	0.303(1.549)	1.649(2.122)
R^2	0.25	0.21	0.26	
N	770	770	770	768
Country pairs	101	101	101	101

Notes. A panel of data for 101 country pairs for non-OtO flows estimations for 1995-2009. Model (1)-Model (6) present the OLS, random effect, fixed effect, dynamic GMM, 2^{nd} stage of Instrumental variable, second stage of instrumental variable with fixed effect, respectively. Robust t-statistics in parentheses. Significance at *10%, **5%, ***1%. AR (1) and AR (2) Arellano-Bond autocorrelation test for GMM are, -2.904(0.003) and -1.935(0.060) respectively and AR(2) shows no evidence of autocorrelation at a 5% level of significance.

Table1.22 Migration flows from non-OECD to OECD countries and broadband penetration rate Threshold 0.3 (300 and more people)

Dependant variable: Log of migration flows	(1)	(2)	(3)	(4)
Broadband penetration rate ($BROAD_{ij,t}$)	0.029(0.018)	0.031***(0.009)	-0.005(0.012)	0.008(0.010)
Log of distance ($\log DIST_{ij}$)	-0.090(0.084)	-0.219(0.232)		0.068(0.219)
Log of relative real GDP ($\log RGDP_{ij,t}$)	-0.296***(0.031)	0.052(0.068)	1.042**(0.314)	-0.027(0.073)
Log of wage in the host country ($\log wage_{j,t}$)	-0.006(0.103)	0.055(0.145)	0.140(0.148)	-0.071(0.249)
Unemployment rate in the origin ($Unempr_{i,t}$)	-0.081***(0.009)	0.015(0.011)	0.022*(0.012)	-0.019*(0.011)
Employment rate in the host ($Empr_{j,t}$)	-0.029***(0.004)	-0.006(0.011)	0.020(0.017)	-0.024(0.022)
Dummy=1if no restriction ($FREE_{ij,t}$)	-0.158(0.275)	0.731***(0.166)	0.827***(0.156)	0.384***(0.104)
Years since broadband introduced ($T^B_{ij,t}$)	0.192(0.156)	-0.044(0.053)	-0.185**(0.056)	-0.045(0.060)
Constant	4.263***(0.998)	2.765(2.134)	-0.277(1.557)	2.241(2.536)
R^2	0.23	0.25	0.30	
N	702	702	702	700
Country pairs	92	92	92	92

Notes. A panel of data for 92 country pairs for non-OtO flows estimations for 1995-2009. Model (1)-Model (6) present the OLS, random effect, fixed effect, dynamic GMM, 2nd stage of Instrumental variable, second stage of instrumental variable with fixed effect, respectively. Robust t-statistics in parentheses. Significance at *10%, **5%, ***1%. AR (1) and AR (2) Arellano-Bond autocorrelation test for GMM are, -2.958(0.003) and -1.744(0.081) respectively and AR (2) shows no evidence of autocorrelation at a 5% level of significance.

Table1.23 Migration flows from non-OECD to OECD countries and broadband penetration rate Threshold 0.5(500 and more people)

Dependant variable: Log of migration flows	(1)	(2)	(3)	(4)
Broadband penetration rate ($BROAD_{ij,t}$)	0.008(0.016)	0.027**(0.009)	-0.007(0.013)	-0.002(0.009)
Log of distance ($\log DIST_{ij}$)	-0.362***(0.070)	-0.394*(0.203)		-0.312(0.266)
Log of relative real GDP ($\log RGDP_{ij,t}$)	-0.225***(0.026)	0.029(0.063)	0.877**(0.342)	0.091(0.090)
Log of wage in the host country ($\log wage_{j,t}$)	0.346***(0.077)	0.159(0.168)	0.202(0.180)	0.085(0.166)
Unemployment rate in the origin ($Unempr_{i,t}$)	-0.075***(0.008)	0.006(0.011)	0.017(0.013)	-0.016(0.015)
Employment rate in the host ($Empr_{j,t}$)	-0.029(0.003)	-0.008(0.011)	0.025(0.019)	-0.011(0.020)
Dummy=1if no restriction ($FREE_{ij,t}$)	0.574**(0.263)	0.735**(0.214)	0.813***(0.202)	0.441***(0.11
Years since broadband introduced ($T^B_{ij,t}$)	0.179(0.155)	-0.050(0.054)	-0.182**(0.060)	-0.061(0.071)
Constant	3.865***(0.774)	3.858**(1.924)	-0.755(1.815)	3.461(2.266)
R^2	0.31	0.20	0.25	
N	575	575	575	573
Country pairs	76	76	76	76

Notes. A panel of data for 76 country pairs for non-OtO flows estimations for 1995-2009. Model (1)-Model (6) present the OLS, random effect, fixed effect, dynamic GMM, second stage of Instrumental variable, second stage of instrumental variable with fixed effect, respectively. Robust t-statistics in parentheses. Significance at *10%, **5%, ***1%. AR (1) and AR (2) Arellano-Bond autocorrelation test for GMM are, -2.835(0.005) and -1.598(0.110) respectively and AR (2) shows no evidence of autocorrelation at a conventional level of significance.

APPENDIX E

Table1.24 Diffusion curve for first stage of Instrumental Variable Model: OtO flows at Threshold 0.1 (100 and more people)

	Dependent variable: MOB_{ij}	**Dependent variable::** $ISDN_{ij}$
Voice telephony penetration rate ($VOICE_{ij,1997}$)	0.235*(0.122)	0.032*(0.002)
Cable TV penetration rate ($CABLE_{ij,1997}$)	-0.534(0.326)	0.010(0.008)
Diffusion speed (β)	0.403**(0.195)	0.117***(0.010)
Inflexion point (τ)	2003.572***(2.845)	1995.204***(0.232)
Constant	-0.132 (0.780)	6.087***(0.221)
R^2	0.11	0.19
N	2078	1794
F-test (p-values in parenthesis)	122.12(0.000)	117.83(0.000)

Table1.25 Diffusion curve for first stage of Instrumental Variable Model: OtO flows at Threshold 0.3 (300 and more people)

	Dependent variable: MOB_{ij}	**Dependent variable::** $ISDN_{ij}$
Voice telephony penetration rate ($VOICE_{ij,1997}$)	0.265*(0.149)	0.034*(0.002)
Cable TV penetration rate ($CABLE_{ij,1997}$)	-0.627(0.401)	0.004(0.008)
Diffusion speed (β)	0.415*(0.238)	0.122***(0.010)
Inflexion point (τ)	2003.440***(3.172)	1995.082***(0.231)
Constant	-0.403(0.914)	5.917***(0.215)
R^2	0.11	0.19
N	1475	1275
F-test (p-values in parenthesis)	99.16(0.000)	98.12(0.000)

Table1.26 Diffusion curve for first stage of Instrumental Variable Model: OtO flows at Threshold 0.5(500 and more people)

	Dependent variable: MOB_{ij}	**Dependent variable::** $ISDN_{ij}$
Voice telephony penetration rate ($VOICE_{ij,1997}$)	0.069(0.036)	0.033*(0.003)
Cable TV penetration rate ($CABLE_{ij,1997}$)	-0.183(0.086)	0.015(0.010)
Diffusion speed (β)	0.396*(0.104)	0.117***(0.012)
Inflexion point (τ)	2003.343***(1.745)	1995.064***(0.280)
Constant	2.008*(0.734)	5.999***(0.262)
R^2	0.30	0.19
N	1177	1014
F-test (p-values in parenthesis)	91.08(0.000)	87.11(0.000)

In ***Table 1.23-1.25***, MOB_{ij} is calculated as $MOB_i \times MOB_j$ where and MOB_i are the mobile phone subscribers per 100 inhabitants in the origin and MOB_j are the mobile phone subscribers per 100 inhabitants in the host. $ISDN_{ij}$ is calculated as $ISDN_i \times ISDN_j$ where $ISDN_i$ is the integrated services digital network subscribers per 100 in the origin and $ISDN_j$ is the integrated services digital network subscribers per 100 in the host.

Table1.27 Diffusion curve for first stage of Instrumental Variable Model: non-OtO flows at Threshold 0.1 (100 and more people)

	Dependent variable: MOB_{ij}	Dependent variable:: $ISDN_{ij}$
Voice telephony penetration rate ($VOICE_{ij,1997}$)	0.191*(0.074)	0.000(0.011)
Cable TV penetration rate ($CABLE_{ij,1997}$)	-0.353*(0.167)	0.125*(0.055)
Diffusion speed (β)	0.785**(0.296)	-9.193(5.081)
Inflexion point (τ)	2005.563***(0.980)	2008.178***(9.872)
Constant	0.815**(0.239)	6.419***(0.065)
R^2	0.29	0.14
N	1425	1163
F-test (p-values in parenthesis)	7.33(0.000)	6.11(0.000)

Table1.28 Diffusion curve for first stage of Instrumental Variable Model: non-OtO flows at Threshold 0.3 (300 and more people)

	Dependent variable: MOB_{ij}	Dependent variable:: $ISDN_{ij}$
Voice telephony penetration rate ($VOICE_{ij,1997}$)	0.201*(0.082)	0.000(0.010)
Cable TV penetration rate ($CABLE_{ij,1997}$)	-0.300(0.170)	0.072(0.055)
Diffusion speed (β)	0.789**(0.336)	-7.866(4.708)
Inflexion point (τ)	2005.558***(1.098)	2008.355***(21.283)
Constant	0.635**(0.203)	6.112***(0.066)
R^2	0.29	0.15
N	1275	1047
F-test (p-values in parenthesis)	6.15(0.000)	5.39(0.000)

Table1.29 Diffusion curve for first stage of Instrumental Variable Model: non-OtO flows at Threshold 0.5(500 and more people)

	Dependent variable: MOB_{ij}	Dependent variable:: $ISDN_{ij}$
Voice telephony penetration rate ($VOICE_{ij,1997}$)	0.247(0.108)	0.008(0.012)
Cable TV penetration rate ($CABLE_{ij,1997}$)	-0.320(0.195)	0.233(0.062)
Diffusion speed (β)	0.836*(0.446)	-7.791(7.523)
Inflexion point (τ)	2005.527***(1.243)	2008.398***(38.495)
Constant	0.373**(0.185)	5.351***(0.075)
R^2	0.28	0.15
N	1035	855
F-test (p-values in parenthesis)	5.12(0.000)	4.27(0.000)

In ***Table 1.26-1.28*** MOB_{ij} is calculated as $MOB_i \times MOB_j$ where and MOB_i is the mobile phone subscribers per 100 inhabitants in the origin and MOB_j is the mobile phone subscribers per 100 inhabitants in the host. $ISDN_{ij}$ is calculated as $ISDN_i \times ISDN_j$ where $ISDN_i$ is the integrated services digital network subscribers per 100 in the origin and $ISDN_j$ is the integrated services digital network subscribers per 100 in the host.

APPENDIX F

Table1.30 Additional Robustness Checks for OtO Flows

Dependant variable: Log of migration flows	(1)	(2)	(3)
Predicted penetration rate ($BROAD_{ij,t}\_hat$)	0.0447***(0.0130)	0.0359***(0.0124)	0.0370***(0.0138)
Log of distance ($\log DIST_{ij}$)	-0.689***(0.208)	-0.744***(0.222)	-0.489**(0.224)
Log of relative real GDP ($\log RGDP_{ij,t}$)	-0.327***(0.0742)	-0.439***(0.0734)	-0.390***(0.0778)
Log of wage in the host country ($\log wage_{j,t}$)	0.0442*(0.0254)	0.0342(0.0232)	0.0323(0.0253)
Unemployment rate in the origin ($Unempr_{i,t}$)	0.003(0.00964)	0.00517(0.00949)	0.00712(0.0112)
Employment rate in the host ($Empr_{j,t}$)	-0.0193(0.0128)	0.0224**(0.0111)	0.0273**(0.0119)
Dummy=1if no restriction $(FREE_{ij,t})$	0.675***(0.148)	0.912***(0.151)	0.929***(0.177)
Predicted years $(T_{ij,t}^{\beta}\_hat)$	0.009(0.017)	0.007(0.015)	-0.002(0.016)
TEL_{ij}	0.577(0.581)	0.836(0.587)	0.650(0.707)
$CABLE_{ij}$	-0.748(0.522)	-1.665 (0.541)	-1.354*(0.692)
Constant	3.697**(1.605)	4.042**(1.601)	2.136(1.560)
R^2	0.26	0.34	0.34
Country pairs	148	118	100

Table1.31 Additional Robustness Checks for non-OtO Flows

Dependant variable: Log of migration flows	(1)	(2)	(3)
Predicted penetration rate ($BROAD_{ij,t}\_hat$)	0.086***(0.016)	0.086***(0.015)	0.091***(0.018)
Log of distance ($\log DIST_{ij}$)	-0.073(0.29)	-0.172(0.252)	-0.395*(0.240)
Log of relative real GDP ($\log RGDP_{ij,t}$)	-0.312***(0.100)	-0.260***(0.094)	-0.183**(0.092)
Log of wage in the host country ($\log wage_{j,t}$)	0.071*(0.043)	0.089**(0.037)	0.100***(0.036)
Unemployment rate in the origin ($Unempr_{i,t}$)	0.002(0.012)	0.001(0.013)	0.005(0.014)
Employment rate in the host ($Empr_{j,t}$)	0.015(0.017)	0.018(0.016)	0.012(0.017)
Dummy=1if no restriction $(FREE_{ij,t})$	0.785***(0.157)	0.807***(0.163)	0.847***(0.209)
Predicted years $(T_{ij,t}^{\beta}\_hat)$	-0.052(0.0526)	-0.065(0.0496)	-0.096(0.065)
TEL_{ij}	-0.578(0.395)	-0.874*(0.392)	-0.768*(0.395)
$CABLE_{ij}$	0.195(0.279)	0.498(0.242)	0.274(0.257)
Constant	-1.233(2.500)	0.941(2.293)	3.540*(2.029)
R^2	0.32	0.35	0.33
Country pairs	101	92	76

APPENDIX G

Table1.32 Robustness check with additional control variables: OtO for Thresholds 0.1 0.3 0.5

Dependant variable: Log of migration flows	(1)	(2)	(3)
Predicted penetration rate ($BROAD_{ij,t}\_hat$)	0.011(0.017)	0.035*(0.017)	0.044**(0.018)
Log of distance ($\log DIST_{ij}$)	-0.528**(0.045)	-0.364**(0.046)	-0.175***(0.048)
Log of relative real GDP ($\log RGDP_{ij,t}$)	-0.267**(0.018)	-0.275**(0.016)	-0.224***(0.018)
Log of wage in the host country ($\log wage_{j,t}$)	0.094*(0.036)	-0.042(0.033)	-0.025(0.031)
Unemployment rate in the origin ($Unempr_{i,t}$)	0.049*(0.009)	0.051*(0.009)	0.043**(0.010)
Employment rate in the host ($Empr_{j,t}$)	-0.018(0.003)	-0.011(0.003)	-0.001(0.003)
Dummy=1if no restriction $(FREE_{ij,t})$	0.260*(0.105)	0.114*(0.107)	0.289**(0.109)
Predicted years $(T_{ij,t}^{\beta}\_hat)$	0.113(0.025)	0.081(0.023)	0.054(0.024)
Voice telephony penetration rate($\log\_TEL_{ij}$)	0.688(0.098)	0.465(0.101)	0.324*(0.104)
Constant	4.699***(0.515)	4.517***(0.512)	2.417***(0.532)
R^2	0.18	0.16	0.13
N	2064	1644	1409
Country pairs	148	118	100

Estimation results for the second stage results for panels of 148, 118, and 100 OtO country pairs in **(I), (II), (III)** respectively. Here, $\log TEL_{ij}$ is the digital landline telephone penetration rate per 100 inhabitants, obtained from the ITU (International Telecommunication Union) ICT Database.

Table1.33 Robustness check with additional control variables non-OtO for Thresholds 0.1 0.3 0.5

Dependant variable: Log of migration flows	(1)	(2)	(3)
Predicted penetration rate ($BROAD_{ij,t}\_hat$)	0.073**(0.013)	0.097***(0.013)	0.076***(0.013)
Log of distance ($\log DIST_{ij}$)	-0.045(0.072)	-0.216**(0.067)	-0.462**(0.058)
Log of relative real GDP ($\log RGDP_{ij,t}$)	-0.295**(0.023)	-0.238**(0.022)	-0.191**(0.020)
Log of wage in the host country ($\log wage_{j,t}$)	0.082*(0.041)	0.047(0.041)	0.197***(0.038)
Unemployment rate in the origin ($Unempr_{i,t}$)	-0.063(0.007)	-0.057(0.007)	-0.059(0.006)
Employment rate in the host ($Empr_{j,t}$)	-0.030(0.003)	-0.022(0.003)	-0.022(0.003)
Dummy=1if no restriction $(FREE_{ij,t})$	0.076(0.298)	0.140*(0.300)	0.959***(0.265)
Predicted years $(T_{ij,t}^{\beta}\_hat)$	0.021(0.073)	-0.078(0.072)	-0.215*(0.081)
$\log\_TEL_{ij}$	0.062(0.047)	-0.092(0.046)	-0.045(0.043)
Constant	3.211***(0.624)	4.269***(0.570)	5.522***(0.503)
R^2	0.20	0.20	0.28
N	1397	1277	1049
Country pairs	148	118	100

Estimation results for the second stage results for panel of 148, 118, and 100 OtO country pairs in **(I), (II), (III)** respectively. Here, $\log TEL_{ij}$ is the digital landline telephone rate per 100 inhabitants, obtained from the ITU (International Telecommunication Union) ICT Database.

Table1.34 Robustness check with additional control variables: OtO for Thresholds 0.1 0.3& 0.5

Dependant variable: Log of migration flows	**(1)**	**(2)**	**(3)**
Predicted penetration rate ($BROAD_{ij,t}\_hat$)	0.022*(0.016)	0.026*(0.016)	0.038**(0.017)
Log of distance ($\log DIST_{ij}$)	-0.745**(0.045)	-0.528**(0.045)	-0.329**(0.047)
Log of relative real GDP ($\log RGDP_{ij,t}$)	-0.694**(0.024)	-0.605**(0.027)	-0.529**(0.028)
Log of wage in the host country ($\log wage_{j,t}$)	0.001*(0.000)	0.002*(0.000)	0.002*(0.000)
Unemployment rate in the origin ($Unempr_{i,t}$)	0.058*(0.008)	0.056*(0.009)	0.053*(0.009)
Employment rate in the host ($Empr_{j,t}$)	0.007**(0.003)	0.004(0.003)	0.011(0.003)
Dummy=1if no restriction $(FREE_{ij,t})$	0.039(0.090)	-0.085(0.096)	0.062(0.096)
Predicted years $(T^{\beta}_{ij,t}\_hat)$	0.066*(0.023)	0.060(0.022)	0.046(0.023)
$\log\_phntraffic_{ij}$	0.872*(0.034)	0.659*(0.037)	0.587*(0.037)
Constant	-13.937***(0.804)	-10.243***(0.871)	-10.399***(0.875)
R^2	0.35	0.29	0.25
N	1906	1517	1300
Country pairs	148	118	100

Models (I), (II), (III) present the results for OtO flows with 0.1, 0.3 and 0.5 rate thresholds, respectively. Here, $\log\_phntraffic_{ij}$ is calculated as international incoming fixed-telephone traffic $\log\_trafficin_i$ in the origin times by international outgoing fixed-telephone traffic $\log\_trafficout_j$ in the host in minutes, respectively.

Table1.35 Robustness check with additional control variables: non-OtO for Thresholds 0.1, 0.3 & 0.5

Dependant variable: Log of migration flows	**(1)**	**(2)**	**(3)**
Predicted penetration rate ($BROAD_{ij,t}\_hat$)	0.077***(0.013)	0.087***(0.013)	0.106***(0.013)
Log of distance ($\log DIST_{ij}$)	-0.125*(0.070)	-0.237**(0.065)	-0.429**(0.058)
Log of relative real GDP ($\log RGDP_{ij,t}$)	-0.556**(0.033)	-0.491**(0.034)	-0.380**(0.031)
Log of wage in the host country ($\log wage_{j,t}$)	0.010(0.007)	0.011*(0.006)	0.011*(0.008)
Unemployment rate in the origin ($Unempr_{i,t}$)	-0.053(0.007)	-0.051(0.007)	-0.052(0.007)
Employment rate in the host ($Empr_{j,t}$)	-0.023(0.003)	-0.016(0.003)	-0.015(0.003)
Dummy=1if no restriction $(FREE_{ij,t})$	0.162(0.297)	0.246(0.295)	0.793*(0.273)
Predicted years $(T^{\beta}_{ij,t}\_hat)$	0.039(0.081)	-0.076(0.080)	-0.191*(0.086)
$\log\_phntraffic_{ij}$	0.670(0.070)	0.623(0.069)	0.429*(0.062)
Constant	-10.366***(1.513)	-8.037***(1.493)	-2.155(1.364)
R^2	0.30	0.28	0.33
N	1243	1132	923
Country pairs	101	92	76

Models (I), (II), (III) present the results for non-OtO flows with 0.1, 0.3 and 0.5 rate thresholds, respectively. Here, $\log\_phntraffic_{ij}$ is calculated as international incoming fixed-telephone traffic $\log\_trafficin_i$ in the origin multiplied by international outgoing fixed-telephone traffic $\log\_trafficout_j$ in the host in minutes, respectively.

Table1.36 Robustness check OtO for Thresholds 0.1, 0.3 & 0.5

Dependant variable: Log of migration flows	(1)	(2)	(3)
Predicted penetration rate ($BROAD_{ij,t}\_hat$)	0.006(0.017)	0.007*(0.018)	0.014*(0.019)
Log of distance ($\log DIST_{ij}$)	-0.931***(0.050)	-0.740***(0.048)	-0.603***(0.053)
Log of relative real GDP ($\log RGDP_{ij,t}$)	0.213(0.057)	-0.178*(0.059)	-0.197*(0.064)
Log of wage in the host country ($\log wage_{j,t}$)	0.010(0.001)	0.011(0.006)	0.012*(0.001)
Unemployment rate in the origin ($Unempr_{i,t}$)	0.030**(0.009)	0.022*(0.009)	0.026**(0.010)
Employment rate in the host ($Empr_{j,t}$)	0.010**(0.004)	0.006(0.004)	0.009*(0.004)
Dummy=1if no restriction ($FREE_{ij,t}$)	-0.309(0.086)	-0.399(0.092)	-0.281(0.095)
Predicted years ($T^{\beta}_{ij,t}\_hat$)	0.079(0.028)	0.081(0.029)	0.064(0.031)
Log of incoming phone traffic in origin ($\log\_trafficin_i$)	0.135*(0.055)	0.069(0.054)	0.045(0.060)
Log of outgoing phone traffic in host ($\log\_trafficout_j$)	1.186**(0.066)	1.055**(0.072)	0.979***(0.077)
Constant	-22.051***(1.251)	-18.670***(1.385)	-17.514***(1.377)
R^2	0.54	0.45	0.41
N	1257	1003	859
Country pairs	148	118	100

Models (I), (II), (III) present the results for non-OtO flows with 0.1, 0.3 and 0.5 rate thresholds, respectively. Here, $\log\_phntraffic_{ij}$ is calculated as international incoming fixed-telephone traffic $\log\_trafficin_i$ in the origin multiplied by international outgoing fixed-telephone traffic $\log\_trafficout_j$ in the host in minutes, respectively.

Table1.37 Robustness check non-OtO for Thresholds 0.1, 0.3 &0. 5

Dependant variable: Log of migration flows	(1)	(2)	(3)
Predicted penetration rate ($BROAD_{ij,t}\_hat$)	0.028**(0.013)	0.049***(0.013)	0.065***(0.013)
Log of distance ($\log DIST_{ij}$)	-0.701***(0.075)	-0.767***(0.068)	-0.835***(0.061)
Log of relative real GDP ($\log RGDP_{ij,t}$)	-0.154(0.044)	-0.195(0.043)	-0.117(0.041)
Log of wage in the host country ($\log wage_{j,t}$)	0.011*(0.002)	0.009(0.006)	0.004*(0.007)
Unemployment rate in the origin ($Unempr_{i,t}$)	-0.007(0.007)	-0.006(0.007)	-0.019(0.007)
Employment rate in the host ($Empr_{j,t}$)	-0.023(0.003)	-0.019(0.003)	-0.020(0.003)
Dummy=1if no restriction ($FREE_{ij,t}$)	0.921**(0.330)	0.897**(0.325)	1.198***(0.336)
Predicted years ($T^{\beta}_{ij,t}\_hat$)	0.034(0.121)	-0.059(0.118)	-0.159(0.134)
Log of incoming phone traffic in origin ($\log\_trafficin_i$)	0.300(0.060)	0.239(0.060)	0.200(0.057)
Log of outgoing phone traffic in host ($\log\_trafficout_j$)	0.973**(0.057)	0.928***(0.056)	0.718*(0.050)
Constant	-18.830***(1.376)	-15.963***(1.359)	-9.676***(1.312)
R^2	0.43	0.43	0.46
N	1012	929	744
Country pairs	101	92	76

Models (I), (II), (III) present the results for non-OtO flows with 0.1, 0.3 and 0.5 rate thresholds, respectively. Here, $\log\_phntraffic_{ij}$ is calculated as international incoming fixed-telephone traffic $\log\_trafficin_i$ in the origin multiplied by international outgoing fixed-telephone traffic $\log\_trafficout_j$ in the host in minutes, respectively.

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CHAPTER 2

The Impact of Immigration on Productivity:

Industry-level Evidence for Germany, the Netherlands, Spain and the UK

"Productivity is not everything, but in the long run it is almost everything"

Paul Krugman (1990, p.9)

2.1. Introduction

Over the last two decades, labour has become increasingly mobile but little attention has been paid to its effect on firms' productivity in the host country. By contrast, the effect of labour mobility has been extensively analysed for the host county's wages, employment, unemployment, house prices, Gross Domestic Product, imports, exports, public welfare, foreign direct investment, labour costs and business activity (Angrist and Kugler, 2003; Rowthorn, 2008; González and Ortega, 2008; Borjas, 1994:1995; Zorlu and Hartog, 2005; Card, 2005; Mete, 2004). Immigration's effect on firms' productivity remains unnoticed, and only a few studies have recently paid attention to it. As Gatto *et al*. (2011) pointed out in their extended survey on productivity measurement, attention on productivity research has moved from country level towards firm level, since the effects on productivity can be investigated more clearly at a disaggregate level.

One motivation of this chapter is to explore the various ways there are for measuring productivity and we provide further insights on this in Section 2.2.3. Another motivation is to focus on the productivity effect of migration on the host country's firms, to redress the absence of such studies.

The chapter will focus on the productivity effects of migration in four European Union (EU) countries: the UK, Spain and the Netherlands for 1995-2008 and Germany for 2002-2008. This analysis was carried out using EU Labour Force Survey (LFS) and EU-KLEMS data.

Though potentially interesting, it was not possible to investigate the migration and productivity links for Italy, France, Belgium and Sweden because of data limitations. Limited industry codes were available for Belgium and Finland. For Italy, we only found three discontinuous years of migration data. Finally, for Sweden we could not find enough labour input variables. Detailed descriptions of the databases are provided in Section 2.3.

The UK and Germany have similar long histories of migration as they have both attracted numerous migrants from across the world. Spain has become a new popular alternative host in the 1990s and early 2000s. The Netherlands has been a host with steady migration flows and stock according to figures from the OECD Migration Database. The different migration patterns for these countries mean that we are able to analyse their effect on different productivity outcomes. To do this, the EU KLEMS Growth and Productivity Accounts Database and the EU LFS database are used together. The EU KLEMS database captures a wide range of productivity variables such as gross output, gross value added and intermediate inputs. The EU LFS is used to calculate migrant labour composition, which enables us to disaggregate immigrant workers by their educational attainment. Because the demand for skill groups may differ across host countries (Bauer and Kunze, 2004), we expect to observe variation in the productivity results.

In this chapter, the large range of productivity variables provided by the EU KLEMS database is combined with the EU LFS, so that detailed information on the share of migrants in each industry is calculated. Descriptions for all the variables in the EU KLEMS database are available in Timmer *et al*. (2007a).

According to the EU LFS database, a migrant is defined as someone whose country of birth is different from their country of residence. The productivity implications of migration are more likely to be seen in the long run than in the short-run. Using a Cobb Douglas production function, we provide both the short-run and long-run effects of migration across industries for the four EU countries. While doing so, we desegregate migrants into high, medium and low skill groups as described by the International Standard Classification of Education (ISCED) (5-6), ISCED (3-4), ISCED (1-2) codes within the EU LFS database. This allows us to pay attention to the different effects of migration by different skill groups.

In order to investigate the long-run impact of migration on firm productivity, we apply the Pooled Mean Group (PMG) variant for the autoregressive distributed-lag (ARDL) estimator. The PMG estimator constrains the long-run coefficients to be identical across firms but allows short-run coefficients and error variances to vary across units. The PMG estimator has been shown to deliver consistent results if the lag order is specified correctly (Pesaran *et al*. 2012). We use the Akaike information criterion (AIC) to determine the optimal lag length.

The chapter proceeds as follows. Section 2.2 reviews the literature in two dimensions. First, it covers the general effects of migration on the host country's economic activity; it then continues by reviewing the literature on the effects of migration on in the host country at country and industry level. Section 2.3 describes the data capture while Section 2.4 empirically analyses the data and present the results, and provide some robustness checks.

Section 2.5 concludes and summarises the results. ***Appendix H*** presents descriptive statistics for the UK, Spain, the Netherlands and Germany. Finally, ***Appendix I*** provides some additional robustness checks.

2.2. Literature Review

2.2.1. Effect of international migration on the economic activity of the host country

Numerous studies have shown that there is an absolute effect of migration on the host country's economy in several ways. For instance, Mete (2004) showed that migration had a positive and significant effect on GDP per capita, and an adverse and significant effect on unemployment, in Finland between 1981 and 2001. Nikolaj *et al*. (2009) investigated whether immigrant workers take jobs away from native workers by looking at the Integrated Database of Labour Market Research (IDA) for Denmark for 1980-2004 and found no strong evidence of this, but stated that a negligible number of highly skilled workers may be displaced by migrant workers. Similarly, Venturini and Villosio (2006) analysed whether migrant workers displaced natives' job in regions of Italy between 1993 and 1997, and found a positive but not remarkable effect; in fact natives and migrant workers were found to complement each other. However, Angrist and Kugler (2003) found a significant adverse effect of migration on natives' employment opportunities within European countries from 1983 to 1999.

Looking at the well-known Mariel Boatlift migration of unskilled workers from Cuba to Miami in the 1980s, Card (1990) showed no negative migration effect on the unemployment and wages of non-Cuban workers but in the long run it result in a decrease in the number of Cuban migrants. Borjas *et al*. (1996) suggested that migration effects on native workers' outcomes may depend on regional labour market conditions, and found a negative effect on low skilled native wages, but a slightly positive effect on medium skilled native wages in the American labour market in the 1980s and 1990s. Following this, Borjas (2003) pointed out that in general, migration was found to have an adverse wage effect on natives in the USA between 1960 and 2000, but the magnitude of the effect varies across different age groups of natives. Card (2005), however, found little evidence of migration's effect on low skilled native wages in the USA in the 1990s. Most empirical research has found that in the long run migrants earn more than native workers, and have an adverse effect on the employment opportunities of natives, and yet make a promising positive contribution to the host country's economy (Borjas 1994, 1995; Friedberg and Hunt 1995; Zorlu and Hartog 2005). According to Gonzáles and Ortega (2008), immigration has a negative employment rate effect on Spanish industries only for low-educated workers, using cross-section data OLS with effects fixed for region and education. The migration effect is not limited to the host country's economy; there is also bilateral trade between home country and host country, as migrants have good knowledge of market opportunities in both country pairs. For instance, Head and Ries (1998) showed that migrants contributed to trade between Canada and 136 different origin countries between 1980 and1992. Also, migration may have different effects in regard to immigrants' legal status. As Borjas and Tienda (1993) pointed out, legal migrants tend to earn much more than those who are illegal. To an extent, legal migrants may find better quality jobs than illegal migrants, whereas illegal migrants might take less well paid and more demanding jobs as they are not in a position to be selective. Jean and Jiménez (2011) found no significant effect of migration on any economic activity of the host country, but found a slight adverse impact on native employment in the long run within eighteen OECD countries for 19 years. Rowthorn (2008) investigated advanced economics with a high percentage of migration to examine whether migration caused any fiscal issues in the host country, but found no evidence of positive or negative effect, only a slight adverse effect for temporary migration. Migration's effect on the labour market is generally found to crucially depend on skill distribution, meaning that if the skill of migrants and natives is perfectly elastic, or in another word, they are perfect substitutes, then no essential adverse effect of migration on the labour market is observed, but it is negative and significant if otherwise (Dustmann *et al*., 2008; D'Amuri et al., 2010; Card, 1997; Brücker and Jahn, 2011).

Thus, migration appears to affecting the host countries' economy in several ways, depending upon the migrants' skill distribution, the prosperity of the host country, migration policy in the host, the duration of stay in the host country and suchlike. The following section will capture the productivity effect of migration at country and firm level separately.

2.2.2. Migration and productivity

In order to gain a general perspective on the productivity effect of migration, we review both country and firm level effects of productivity separately as follows:

2.2.2.1. Country level

Rozelle *et al*. (1999) suggested that migrants have negative and significant effects on agricultural productivity, at least in the short run, under the consideration of households and migrants characteristics using a survey of 787 farm households across 31 villages in north-east China in 1995. Based on the fact that over 130 million farmers migrated to rural China, Bhattacharyya and Parker (1999) showed that in the short run there was a negligible contribution of migration on agriculture productivity in rural regions of China, however the productivity appeared to increase in the longer run, using the Chinese Agricultural Statistics Yearbooks for 1980-1995. Taylor and Feldman (2010) looked at a contrasting perspective that a higher migration share raised the rural productivity of the origin country via flows of remittance in the Mexico-to-US case, looking at the extent to which flows of remittance can be considered as capital flows to an origin country which results in increasing productivity. According to Peri (2012), migration is found to have a significant contribution to the total factor productivity of US states amongst less skilled jobs. On the contrary he found that high skilled immigrants affect the total factor productivity adversely. Because, although there is no shortage of high skilled natives in the US states, they are replaced by high skilled migrant for less wage but do not perform as natives particularly for a short period. Goldsmith *et al*. (2004), suggested that migrants from rural to urban areas of Senegal increased investment in agriculture significantly, which resulted in a productivity increase in agriculture. Using establishment-level database and census population data for 1990 and 2000, Lewis (2003) showed that migration has little impact on the industry mix and wages across firms in the USA. He suggested that the change in the industry mix of labour result in the technology adoption of those firms which is followed up by the change in productivity of firms.

Conde-Ruiz *et al*. (2008) found a significant and negative effect of migration on the productivity of regions in Spain between 2000 and 2006. This time period spans the period when new EU countries joined the EU in 2004. As a result, a sudden rise in migration shares in several regions of Spain reduced labour costs and that is believed to have decreased productivity. However, observing the effect of a sudden change of migration on productivity for only two years may not be enough to analyse the genuine productivity effect.

2.2.2.2. Firm level

In contrast to country level productivity patterns, the impact of migration on productivity at firm level has been paid much less attention. Considering how migrant workers become included in the labour force of a host country and how this changes the composition of employment across hiring companies, this impact might well deserve investigation. To begin with, Grossman (1982) showed that although migration led capital growth and a small price elasticity difference between natives and migrants, in the long run migration was found to have a negative contribution across firms in terms of migrants' effects on natives' employability in the short run, and the wages of natives in the long run in the USA in the 1970s. Moreover, Winkelman (2001) drew attention to firms recruiting highly educated migrants by conducting a survey across 850 firms in Germany, the UK, the Netherlands and France in 2000, and found that despite the proportion of migrants that firms hired being low, the main reasons why firms hire migrants is because it allowed firms to exchange information, build rapport in respect of bilateral trade and fulfil a need for a composition of labour skills that complements the labour where it is needed most. Thus, it is safe to assume that the demand for immigrant workers results from firms taking their productivity into account by balancing what they have and what they need. According to Quispe-Agnoli and Zavodny (2002), a high foreign share of employees in both low and high skill sectors – but especially in high skill sectors - resulted in smaller increases in the productivity of firms across US firms between 1982 and 1992, this is the fact that the obstacles that immigrants have, such as language. However, they found that migration have almost no effect on the total output mix of firms. In their paper, the effect of migration on the productivity of firms appeared to be more severe if migrants were disaggregated by their skill level. Paserman (2013) investigated whether high skilled immigrants from the former Soviet Union increased the productivity of manufacturing firms in Israel between 1990 and 1999 by applying both panel data and pooled OLS regression, and showed that neither a pooled nor cross-section analysis found any correlation between high skilled migrants and productivity across industries in Israel in the 1990s, while their first difference results indicated some negative effect although not very significant effect on productivity of manufacturing firms, especially amongst low-tech firms compared to high-tech firms, by combining Israel's Industrial survey and labour force survey. More comprehensively, Robinson *et al*. (2010) analysed how EU and non-EU migrants affected productivity across 13 EU countries in various firms using the econometric estimation of the Cobb-Douglas production function and growth accounting method. They aggregated all industries in those 13 EU countries which can give a snapshot of general productivity effect of migration. We believe this effect varies for individual host countries in the sample- and this is the reason why we investigate such link between migration and productivity per country at a time. They also took ICT (information and computing technology)/non-ICT based industries into account separately, and concluded that migration had a positive contribution to the productivity of the host countries' industries, mainly in ICT based firms. Kangasniemi *et al*. (2012) analysed productivity changes in Spain and the UK in 1984-2005 by using Spain and the UK's Labour Force Surveys (LFS) for the composition of migration, respectively, combining these datasets with growth accounting variables provided by the EU KLEMS database. They showed negative effects of migration for Spain and positive effects for the UK. Accetturo *et al*. (2012) drew attention to the effect of low skilled migrants on capital intensity across Italian manufacturing firms over the period 1996-2007 and found a positive and significant impact. Investigating productivity change in accordance with migration change is challenging. This is mainly due to the fact that there are multiple ways to measure productivity - which will be covered in Section 2.2.3. Another difficult aspect of investigating such relationships is the nature of migrants. For instance, migrants from EU countries and non-EU countries may act differently in the labour market. Moreover, different skill levels might have different effects in the same host country depending upon the skill level need in that country. In order to examine whether results varied in line with migrant features, we disaggregated immigrants into EU and non-EU origins, as well as low, medium and high skill level.

2.2.3. Productivity Measurement and Productivity Performance across Europe

2.2.3.1. Productivity Measurement

Measuring productivity is challenging, because, multiple factors affect productivity at the same time and they may not be easy to either observe or calculate. Several scholars have conducted research on how to measure productivity. For instance, according to Ahn (2001), measuring productivity can be carried out by either observing changes in productivity levels in individual firms relative to the market or observing firm dynamics at a given size of firms. Firm dynamics refer to the growth of a firm since the establishment of the firm. Additionally, the productivity level of a company has been found to be highly correlated with the skill of workers and the technology used in the firms. Thus, labour composition in terms of skills may be seen as a crucial factor in terms of measuring productivity. In the European Company Survey Overview Riedmann *et al*. (2009) gave a broad approach to measuring the productivity of companies. In this report, the number of employees and personnel, work climate, quality of products and services, and quality of the labours were mostly found to be relevant for measuring the productivity of firms. However, some of these factors are qualitative, and the measurements may depend on assessments by the respondents.

Throughout the productivity literature, either gross output (GO) or value added (VA) are considered as output measurements for assessing firms productivity. These factors are positively correlated with both labour and capital inputs. The country or sectoral levels of output measures are GDP, GNP , Multi factor productivity (MFP), value added and gross output, whereas firm level output measurements are considered to be value added, gross output, MFP and TFP. According to Corrado *et al*.'s (2006) revised productivity elements report, MFP is calculated as the real growth of the country/firm minus the real inputs of the country/firm; VA is the cost of both labour and capital inputs; GO is the sum of both finished work and work under process; TFP is every single component that operates the growth. The question here is how to measure labour input or capital input. The following ***Table2.1***and ***Table 2.2*** summarise how the measurement of output and input variables differs for the country and firm level base across studies:

Table2.1 Measurement of country level productivity

Authors	Output Measurement	Labour Input	Capital input	Methodology
Nahm and Tani (2014)	Gross contribution of skilled migrant based on data envelopment analysis.	Skilled migrant compensation per unit	Capital compensation per unit	Econometric estimation of a form of a production function
Kravtsova (2013)	Change in Total Factor Productivity (Hungarian industries are aggregated)	Share of foreign ownership and engagement in exporting	Foreign direct investment	Econometric estimation of Malmquist productivity index
Solow (1957)	GNP per head of employees	% labour force employed	Capital stocks in million dollars	Growth accounting method
Freeman (2008)	GDP	Total hours worked by employees/ alternatively total employment	Output gained per hour	Growth accounting method
Nordhaus (2001)	Growth rate of real income (index is used)	GDP per hour worked (index is used)	Changes in output gained per hour (index is used)	Growth accounting method
Inklaar et al (2003)	Gross value added (four countries' industries are aggregated)	Labour quality growth as measured by the difference between the growth of labour and total hours worked	Capital service flows	Growth accounting method
O'Mahony and Timmer (2009)	Multi factor productivity (value added based)	Changes in labour composition	Changes in capital composition	Growth accounting method
Jorgenson and Griliches (1967)	Total output as an index (first value is private domestic product prices)	Sum of labour services as an index	Sum of capital services as an index	Theory/Econometric estimation of a form of a production function

Table2.2 Measurement of firm level productivity

Authors	Output Measurement	Labour Input	Capital input	Methodology
Kangasniemi *et al*. (2012)	Gross value added	Labour services	Capital services	Growth accounting method
Robinson *et al* (2010)	Multi factor productivity value added based	Total hours worked by employees plus adjustment for migrant labour	ICT and non-ICT capital services	Growth accounting method and econometric estimation of Cobb-Douglas production function
Paserman (2013)	Gross output	Total hours worked by the share of employees plus adjustment for share of migrant labour	Intermediate inputs plus material inputs	Econometric estimation of Cobb-Douglas production function
Bettin *et al*. (2012)	Real output	Average share of foreign employees to total employees	Material plus service inputs	Econometric estimation of generalised Cobb-Douglas production function
Bartelsman *et al*. (2013)	Gross value added	Number of employees minus total overhead per employee	Quasi-fixed total capital stocks	Econometric estimation of Cobb-Douglas production function
Bartelsman (2010)	Gross value added	Knowledge stock as a state of technology and weighted (based on output) labour service	Weighted (based on output) capital-energy and material services	Econometric estimation of generalised Cobb-Douglas production function
Bartelsman *et al*. (2009)	Value added and gross output separately	Weighted number of employees based on expenditure shares of input	Weighted capital stocks based on expenditure shares of input	Growth accounting method
Grossman (1982)	Quantity produced	Number of employees	Capital stock	Econometric estimation of Translog production function
Navaretti *et al*. (2008)	Value added	Total number of employees	Total sales made	Econometric estimation of a form of a production function
Schreyer and Pilat (2001)	Gross output and value added separately	Total hours worked by employees based on gross output and value added	Total machine hours based on gross output and value added	Growth accounting

As can be seen from ***Tables 2.1*** and ***2.2***, labour input is mostly measured by active hours worked by employees, which is why we also consider hours worked by employees as labour input. As for the capital input variable, we take both ICT and non-ICT capital services together into account. Finally, in order to see how immigrant workers affect productivity, we include the migration share of each industry in our model.

The following section will describe the total data sources and deliver descriptive statistics.

2.3. Data and Descriptive Statistics

The EU KLEMS March 2011 March database is used to retrieve measures by industry and year for productivity (as measured by gross value-added), for total hours worked and for capital stocks. Monetary values for output and capital are provided in real terms for each industry, in each year, deflated using each country's GDP PPP price deflator (see O'Mahony and Timmer 2009, p.F381). Output is measured as gross value added (EU KLEMS variable GVA) and we use the capital stock series that is adjusted for Gross Fixed Capital Formation (EU KLEMS variable CAP_GFCF). The GFCF adjustment is based on the assumption that investment in buildings produces returns for many decades while investment in ICT equipment produces returns for less than five years (see O'Mahony and Timmer 2009, p.F398 for details of this). Data for the UK, Spain, and the Netherlands for 1995-2008 and in Germany for 2002-2008.

We then combine this dataset with the EU LFS dataset with its variables of the share of migrants and education attainment of migrants for the same period of time. In order to combine the two datasets we match the same industries and only use the same codes which correspond to the same industries. However, in the EU LFS data the codes are desegregated for electricity and gas supply as D, for water supply as E, for professional, scientific and technical activities as M and for administrative and support service activities as N, whereas in the EU KLMES, the database codes for electricity, gas and water supply are already aggregated as D-E and professional, scientific, technical, administrative and support service activities are aggregated as M-N. Thus, for consistency, we aggregate the industries from the EU LFS such that D is joined with E and M with N, so that we could match the two datasets based on the same industries. ***Table 2.3*** shows the NACE codes with corresponding industries that we use.

Table2.3 NACE codes and corresponding industries

NACE CODES	INDUSTRIES
A	Agriculture, Forestry and Fishing
B	Mining and quarrying
C	Manufacturing
D-E	Electricity, Gas and Water Supply
F	Construction
G	Wholesale and retail; Repair of motor vehicles and motorcycles
H	Transportation and storage
I	Accommodation and food service activities
J	Information and communication
K	Financial and insurance activities
L	Real estate activities
M-N	Professional, Scientific, Technical, Administrative & Support Service Activities
O	Public Administration and Defence; Compulsory Social Security
P	Education
Q	Health and Social Work

In *Appendix H Table 2.24 - 2.27* presents the descriptive statistics for the UK, Spain, the Netherlands and Germany, respectively. We present value added, labour input- total hours worked by employees, capital input- total capital services and a share of migration over the total employment. In addition, we also present the disaggregated migration shares in regard of skill level as well as EU and non-EU origin countries.

The average value added is around 61478.4 for the UK, 42509.75 for Spain, 25877.83 for the Netherlands and 131694.3 for Germany. For the UK, capital input is more or less similar to

Spain, while surprisingly, the total hours worked by persons engaged seem to be almost double comparing to Spain. The average value for total hours worked is quite low in the Netherlands in comparison to other three countries. When presenting the results for the Netherlands in ***Section 2.4.2.3.*** no significance is observed for labour inputs across multiple estimated models and this might be the main reason.

The highest figure of value added and capital input is observed in Germany might be explained by the more advanced industry comparing to the UK, Spain and the Netherlands. According to Central Intelligence Agency (CIA)'s World Factbook (2014), Germany has the largest and most technologically advanced producers of certain materials across the world.

The average labour input –total hours worked by employees 3212.264, 1839.057, 727.8724, and 3577.8 for the UK, Spain, the Netherlands and Germany, respectively. The average capital services are 19528.21, 16174.35, 9008.549, and 44609.67 for the UK, Spain, the Netherlands, and Germany. As can be seen from ***Tables 2.24-2.27*** in ***Appendix H***, migration share figures vary greatly across countries. The share of the average non-EU migrants is around 6 percent in the UK, where only 2% of the immigrants are from EU countries- ***Table 2.24.*** As legal restrictions are much higher for non-EU migrants, we find this figure quite surprising. In Spain it displays different aspects from the UK, having EU and non-EU migrants at around 1% and 3% in average, respectively- ***Table 2.25***. Whereas, for Netherlands the average share of EU immigrants appears to be around 3% of total labour across firms which could reach up to 63 % maximum depending upon industry, the share of non-EU migrants however, is around 3% in average which does not exceed 17 % across industries- ***Table 2.26***.

As can be seen from ***Table 2.27***, Germany, however, seems to have around 3% of its labour from the EU while around 5% from non-EU countries in average. We would expect to have more migration rate in average as Germany is well-known to have hosted multiple numbers of migrants since the 1960s, but we assume that 2nd or 3rd or more generation immigrants are considered as natives in the EU LFS, because according to the EU LFS definition, only individuals whose country of origin is different from the host are considered as migrants (EU LFS user guide, 2012).

2.4. Model and Empirical Analysis

In order to investigate whether migration share has an impact on productivity, we estimate the Cobb-Douglas production function:

$$Y_{it} = K^{\beta_1}\left[L_{D_{it}} + (1+\mu_{EU})L_{EU_{it}} + (1+\mu_{nonEU})L_{nonEU}\right]^{\beta_2} A_{it} \qquad \textbf{(2.1)}$$

where Y is output, K is capital input, L_D are work hours by domestic labour, L_{EU} are work hours non-domestic EU workers, L_{nonEU} are work hours by non-EU migrants and A is time-varying technology usually referred to a Total Factor Productivity (TFP). μ_{EU} and μ_{nonEU} are parameters that capture the higher, or lower if negative, productivity of the two types of migrant workers. β_1 and β_2 are the usual Cobb-Douglas production function parameters. Finally, i indexes the industry and t indexes the year.

We need to log-linearise production function (2.1) in order to estimate it by linear methods. Let us start by dropping the it subscripts to simplify the notation and by defining a new variable L which is total work hours for all worker types. We also define S_D as the share of work hours by domestic workers, S_{EU} as the share of work hours by non-domestic EU workers and S_{nonEU} as the share of work hours by non-EU migrant workers:

$$
\begin{aligned}
Y &= K^{\beta_1} L^{\beta_2} \left[S_D + (1+\mu_{EU})S_{EU} + (1+\mu_{nonEU})S_{nonEU}\right]^{\beta_2} A \\
&= K^{\beta_1} L^{\beta_2} \left[\left(1 - S_{EU} - S_{nonEU}\right) + \left(1+\mu_{EU}\right)S_{EU} + \left(1+\mu_{nonEU}\right)S_{non-EU}\right]^{\beta_2} A \\
&= K^{\beta_1} L^{\beta_2} \left[1 + \mu_{EU} S_{EU} + \mu_{nonEU} S_{nonEU}\right]^{\beta_2} A
\end{aligned}
\qquad \textbf{(2.2)}
$$

The second line in the derivation of equation **(2.2)** is simply due to the fact that the shares in work hours must add up to one: $S_D = 1 - S_{EU} - S_{nonEU}$. Log linearising equation **(2.2)** using the approximation $\ln(1+\mu_{EU} S_{EU} + \mu_{nonEU}) \approx (\mu_{EU} S_{EU} + \mu_{nonEU})$, and then defining two new parameters $\beta_3 = \beta_2 \mu_{EU}$ and $\beta_4 = \beta_2 \mu_{nonEU}$ gives:

$$
\begin{aligned}
\log Y &= \beta_1 \log K + \beta_2 \log L + \beta_2 \log + \left[1 + \mu_{EU} S_{EU} + \mu_{nonEU} S_{nonEU}\right] + \log A \\
&= \beta_1 \log K + \beta_2 \log L + \beta_2 \left[\mu_{EU} S_{EU} + \mu_{nonEU} S_{nonEU}\right] + \log A + \varepsilon \\
&= \beta_1 \log K + \beta_2 \log L + \beta_3 S_{EU} + \beta_4 S_{nonEU} + \log A + \varepsilon
\end{aligned}
\qquad \textbf{(2.3)}
$$

where ε is an error term accommodating approximations in the model but also the measurement error that is always present. Finally, we disaggregate $\ln A$, the measure of TFP, into time-varying and industry-varying components:

$$
\log Y = \beta_1 \log K + \beta_2 \log L + \beta_3 S_{EU} + \beta_4 S_{nonEU} + \alpha_\tau \tau + \sum_{j=1}^{N-1} \alpha_j I_j + \alpha_0 + \varepsilon \qquad \textbf{(2.4)}
$$

where τ is a linear time-trend, and the I_j are industry fixed effect dummies for each N industry except one. If β_3 is greater (less) than zero, then EU migrant workers are more (less) productive per hour than the workforce as a whole. Similarly, if β_4 is greater (less) than zero, then migrant workers from the rest of the world are more (less) productive per hour than the workforce as a whole.

By substituting all the variables into Equation **(2.4)** and taking logs the final estimated equation is:

$$
\begin{aligned}
\log GVA_{it} &= \beta_0 + \beta_1 \ln HRS_{it} + \beta_2 \log CAP_{it} + \beta_4 EUMigShr_{it} + \beta_5 NEUMigShr_{it} \\
&\quad + I_i + T_t + \varepsilon_{it}
\end{aligned}
\qquad \textbf{(2.5)}
$$

Output is measured as gross value added (EU KLEMS variable GVA) and we use the capital stock series that is adjusted for Gross Fixed Capital Formation (EU KLEMS variable CAP_GFCF) as CAP, HRS is the number of hours worked. $EUMigShr$ is the share of EU immigrants, $NEUMigShr$ is the share of non-EU immigrants-we include migration as proportion in total employment and do not differenced or take logarithm to see how the proportion of migrants affects productivity level- ; I_i and T_t are industry and time fixed effects, respectively, and finally $\varepsilon_{i,t}$ is the error term that is assumed to be uncorrelated with the input variables. In order to distinguish between short- and long-run specifications, we alternatively estimate the error correction (ECM) form of Model ***(2.5)***. Additionally, we use a basic autoregressive distributed lag (henceforth ARDL) for Model **(2.5)**:

$$\begin{aligned}\log GVA_{it} &= \beta_0 + \sum_{j=1}^{p} \lambda_{ij} \log GVA_{i,t-j} + \sum_{j=0}^{q} \delta_1 \log HRS_{i,t-j} + \sum_{j=0}^{q} \delta_2 \log CAP_{i,t-j} \\ &+ \sum_{j=0}^{q} \delta_3 EUMigShr_{i,t-j} + \sum_{j=0}^{q} \delta_4 NEUMigShr_{i,t-j} + \varepsilon_{it}\end{aligned} \qquad \textbf{(2.6)}$$

If we stack the time series observations for each industry groups **(2.6)** can be written in the error correction form as (Pesaran *et al*. 2012) where, to make the notation more compact, Y_t represents the dependent variable $\log GVA_t$ and X_t represents the vector at time t of explanatory variables:

$$\Delta Y_i = \Omega\left(Y_{i,-1} - \Pi_i X_i\right) + \sum_{j=1}^{p-1} \lambda_{ij}^{*} \Delta Y_{i,-j} + \sum_{j=0}^{q} \delta_{ij} \Delta X_{i,-j} + \varepsilon_i \qquad \textbf{(2.7)}$$

It is a standard form of ARDL. The change in productivity is a perfect natural experiment but nonetheless, it takes several years to play out. Thus, we include lagged productivity in model. We leave migration share without taking the difference or log to see how far immigration variables with different features will affect the productivity level in **(2.7).** Also, we disaggregate migration shares into different skill groups. The EU LFS data provides international standard classification of education (henceforth ISCED) codes as low-skilled (ISCED 1- 2), medium-skilled (ISCED 3-4) and high-skilled (ISCED 5-6). With this, we expect to see the different migration effects on productivity as each country has different labour force statuses. Also, we expect to have different results for EU and non-EU migrants which may be the result of the skill difference and labour market integration (Dustmann and Frattini, 2011).

As is well known, the productivity function comes with its endogeneity problem. To fix this problem, the GMM method might be useful; however, the number of observations for each country is not sufficient to apply this method. However, according to Pesaran and Shin (1998), ARDL can also produce convenient results if the lag order for ARDL is well specified. Also, one may argue that migration flows could be endogenous as migrants workers may want to choose to work in industries with faster productivity growth. However, when there is a massive inflow of immigration, immigrant workers are generally filling more intensive jobs that are often at the bottom of the career ladder for natives which implies that it is not the decision for immigrant worker to make it rather is a decision for natives to make. Indeed, in comparison to immigrant workers, native workers move more rapidly towards communication-intensive and well paid jobs (Lewis and Peri, 2014). Thus we treat migration flows as exogenous.

We use both Akaike's information criterion (AIC) and Bayesian information criterion (BIC) to determine the number of lags. The number of lags for the UK, Spain, and Netherlands it is suggested to be 2. For the Germany data we can only use 1 lag due to the limited number of observations.

The PMG estimator of ARDL constrains the long-run coefficient to be identical but allows short-run coefficients and error variances to vary across units (Pesaran *et al*. 2012), and this method has been used in several productivity and human capital models (Kangasniemi *et al*., 2012; Goswami and Junayed, 2006; O'Mahony and Vecchi, 2005; Bassanini and Scarpetta, 2002). We use *xtpmg* command in Stata13 to obtain estimation results. This command provides both short run and long run results. In order to distinguish between the PMG estimator and standard estimations, we also apply OLS, fixed effect (FE thereafter) and first difference (FD thereafter).

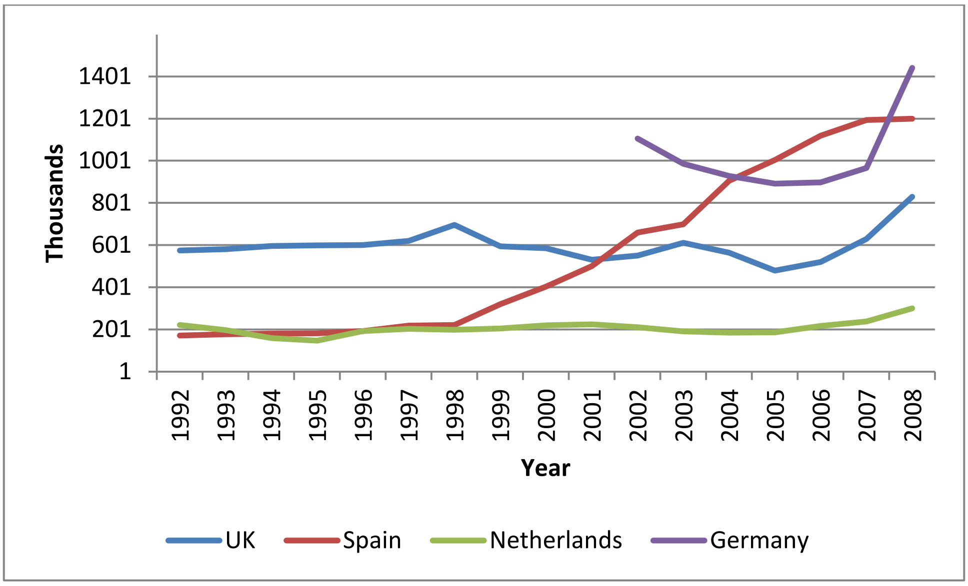
One disadvantage of the PMG estimator is that it can only be applied if there is enough time period – that is 14 for the UK, Spain and the Netherlands, and but only 7 for Germany. Therefore, we are not able to apply the PMG to Germany. However, we use the alternative pooled estimate, the dynamic fixed effect (thereafter DFE), which constrains both short- and long-run coefficients to be identical (Pesaran *et al*., 2012). Thus, for Germany some caution should be used when interpreting the results.

2.4.1. Effects of 2004 accession on EU migrant shares

Our sample captures the years from 1995 to 2008 for the UK, Spain and the Netherlands, and 2002 to 2008 for Germany. One concern is the trend in the share of migration after the 2004 EU accession. Because, although the sudden increase in migrants is a natural experiment we still need to check how it affects productivity. To be able to see how this sudden change effects productivity we control for the sudden increase particularly after 2007 in the share of EU migrants and set a dummy that is equal to 1 for the year 2007 and 2008, and zero otherwise. According to EUROSTAT, Germany allowed workers from 2004-EU member states to work from 1st May 2011, while the UK, Spain, and the Netherlands allowed them to work right after accession.

One way to check whether there was a particular change in migration share after 2004 is to plot a graph of all four host countries with the number of EU-Migrants. The numbers of EU migrants (thousands) are presented in ***Figure 2.1*** and it should be noted that the new accession countries in 2004 and 2007 are classified into non-EU countries. As can be seen from the ***Figure 2.1*** both the UK and the Netherlands show a gradual increase from approximately 2005, and we believe that this may not cause a serious bias in our sample. Spain illustrates a different pattern, in that the number of EU migrants is almost stable from 1995 to 1998 and increases gradually thereafter. However, for Germany a sharp increase in migration share after 2007 is not unnoticeable. In order to take this sudden increase into account we set a time dummy i.e. $D2007$ that is equal to 1 for the years 2007 and 2008 where a sharp increase seen in EU migration share, and 0 otherwise. Still, caution is again to be taken with Germany when interpreting the results.

Figure2.1 Numbers of EU-Migrants in the host country



2.4.2. Empirical Results

Results are presented for the UK, Spain, Netherland and Germany as follows:

2.4.2.1. Results for the UK

Table 2.4 presents the results for the UK without distinction of skill level. ***Table 2.5, Table 2.6,*** and ***Tables 2.7*** show the results with high skilled, medium skilled, and low skilled EU/ non-EU and total migration share, respectively. As much as we look for the impact of migration share on the productivity, we additionally split EU and non-EU migration share in the same model to be able to see if they operate in the same or the opposite directions. ***Model (1)-(2)*** of ***Table 2.4*** presents the OLS results, ***Model (3)-(4)*** fixed effect results, ***Model (5)-(6)*** first difference results, ***Model(7)-(9)*** short run PMG, and ***Model (8)-(10)*** presents long run PMG results.

The OLS result, that is ***Model (1)-(2),*** displays quite significant and positive results across all independent variables, although biased due to endogeneity. We present an industry and time fixed effect in ***Model (3)-(4),*** both labour input variable- that is total hours worked by employees- and capital input variables – that is capital stocks- have quite a positive and significant impact on value added, whereas migration share (EU, non-EU and total) shows a non-significant impact, although positive. We apply FD in ***Model (5)-(6)*** in order to resolve the possible omitted variable bias. However, FD suggests that the only significant variable that affects productivity is hours worked by employees, which might indeed be the case in the short run. When working on productivity functions, it is too simplistic to assume that FD will solve the endogeneity problem. In addition, one should not expect to see the effects of any input variables on productivity in the short run, since it needs several years to see the outcomes play out. Therefore, we apply PMG, which produces both short- and long-run effects. The PMG estimator of ARDL constrains the long-run coefficient to be identical, and as mentioned in ***2.1. Introduction*** section, as long as the lag order is specified correctly, it produces unbiased results in spite of the endogeneity. ***Model (7)-(9)*** and ***Model (8)-(10)*** of ***Table 2.4*** presents the short and long-run PMG results, respectively. Both short and long run results show the significance of labour and capital inputs, whereas EU migration share remains insignificant both in the short and long run. Non-EU migration share, on the other hand, appears to be positive and significant only in the long run. When it comes to the total migration share, the impact appears to be insignificant in the short run, positive and significant in the long run, suggesting that non-EU migrants contributes to productivity significantly in the long run. The positive and significant impact of non-EU migration share could be explained by the fact that selective migration policies for non-EU countries.

As to the total migration share from EU and non-EU effect on productivity, in the short run, migration share appears to have an insignificant effect on the added value, confirmed by ***Model (9)*** of the ***Table 2.4***. In the long run, however, this impact appears to be positive and quite significant. It may suggest that the impact of non- EU migration share outweighs the impact of EU migration share.

Table2.4 Value added regressions for UK

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\log VA_{it}$	**OLS**	**OLS**	**FE**	**FE**	**FD**	**FD**	**PMG-SR**	**PMG-LR**	**PMG-SR**	**PMG-LR**
$\log HRS_{it}$	0.439*** (0.0202)	0.449*** (0.0206)	0.950** (0.384)	0.952** (0.382)	0.628*** (0.158)	0.629*** (0.159)	0.180* (0.128)	0.451*** (0.0796)	0.312** (0.123)	0.552*** (0.0473)
$\log Cap_{it}$	0.322*** (0.0557)	0.314*** (0.0543)	0.186* (0.0938)	0.186* (0.0936)	0.0669* (0.0778)	0.0668* (0.0775)	0.281*** (0.0785)	0.549*** (0.0796)	0.273*** (0.0770)	0.448*** (0.0473)
$EUMigShr_{it}$	0.499*** (0.171)		1.277 (0.949)		-0.0535 (0.113)		-0.544 (1.218)	-0.3451 (0.4921)		
$NEUMigShr_{it}$	0.448** (0.191)		0.831 (1.249)		0.0387 (0.132)		-0.0736 (0.195)	0.4231** (0.2115)		
$MigShr_{it}$		0.207 (0.154)		0.884 (1.174)		0.0195 (0.102)			-0.230 (0.297)	0.192** (0.094)
Constant	4.349*** (0.534)	4.408*** (0.526)	1.721 (2.519)	1.711 (2.513)	0.0418*** (0.00370)	0.0418*** (0.00366)	0.498* (0.276)	-0.0484* (0.0291)	0.0184 (0.0176)	-0.0337 (0.0590)
N	210	210	210	210	195	195	180	180	180	180
R^2	0.692	0.685	0.513	0.513						

(1)-(2) present OLS results, (3)-(4) is the time fixed effect, (5)-(6) the first differenced effect (7)-(9) short-run results of the PMG model (8)-(10) long-run results of the PMG model Clustered t-stats are in parenthesis for (1),(2),(3),(4),(7),(8),(9),(10) and bootstrap z-stats in parenthesis for (5),(6) *, ** and *** indicate 10%, 5% and 1% significance, respectively.

We also aim to investigate whether migration with different skill groups acts differently on the output. To do that, we disaggregate educational attainment as high, medium and low skilled. The EU LFS database uses ISCED codes 5 and 6 for high educated immigrants, ISCED 4 and 3 for medium educated immigrants, and finally ISCED codes 2 and 1 for low educated immigrants.

Table 2.5 presents the results with high skilled EU, non-EU and total migration share in the UK. ***Model (1)-(2)*** presents the OLS results and as can be seen from ***Table 2.5*** all input variables as well as high skilled EU, non-EU and total migration share seem to be quite significant and positive, although biased. We fail to see any significant effect of high skilled migration effect on productivity both in FE and FD models in ***Model (3)-(4)*** and ***Model (5)-(6),*** respectively. Labour input as total hours worked by employees is found to be positive and significant at all times across all models. We find no significance of EU, non-EU and total migration share in the short run- that is ***Model (7)-(9).*** In the long run - ***Model*** **(8)-(10)** – however, high skilled non-EU migration share seem to have significant effects while no significance is observed for high skilled EU migration share, and we believe that the significance in the total immigration share comes from the predominant effects of non-EU migrants. This result may again be explained by the selective migration policies for non-EU countries.

Table2.5 Value added regressions for high skilled UK

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\log VA_{it}$	**OLS**	**OLS**	**FE**	**FE**	**FD**	**FD**	**PMG-SR**	**PMG-LR**	**PMG-SR**	**PMG-LR**
$\log HRS_{it}$	0.445*** (0.0205)	0.452*** (0.0208)	0.932** (0.391)	0.940** (0.390)	0.630*** (0.158)	0.630*** (0.159)	0.241** (0.118)	0.542*** (0.0684)	0.286** (0.118)	0.540*** (0.0506)
$\log Cap_{it}$	0.308*** (0.0526)	0.311*** (0.0526)	0.188* (0.0941)	0.188* (0.0943)	0.0668* (0.0775)	0.0668* (0.0777)	0.289*** (0.0763)	0.458*** (0.068)	0.270*** (0.0771)	0.460*** (0.0506)
$EUMigShr_{it}$	0.864*** (0.305)		0.394 (0.198)		-0.0477 (0.678)		0.156 (0.356)	0.098 (0.0.47)		
$NEUMigShr_{it}$	0.939** (0.433)		1.103 (1.812)		0.0582 (0.828)		0.199 (0.195)	0.1122* (0.7233)		
$MigShr_{it}$		0.267* (0.279)		1.400 (1.777)		0.0419 (0.744)			-0.225 (0.809)	0.1094* (0.097)
Constant	4.480*** (0.515)	4.417*** (0.516)	1.872 (2.578)	1.815 (2.573)	0.0418*** (0.00362)	0.0418*** (0.00361)	0.428** (0.180)	-0.0724** (0.0349)	0.0231 (0.0142)	-0.0337 (0.0499)
N	210	210	210	210	195	195	180	180	180	180
R^2	0.687	0.684	0.506	0.504						

(1)-(2) present OLS results, (3)-(4) is the time fixed effect, (5)-(6) the first differenced effect (7)-(9) short-run results of the PMG model (8)-(10) long-run results of the PMG model Clustered t-stats are in parenthesis for (1),(2),(3),(4),(7),(8),(9),(10) and bootstrap z-stats in parenthesis for (5),(6) *, ** and *** indicate 10%, 5% and 1% significance, respectively.

Apart from high skilled migrants, we introduce the results for medium skilled EU, non-EU and total migration share in ***Table 2.6. Model (1)-(2)*** present OLS results, ***Model (3)-(4)*** FE, ***Model (5)-(6)*** FD, Model ***(7)-(9)*** short run PMG, and ***Model (8)-(10)*** presents the long run PMG results. Both labour and capital input variables are positive and significant across all models. The labour input variable displays a positive and significant effect on productivity across all ***Models (1)-(10),*** so as the capital input variables apart from first differenced results- ***Model (5)-(6)***. The medium skilled non-EU migration share shows no significant effect in the short- ***Model (7)*** or long run-***Model (8)***. When it comes to medium skilled EU migrants, it has an insignificant effect on productivity in the short run –***Model (7)***, but negative and significant effects in the long run- ***Model (8).*** As to total migration shares as can be seen from ***Model (9) - (10)*** of ***Table 2.6.*** in the long run does the significance of total migration share make us consider that the effect of medium skilled EU migration share outweighs the effect of the medium skilled non-EU migrant share on productivity, because we detect no significant effect of the medium skilled non-EU migrant share, while it is negative and significant for total migration share. The negative impact of medium skilled migrants might be explained due to the fact that the mobility across medium skill jobs may be greater comparing to low or high skilled jobs due to skill mismatch.

Table2.6 Value added regressions for medium skilled UK

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\log VA_{it}$	**OLS**	**OLS**	**FE**	**FE**	**FD**	**FD**	**PMG-SR**	**PMG-LR**	**PMG-SR**	**PMG-LR**
$\log HRS_{it}$	0.443*** (0.0199)	0.451*** (0.0206)	0.952** (0.386)	0.953** (0.385)	0.628*** (0.157)	0.629*** (0.158)	0.229* (0.133)	0.109* (0.0876)	0.306** (0.131)	0.598*** (0.0650)
$\log Cap_{it}$	0.321*** (0.0554)	0.313*** (0.0542)	0.187* (0.0948)	0.187* (0.0945)	0.0669 (0.0776)	0.0668 (0.0776)	0.308*** (0.0741)	1.109*** (0.0876)	0.269*** (0.0775)	0.402*** (0.0650)
$EUMigShr_{it}$	0.724 (0.284)		1.474 (1.515)		-0.0393 (0.226)		-0.247 (2.577)	-0.192* (6.520)		
$NEUMigShr_{it}$	-0.667* (0.344)		0.769 (1.639)		0.0325 (0.157)		0.1002 (0.0801)	-0.0782 (0.3287)		
$MigShr_{it}$		0.300 (0.275)		0.863 (1.489)		0.0183 (0.136)			-0.235 (0.546)	-0.855* (0.215)
Constant	4.341*** (0.535)	4.405*** (0.526)	1.728 (2.537)	1.724 (2.534)	0.0418*** (0.00368)	0.0418*** (0.00367)	-0.0251 (0.0220)	-0.250 (0.250)	0.0782 (0.0557)	-0.0782 (0.0557)
N	210	210	210	210	195	195	180	180	180	180
R^2	0.689	0.684	0.504	0.504						

(1)-(2) present OLS results, (3)-(4) is the time fixed effect, (5)-(6) the first differenced effect (7)-(9) short-run results of the PMG model (8)-(10) long-run results of the PMG model Clustered t-stats are in parenthesis for (1),(2),(3),(4),(7),(8),(9),(10) and bootstrap z-stats in parenthesis for (5),(6) *, ** and *** indicate 10%, 5% and 1% significance, respectively.

When it comes to the low skilled immigrants which are presented in ***Table 2.7*** for EU, non-EU and total migration share**,** the results draw attention to the positive and significant impact of EU and non-EU migration share on productivity in the long run- ***Model (8),*** and not surprisingly positive and significant impact of total migration share on productivity in the long run- ***Model (10).*** In the short run- ***Model (7)-(9)***, however, we observe an adverse impact of the EU and non-EU migration share, where the former is positive but insignificant and latter is negative and still insignificant. One explanation for the different effects of low skilled EU and non-EU immigrants could be the fact that non-EU migrants are less advantageous than EU migrants in terms of migration costs, and tend to work in less skilled jobs. Thus, it takes longer for non-EU migrants to settle in.

Table2.7 Value added regressions for low skilled UK

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\log VA_{it}$	**OLS**	**OLS**	**FE**	**FE**	**FD**	**FD**	**PMG-SR**	**PMG-LR**	**PMG-SR**	**PMG-LR**
$\log HRS_{it}$	0.444*** (0.0208)	0.441*** (0.0203)	0.944** (0.387)	0.943** (0.392)	0.626*** (0.161)	0.633*** (0.162)	0.159 (0.131)	0.112* (0.0681)	0.304*** (0.114)	0.537*** (0.0368)
$\log Cap_{it}$	0.350*** (0.0716)	0.337*** (0.0662)	0.188* (0.0961)	0.189* (0.0955)	0.0669 (0.0788)	0.0669 (0.0774)	0.296*** (0.0819)	0.888*** (0.0681)	0.296*** (0.0743)	0.463*** (0.0368)
$EUMigShr_{it}$	0.247** (0.116)		-5.777 (7.195)		-0.685 (1.168)		0.099 (0.115)	0.379* (0.186)		
$NEUMigShr_{it}$	0.232 (0.274)		2.692 (4.907)		0.626 (0.548)		-0.731 (1.891)	0.367* (0.816)		
$MigShr_{it}$		0.628* (0.323)		0.904 (3.175)		0.254 (0.496)			0.288 (0.461)	0.295* (0.499)
Constant	4.032*** (0.690)	4.199*** (0.629)	1.824 (2.536)	1.811 (2.583)	0.0417*** (0.00376)	0.0418*** (0.00367)	0.0481* (0.0267)	-0.0279 (0.0449)	0.0600 (0.0598)	-0.0311 (0.0561)
N	210	210	210	210	195	195	180	180	180	180
R^2	0.701	0.696	0.500	0.495						

(1)-(2) present OLS results, (3)-(4) is the time fixed effect, (5)-(6) the first differenced effect (7)-(9) short-run results of the PMG model (8)-(10) long-run results of the PMG model Clustered t-stats are in parenthesis for (1),(2),(3),(4),(7),(8),(9),(10) and bootstrap z-stats in parenthesis for (5),(6) *, ** and *** indicate 10%, 5% and 1% significance, respectively.

2.4.2.2. Results for Spain

Compared to the UK, the labour market composition, demand in the labour market and working conditions are not the same in Spain. Therefore, we do not expect to find exactly the same results here. ***Table 2.8*** presents the results for Spain without distinction of skill level of immigrants. The OLS results, ***Model (1)-(2),*** display positive and very significant effects of the input variables as well as EU/non-EU/ total migration share, although biased due to endogeneity. The labour and capital input variables are also found to be positive and significant in the FE and FD models - ***Models (3)-(4)*** and ***Model (5)-(6),*** respectively**,** but no significance found for EU, non-EU and total migration share. ***Model (7)* and *(9)*** suggest that there is no significant effect of EU migration share on productivity in the short run, while it is positive and significant for non-EU migration share. This is again, could be result of the selective migration policy for non-EU migrants. The effect of non-EU migration share remains the same in the long run, which can be seen in ***Model (8)*** and ***(10***), of ***Table 2.8.*** When it comes to the total migration share, both short run and long run results show positive impact on productivity with only latter is significant. Thus, in general, it can be said that migrants contribute to productivity in Spain.

Table2.8 Value added regressions for Spain

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\log VA_{it}$	**OLS**	**OLS**	**FE**	**FE**	**FD**	**FD**	**PMG-SR**	**PMG-LR**	**PMG-SR**	**PMG-LR**
$\log HRS_{it}$	0.384*** (0.0173)	0.384*** (0.0172)	0.624*** (0.134)	0.613*** (0.130)	0.465*** (0.140)	0.466*** (0.139)	0.439*** (0.0971)	0.0526* (0.0307)	0.420*** (0.0948)	0.294** (0.0364)
$\log Cap_{it}$	0.512*** (0.0219)	0.512*** (0.0218)	0.426*** (0.0726)	0.435*** (0.0688)	0.179*** (0.0488)	0.179*** (0.0486)	0.141** (0.0648)	0.947*** (0.0307)	0.146** (0.0653)	0.971*** (0.0364)
$EUMigShr_{it}$	1.089*** (0.274)		0.238 (0.0806)		0.0275 (0.385)		-0.223 (0.158)	-0.279 (0.171)		
$NEUMigShr_{it}$	1.521*** (0.263)		0.610 (0.409)		0.0144 (0.229)		0.198* (0.370)	0.359** (0.355)		
$MigShr_{it}$		1.360*** (0.226)		0.445 (0.285)		0.0208 (0.172)			0.255 (0.266)	0.182* (0.467)
Constant	2.861*** (0.158)	2.863*** (0.158)	2.015*** (0.661)	2.009*** (0.657)	0.0375*** (0.00649)	0.0375*** (0.00645)	0.109** (0.0425)	0.111* (0.0668)	0.0862*** (0.0324)	0.105 (0.0703)
N	210	210	210	210	195	195	180	180	180	180
R^2	0.921	0.921	0.911	0.910						

(1)-(2) present OLS results, (3)-(4) is the time fixed effect, (5)-(6) the first differenced effect (7)-(9) short-run results of the PMG model (8)-(10) long-run results of the PMG model Clustered t-stats are in parenthesis for (1),(2),(3),(4),(7),(8),(9),(10) and bootstrap z-stats in parenthesis for (5),(6) *, ** and *** indicate 10%, 5% and 1% significance, respectively.

When disaggregating in to skill level, the results for high skilled EU, non-EU and total migration share is presented in ***Table 2.9.***Both labour and capital input variables are positive and significant across all models. We find no significance of EU and non-EU migration share effect on productivity in OLS – ***Model (1),*** although it is positive and significance for total migration share- ***Model (2).*** Fixed effect models – ***Model(3)-(4)*** suggest a negative effect for EU migration share, positive for non-EU and total migration share, where all quite significant. No significant impact is observed in first differenced models- ***Model (5)-(6)*** for any migration shares. As can be seen from ***Model (7)*** and ***(8)*** of ***Table 2.9*** , high skilled EU migrants has no significant affect in the short run but it is negative and significant in the long run, whereas high skilled non-EU migration share appears to be positive and significant both in the short run and in the long run. As to the total migration share effect, in ***Model (9)*** and ***(10),*** we observe no significance in the short run, although positive, but it is positive and significant in the long run. As can be seen from ***Model (8)*** of ***Table 2.8*** the negative impact of non-EU migration share remains same with high skilled EU migration share- ***Model (8)*** of ***Table 2.9.*** This can be explained by the fact that in Spain - as a member of EU- , migrants from EU countries are more likely to be substitutes due to similar labour market conditions than non-EU countries.

Table2.9 Value added regressions for High skilled Spain

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\log VA_{it}$	**OLS**	**OLS**	**FE**	**FE**	**FD**	**FD**	**PMG-SR**	**PMG-LR**	**PMG-SR**	**PMG-LR**
$\log HRS_{it}$	0.402*** (0.0179)	0.404*** (0.0174)	0.668*** (0.119)	0.603*** (0.138)	0.473*** (0.139)	0.466*** (0.140)	0.415*** (0.0888)	0.0116** (0.0291)	0.323*** (0.0796)	0.403*** (0.0175)
$\log Cap_{it}$	0.494*** (0.0228)	0.494*** (0.0223)	0.365*** (0.0680)	0.460*** (0.0647)	0.183*** (0.0490)	0.183*** (0.0490)	0.149** (0.0659)	0.988*** (0.0291)	0.150** (0.0672)	0.597*** (0.0175)
$EUMigShr_{it}$	-0.241 (0.232)		-0.171*** (0.377)		-0.354 (0.153)		-0.189 (0.126)	-0.191*** (0.568)		
$NEUMigShr_{it}$	0.347 (0.273)		0.104*** (0.209)		0.270 (0.507)		0.392* (0.211)	0.476* (0.146)		
$MigShr_{it}$		0.298*** (0.356)		0.192** (0.552)		-0.626 (0.208)			0.167 (0.113)	0.171*** (0.290)
Constant	2.947*** (0.171)	2.944*** (0.166)	2.239*** (0.568)	1.860** (0.699)	0.0372*** (0.00621)	0.0377*** (0.00633)	0.0855** (0.0336)	-0.118* (0.0718)	0.223** (0.103)	-0.121* (0.0651)
N	210	210	210	210	195	195	180	180	180	180
R^2	0.911	0.910	0.935	0.905						

(1)-(2) present OLS results, (3)-(4) is the time fixed effect, (5)-(6) the first differenced effect (7)-(9) short-run results of the PMG model (8)-(10) long-run results of the PMG model Clustered t-stats are in parenthesis for (1),(2),(3),(4),(7),(8),(9),(10) and bootstrap z-stats in parenthesis for (5),(6) *, ** and *** indicate 10%, 5% and 1% significance, respectively.

Regarding medium skilled immigrants, ***Table 2.10*** present the results for medium skilled EU, non-EU and total migration share. As can be seen from ***Model (1)-(10),*** all input variables are positive and quite significant**.** OLS results –***Model (1)-(2) -*** suggest that both medium skilled EU and non-EU migration share as well as total migration share has significant contribution to productivity. On the other hand, no significance is observed in FE, that is ***Model (3)-(4),*** as well as FD models, that is ***Model (5)-(6),*** apart from EU migration share. Medium skilled EU migration share has no significant impact on productivity, although negative, in the short run, that is ***Model (7)***, but it is quite significant in the long run, that is ***Model (8)***, although the coefficient is smaller. When it comes to the medium skilled non-EU migration share, both in the short run and in the long run, the impact is seen to be positive and significant as can be seen from ***Model (7)-(8)***. However, in total, medium skilled migration shares has negative and significant impact on productivity in the long run. Thus, the effect of EU migration shares happen to outweighs the effect of non-EU migration. One explanation could be the fact that the share of medium skilled non-EU migrants is far less than that of medium skilled EU migrants in in Spain (EU LFS Database).

Table2.10 Value added regressions for Medium skilled Spain

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\log VA_{it}$	**OLS**	**OLS**	**FE**	**FE**	**FD**	**FD**	**PMG-SR**	**PMG-LR**	**PMG-SR**	**PMG-LR**
$\log HRS_{it}$	0.385*** (0.0174)	0.385*** (0.0173)	0.616*** (0.130)	0.606*** (0.126)	0.464*** (0.139)	0.465*** (0.138)	0.420*** (0.0881)	0.0506* (0.0288)	0.416*** (0.0915)	0.0168** (0.0361)
$\log Cap_{it}$	0.510*** (0.0223)	0.510*** (0.0222)	0.427*** (0.0705)	0.435*** (0.0675)	0.179*** (0.0489)	0.179*** (0.0487)	0.137** (0.0685)	0.949*** (0.0288)	0.145** (0.0668)	0.983*** (0.0361)
$EUMigShr_{it}$	0.459*** (0.117)		0.112*** (0.360)		0.161 (1.553)		-0.137 (0.932)	-0.454* (0.057)		
$NEUMigShr_{it}$	0.788*** (0.109)		0.303 (0.197)		0.0510 (1.057)		0.387* (0.211)	0.118* (0.151)		
$MigShr_{it}$		0.666*** (0.101)		0.221 (0.133)					0.1482 (0.1190)	-0.319* (0.179)
Constant	2.883*** (0.160)	2.883*** (0.159)	2.066*** (0.636)	2.055*** (0.636)	0.0376*** (0.00650)	0.0375*** (0.00647)	0.115** (0.0518)	0.112 (0.0775)	0.0890*** (0.0344)	0.108 (0.0741)
N	210	210	210	210	195	195	180	180	180	180
R^2	0.922	0.921	0.912	0.911						

(1)-(2) present OLS results, (3)-(4) is the time fixed effect, (5)-(6) the first differenced effect (7)-(9) short-run results of the PMG model (8)-(10) long-run results of the PMG model Clustered t-stats are in parenthesis for (1),(2),(3),(4),(7),(8),(9),(10) and bootstrap z-stats in parenthesis for (5),(6) *, ** and *** indicate 10%, 5% and 1% significance, respectively.

Finally, as to the results with low skilled migration share ***Table 2.11*** present the results for low skilled EU, non-EU and total migration share, respectively. The long-run results – that is ***Model (8)*** and ***(10)*** of ***Table 2.11***- show that both EU and non-EU migrants determine the gross output positively and significantly, where the coefficient for EU migrants share is much higher than the non-EU migrant share, and in total the coefficient is getting smaller, although it remains positive and significant. The OLS results – ***Model (1)-(2)*** of ***Tables 2.11*** - suggest that all input variables as well as EU/non-EU/total migration share significantly contribute to productivity, although biased. The FE and FD results - ***Model (3)-(4)*** and ***Model (5)-(6)*** from ***Table 2.11-*** found no significance for migration share. Similarly, short run results- ***Model (7) and (9)*** of ***Table 2.11*** displays no significant effect of low skilled of EU/non-EU/total migration share on productivity, although positive.

Table2.11 Value added regressions for Low Skilled Spain

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\log VA_{it}$	**OLS**	**OLS**	**FE**	**FE**	**FD**	**FD**	**PMG-SR**	**PMG-LR**	**PMG-SR**	**PMG-LR**
$\log HRS_{it}$	0.384*** (0.0173)	0.385*** (0.0171)	0.632*** (0.139)	0.629*** (0.133)	0.469*** (0.140)	0.468*** (0.139)	0.434*** (0.0956)	0.222*** (0.0204)	0.408*** (0.0958)	0.405*** (0.0178)
$\log Cap_{it}$	0.513*** (0.0216)	0.512*** (0.0214)	0.419*** (0.0772)	0.421*** (0.0742)	0.179*** (0.0488)	0.179*** (0.0487)	0.141* (0.0726)	0.778*** (0.0204)	0.144** (0.0674)	0.595*** (0.0178)
$EUMigShr_{it}$	0.354*** (0.049)		0.840*** (0.240)		0.0829 (0.684)		0.2589 (0.198)	0.697*** (0.316)		
$NEUMigShr_{it}$	0.226*** (0.040)		1.160 (0.830)		0.130 (0.325)		0.463 (0.283)	0.0374 (0.217)		
$MigShr_{it}$		0.242*** (0.348)		1.097 (0.664)		0.111 (0.243)			0.153 (0.162)	0.105*** (0.029)
Constant	2.861*** (0.158)	2.861*** (0.158)	2.016*** (0.647)	2.021*** (0.639)	0.0371*** (0.00643)	0.0372*** (0.00638)	0.154*** (0.0581)	0.142** (0.0634)	0.193** (0.0819)	0.128** (0.0594)
N	210	210	210	210	195	195	180	180	180	180
R^2	0.920	0.919	0.912	0.912						

(1)-(2) present OLS results, (3)-(4) is the time fixed effect, (5)-(6) the first differenced effect (7)-(9) short-run results of the PMG model (8)-(10) long-run results of the PMG model Clustered t-stats are in parenthesis for (1),(2),(3),(4),(7),(8),(9),(10) and bootstrap z-stats in parenthesis for (5),(6) *, ** and *** indicate 10%, 5% and 1% significance, respectively.

2.4.2.3. Results for the Netherlands

Table 2.12 presents the results for the EU migration share, non-EU migration share and total migration share, without distinction of skill level. Both labour and capital variables are positive and quite significant in our short run and long run PMG models, ***Model (7)*** and ***(9)*** and ***Model (8)*** and ***(10),*** respectively. As can be seen from ***Model (7)-(10),*** unlike the results in Spain and the UK, EU migration share has quite significant contribution to productivity both in the short run and long run. Non-EU migration share, however, seem to affect productivity in Netherlands quite the opposite, which is significant in the long run only. As to the total migration share, the effect of migration share still has positive and significant impact on productivity of industries. Another difference here in comparison to both the UK and Spain is that capital inputs seem to be positive and significant across all ***Models (1)-(10.*** But the labour input variable is insignificant for the FE that is ***Model (3)-(4),*** and FD models that is ***Model (5)-(6)***. This situation is opposite for the UK and Spain. In other words, the labour inputs is positive and significant across all models, while capital inputs found insignificant mostly in FE and FD results. This might suggest that firms in the Netherlands are more capital intensive and less labour intensive firms, whereas the UK and Spain have more labour intensive and less capital intensive firms.

Table2.12 Value added regressions for Netherlands

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\log VA_{it}$	**OLS**	**OLS**	**FE**	**FE**	**FD**	**FD**	**PMG-SR**	**PMG-LR**	**PMG-SR**	**PMG-LR**
$\log HRS_{it}$	0.341*** (0.0146)	0.341*** (0.0146)	0.423 (0.336)	0.426 (0.335)	0.0609 (2.325)	0.0611 (2.335)	0.673*** (0.128)	0.246*** (0.0132)	0.607*** (0.114)	0.417*** (0.0198)
$\log Cap_{it}$	0.527*** (0.0156)	0.527*** (0.0153)	0.664*** (0.0959)	0.665*** (0.0957)	0.347*** (0.131)	0.347*** (0.125)	0.355*** (0.0741)	0.754*** (0.0132)	0.376*** (0.0663)	0.583*** (0.0198)
$EUMigShr_{it}$	0.455*** (0.154)		0.154 (0.129)		0.0471 (0.524)		0.481* (0.531)	0.530*** (0.108)		
$NEUMigShr_{it}$	0.171 (0.347)		-0.783** (0.312)		0.189 (1.496)		-0.463 (0.454)	-0.479** (0.400)		
$MigShr_{it}$		0.371*** (0.0823)		0.181 (0.151)		0.0487 (0.333)			0.304 (0.380)	0.3012*** (0.103)
Constant	3.258*** (0.157)	3.259*** (0.156)	1.547 (1.501)	1.536 (1.495)	0.0310* (0.0184)	0.0310* (0.0178)	0.0825 (0.101)	-0.0409 (0.0418)	-0.291*** (0.0637)	-0.0831*** (0.0172)
N	210	210	210	210	195	195	180	180	180	180
R^2	0.892	0.891	0.848	0.847						

(1)-(2) present OLS results, (3)-(4) is the time fixed effect, (5)-(6) the first differenced effect (7)-(9) short-run results of the PMG model (8)-(10) long-run results of the PMG model Clustered t-stats are in parenthesis for (1),(2),(3),(4),(7),(8),(9),(10) and bootstrap z-stats in parenthesis for (5),(6) *, ** and *** indicate 10%, 5% and 1% significance, respectively.

Table 2.13 presents the results for high skilled EU, non-EU and total migration share. Migration share seems to be positive but insignificant in the short run as can be seen from ***Model (7)*** and ***(9)***, for high skilled EU, non-EU and total migrants in Netherlands. The long-run results - that is in ***Model (8)*** and ***(10)*** of ***Table 2.13*** suggest that high skilled EU and non-EU migration share, and so not surprisingly total migration share, has significant contribution to productivity. Again, capital inputs seem to contribute to productivity significantly across all models, as does labour inputs apart from FE and FD – that are ***Model (3)- (4)*** and ***(5)-(6),*** respectively. OLS results that are ***Model (1)-(2)*** of ***Table 2.13*** display significant and positive results for all inputs as well as migration share, although biased.

Table2.13 Value added regressions for High Skilled Netherlands

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\log VA_{it}$	**OLS**	**OLS**	**FE**	**FE**	**FD**	**FD**	**PMG-SR**	**PMG-LR**	**PMG-SR**	**PMG-LR**
$\log HRS_{it}$	0.340*** (0.0145)	0.340*** (0.0144)	0.429 (0.334)	0.436 (0.336)	0.0801 (2.536)	0.0658 (2.309)	0.655*** (0.137)	0.242*** (0.0108)	0.655*** (0.126)	0.113*** (0.0114)
$\log Cap_{it}$	0.528*** (0.0154)	0.529*** (0.0155)	0.666*** (0.0955)	0.669*** (0.0962)	0.348** (0.157)	0.347*** (0.124)	0.360*** (0.0783)	0.758*** (0.0108)	0.349*** (0.0793)	0.887*** (0.0114)
$EUMigShr_{it}$	0.109 (0.934)		0.0866 (0.533)		-0.229 (7.216)		0.3331 (0.2032)	0.527*** (0.422)		
$NEUMigShr_{it}$	0.705*** (0.246)		0.175** (0.618)		0.131 (0.265)		0.5023 (0.1411)	0.178* (0.466)		
$MigShr_{it}$		2.846*** (0.634)		0.802 (0.680)		0.223 (5.270)			0.178 (0.109)	0.156*** (0.486)
Constant	3.251*** (0.156)	3.252*** (0.156)	1.483 (1.477)	1.456 (1.483)	0.0307* (0.0184)	0.0310* (0.0176)	0.0267 (0.0469)	0.00488 (0.0584)	-0.00299 (0.0463)	-0.00141 (0.0451)
N	210	210	210	210	195	195	180	180	180	180
R^2	0.893	0.893	0.848	0.846						

(1)-(2) present OLS results, (3)-(4) is the time fixed effect, (5)-(6) the first differenced effect (7)-(9) short-run results of the PMG model (8)-(10) long-run results of the PMG model Clustered t-stats are in parenthesis for (1),(2),(3),(4),(7),(8),(9),(10) and bootstrap z-stats in parenthesis for (5),(6) *, ** and *** indicate 10%, 5% and 1% significance, respectively.

Furthermore, ***Table 2.14*** presents the results for medium skilled EU, non-EU and total migration share, respectively. The capital inputs found to be always positive and significant across all ***Models (1)-(10)***. EU, non-EU and total migration share as well as labour and capital inputs are found to be positive and significant in the OLS results – that is ***Model (1)-(2),*** although biased. Both the FE and FD results suggest no significance of medium skilled EU/non-EU/total migration share as a determinant of productivity as can be seen from ***Model (3)-(4) and Model (5)-(6)*** of ***Table 2.14***. Short run results – that are ***Model (7)*** and ***(9)*** of ***Table 2.14***, showed significance of inputs but no significance for EU, non-EU or total migration share. Finally, the long-run results - that is ***Model (8)*** and ***(10)***. - suggest that both labour and capital input variables significantly contribute to productivity, while medium skilled EU migration has negative and significant impact on productivity. However, non-EU migration share has significant contribution to productivity, which is the same for total migration share.

Table2.14 Value added regressions for Medium Skilled Netherlands

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\log VA_{it}$	**OLS**	**OLS**	**FE**	**FE**	**FD**	**FD**	**PMG-SR**	**PMG-LR**	**PMG-SR**	**PMG-LR**
$\log HRS_{it}$	0.341*** (0.0145)	0.341*** (0.0146)	0.425 (0.332)	0.425 (0.332)	0.0642 (2.285)	0.0599 (2.348)	0.698*** (0.136)	0.243*** (0.00732)	0.622*** (0.120)	0.280*** (0.00805)
$\log Cap_{it}$	0.528*** (0.0156)	0.527*** (0.0154)	0.666*** (0.0954)	0.666*** (0.0952)	0.347*** (0.124)	0.347*** (0.125)	0.348*** (0.0781)	0.757*** (0.00732)	0.373*** (0.0684)	0.720*** (0.00805)
$EUMigShr_{it}$	0.180*** (0.398)		0.386 (0.275)		0.108 (1.108)		0.205 (0.244)	-0.281*** (0.0683)		
$NEUMigShr_{it}$	-0.0335 (0.844)		1.617 (0.806)		0.983 (1.228)		0.011 (1.238)	0.302*** (0.336)		
$MigShr_{it}$		0.822*** (0.207)		0.460 (0.293)		0.151 (0.604)			0.369 (0.794)	0.799*** (0.210)
Constant	3.254*** (0.157)	3.254*** (0.157)	1.516 (1.472)	1.536 (1.473)	0.0309* (0.0173)	0.0310* (0.0179)	0.0259 (0.0490)	-0.0398 (0.0505)	-0.0048 (0.186)	-0.0040 (0.0378)
N	210	210	210	210	195	195	210	210	210	210
R^2	0.892	0.891	0.848	0.848						

(1)-(2) present OLS results, (3)-(4) is the time fixed effect, (5)-(6) the first differenced effect (7)-(9) short-run results of the PMG model (8)-(10) long-run results of the PMG model Clustered t-stats are in parenthesis for (1),(2),(3),(4),(7),(8),(9),(10) and bootstrap z-stats in parenthesis for (5),(6) *, ** and *** indicate 10%, 5% and 1% significance, respectively.

When it comes to the results with low skilled migration share, similar to the results for medium skilled EU, non-EU and total migration share, we observe no significance of low skilled migration in the short run which can be seen from ***Model (7)*** and ***(9)*** of ***Table 2.15.***In the long run, however, although both significant, EU and non-EU migration shares operates in opposite direction, where the latter is positive, ***Model (8)*** and ***(10).*** Repeatedly, capital input is always found to be a positive and significant determinant of productivity across Models ***(1)-(10)*** of ***Table 2.15***. In contrast to high skilled migrants, both medium and low skilled EU migration shares have negative and significant impact on productivity, in the long run. This effect is positive but insignificant in the short run. This makes us consider that in Netherlands, EU migrants with medium or low skills do not accommodate themselves into more demanding and less paid jobs unlike non-EU migrants. The positive and significant effect of the low skilled EU/non-EU/total migration share makes us consider that the Netherlands is in need of low skilled workers. Thus, implementing this scarcity across firms might have a significant contribution on productivity.

In general, it can be said that apart from low and medium skilled EU migration share, migration seems to have a positive and quite significant effect on the gross value added in the Netherlands.

Table2.15 Value added regressions for Low Skilled Netherlands

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\log VA_{it}$	**OLS**	**OLS**	**FE**	**FE**	**FD**	**FD**	**PMG-SR**	**PMG-LR**	**PMG-SR**	**PMG-LR**
$\log HRS_{it}$	0.341*** (0.0141)	0.344*** (0.0145)	0.439 (0.332)	0.445 (0.334)	0.0419 (3.137)	-0.0312 (8.889)	0.650*** (0.134)	0.220*** (0.0173)	0.636*** (0.125)	0.284*** (0.0102)
$\log Cap_{it}$	0.525*** (0.0157)	0.530*** (0.0155)	0.662*** (0.0974)	0.668*** (0.0959)	0.345** (0.153)	0.344 (0.245)	0.370*** (0.0755)	0.780*** (0.0173)	0.374*** (0.0696)	0.716*** (0.0102)
$EUMigShr_{it}$	0.323*** (0.112)		1.064 (0.968)		0.260 (1.227)		0.260 (0.411)	-0.460*** (0.456)		
$NEUMigShr_{it}$	-0.302 (0.929)		-2.196 (2.109)		0.0302 (1.613)		0.325 (2.117)	0.390*** (1.279)		
$MigShr_{it}$		1.202** (0.507)		0.298 (0.563)		0.213 (1.646)			0.170 (1.069)	0.625*** (0.576)
Constant	3.302*** (0.158)	3.213*** (0.157)	1.516 (1.494)	1.402 (1.485)	0.0313 (0.0266)	0.0320 (0.0545)	-0.0125 (0.0409)	-0.0010 (0.0428)	-0.0384 (0.186)	-0.0079 (0.0365)
N	210	210	210	210	195	195	180	180	180	180
R^2	0.892	0.890	0.847	0.846						

(1)-(2) present OLS results, (3)-(4) is the time fixed effect, (5)-(6) the first differenced effect (7)-(9) short-run results of the PMG model (8)-(10) long-run results of the PMG model Clustered t-stats are in parenthesis for (1),(2),(3),(4),(7),(8),(9),(10) and bootstrap z-stats in parenthesis for (5),(6) *, ** and *** indicate 10%, 5% and 1% significance, respectively.

2.4.2.4. Results for Germany

Germany comes with multiple caveats which must be explained. First of all, the EU LFS database only provides data for migration share only for 2002-2008. A seven-year time period might not be enough to analyse such panel data. Secondly, as explained in ***Section 2.4.1***, Germany had a massive EU migration influx after the 2004 EU accession, especially after 2007. We, additionally, control for the sudden increase particularly after 2007 in the share of EU migrants and set a dummy that is equal to 1 for the year 2007 and 2008, and zero otherwise. Also, for the long-run results we are not able to use PMG for the reasons we explained in ***Section 2.4***. In order to picture the long-run trend, we apply another pooled estimator, the Dynamic Fixed Effect (DFE). One difference of DFE in comparison to PMG is that it constrains both the short- and long-run coefficients to be identical. For all these reasons, therefore, one should be careful when interpreting the results for Germany.

Table 2.16 present the results for EU, non-EU and total migration share. As can be seen from short and long run DFE models, which are ***Model (7)-(8)*** of ***Table 2.16***, the effect of non-EU migration share is negative both in the short run and in the long run, although it does not seem to have a significant effect on the output. EU migration share, however, operates in the opposite direction, and yet no significance is observed both in the short and long run. When it comes to the total migration share, both short and long run DFE results, which are ***Model (9)-(10)*** of ***Table 2.16*** suggest again that there is no significant impact of migration share on productivity in Germany, in the short run and in the long run. These long-run effects might have been significant if firms were not measured as identical, or if we were to have more time period available. Only, the FE results – ***Model (3)*** of ***Table 2.16 -*** suggest a positive and significant effect of the EU/total migration share on productivity, but no significance is detected for the non-EU migration share. Apart from the FD results – ***Model (5)***and ***(6)*** of

Table 2.16, the labour input variable, which is total hours worked by employees, is found to be a significant determinant of productivity across all ***Models (1)-(10)*** Capital input variables are found to be significant across all ***Models (1)-(10)***. Time dummy seem to be significant in the short run but insignificant in the long run. This may suggest that the sudden change in the composition of the labour market had affected productivity in the short run, but this mix settled down in the longer period so no more significance of the change observed in the long run. In contrast with the results, we expected to see a significant impact of migration on productivity in Germany, as it has hosted a significant number of immigrants from all around the world. This might be related to the survey by Winkelman (2001), in that native workers believe that immigrants are recruited because of the lack of skilled labours across firms in Germany, but they do not work as hard as they are expected. Thus, migrant workers fill in the scarcity but do not work hard enough to contribute to productivity. We also fail to see any remarkable results in the FD model- that is ***Model (5)-(6)*** of ***Table 2.16***. In fact, FD results suggest no significance across all series, apart from capital input, in which we strongly believe that this might be the result of the very limited number of observations.

Table2.16 Value added regressions for Germany

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\log VA_{it}$	**OLS**	**OLS**	**FE**	**FE**	**FD**	**FD**	**DFE-SR**	**DFE-LR**	**DFE-SR**	**DFE-LR**
$\log HRS_{it}$	0.479*** (0.0517)	0.472*** (0.0515)	0.903*** (0.0120)	0.911*** (0.0111)	0.940 (1.715)	0.940 (1.578)	0.920*** (0.0318)	0.800*** (0.0740)	0.922*** (0.0295)	0.796*** (0.0679)
$\log Cap_{it}$	0.355*** (0.0318)	0.352*** (0.0334)	0.155*** (0.0236)	0.154*** (0.0234)	0.129 (0.0925)	0.128* (0.0754)	0.113*** (0.0417)	0.200*** (0.0740)	0.116*** (0.0376)	0.204*** (0.0679)
$EUMigShr_{it}$	0.404 (2.551)		0.297* (0.146)		0.172 (2.840)		0.161 (0.242)	0.789 (1.085)		
$NEUMigShr_{it}$	-0.582 (1.294)		-0.0198 (0.0865)		-0.0900 (0.610)		-0.0302 (0.118)	-0.085 (0.141)		
$MigShr_{it}$		-0.311 (0.665)		0.110 (0.105)		-0.128 (0.332)			0.0712 (0.185)	0.469 (0.454)
$D2007$	0.031 (0.081)	0.029 (0.090)	0.068** (0.032)	0.071** (0.028)	0.018* (0.012)	0.019* (0.015)	0.012* (0.019)	0.011 (0.014)	0.034* (0.016)	0.036 (0.017)
Constant	4.300*** (0.273)	4.366*** (0.271)	2.877*** (0.160)	2.815*** (0.157)	0.0129 (0.0284)	0.0130 (0.0198)	1.142 (0.704)	-0.326** (0.145)	1.093 (0.687)	-0.323** (0.149)
N	105	105	105	105	90	90	90	90	90	90
R^2	0.862	0.860	0.977	0.977						

(1)-(2) present OLS results, (3)-(4) is the time fixed effect, (5)-(6) the first differenced effect (7)-(9) short-run results of the DFE model (8)-(10) long-run results of the DFE model Clustered t-stats are in parenthesis for (1),(2),(3),(4),(7),(8),(9),(10) and bootstrap z-stats in parenthesis for (5),(6) *, ** and *** indicate 10%, 5% and 1% significance, respectively.

We disaggregated migration shares into their skill level as high, medium and low skilled ones and presented them in ***Tables 2.17-2.19***. To begin with, ***Table 2.17*** presents the results for high skilled EU, non-EU and total migration share. We fail to observe any significant impact of migration share in the short run that is ***Model (7) and (9))*** of ***Tables 2.17.*** Furthermore, we still see no evidence for significance in the long run- ***Model (8)and (10)*** of ***Tables 2.17,*** although the sign of the coefficients remains positive for high skilled EU migrants share and negative for both high skilled non-EU and high skilled total migration share..

The results of the OLS that is ***Model (1)-(2)*** from ***Table 2.17*** in terms of significance repeat for high skilled immigrants for EU and total migrant share, only here, the non-EU migration share displays a negative and significant effect on productivity, yet biased. Time dummy - $D2007$ seem to be positive and significant in the short run, but insignificant in the long run from ***Models (7)-(10)*** of ***Table 2.17***. Again, the sudden change in the composition of the labour market had affected productivity in the short run but in a longer time this affect diminished.

Table2.17 Value added regressions for High Skilled Germany

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\log VA_{it}$	**OLS**	**OLS**	**FE**	**FE**	**FD**	**FD**	**DFE-SR**	**DFE-LR**	**DFE-SR**	**DFE-LR**
$\log HRS_{it}$	0.476*** (0.0491)	0.466*** (0.0513)	0.886*** (0.0194)	0.906*** (0.0179)	0.903 (2.326)	0.958 (1.530)	0.917*** (0.0386)	0.807*** (0.0770)	0.923*** (0.0301)	0.798*** (0.0661)
$\log Cap_{it}$	0.365*** (0.0310)	0.353*** (0.0334)	0.154*** (0.0237)	0.154*** (0.0234)	0.134 (0.127)	0.126* (0.0743)	0.110** (0.0464)	0.193** (0.0770)	0.118*** (0.0344)	0.202*** (0.0661)
$EUMigShr_{it}$	0.398 (0.296)		0.626** (0.682)		0.517 (0.701)		0.2926 (0.406)	0.9548 (0.1412)		
$NEUMigShr_{it}$	-0.404** (16.82)		0.114 (1.912)		-0.177 (0.241)		-0.1930 (0.1925)	-0.2824 (0.3270)		
$MigShr_{it}$		-0.658 (17.42)		1.929 (2.143)		-4.135 (8.119)			0.125 (0.2214)	0.3555 (0.5639)
$D2007$	0.028 (0.079)	0.026 (0.092)	0.071** (0.031)	0.074** (0.030)	0.020* (0.013)	0.017* (0.019)	0.014* (0.020)	0.013 (0.014)	0.033* (0.018)	0.034 (0.019)
Constant	4.242*** (0.268)	4.386*** (0.274)	3.007*** (0.142)	2.858*** (0.144)	0.0114 (0.0505)	0.0145 (0.0210)	1.205 (0.769)	-0.327** (0.138)	1.060 (0.708)	-0.312** (0.148)
N	105	105	105	105	90	90	90	90	90	90
R^2	0.868	0.859	0.977	0.977						

(1)-(2) present OLS results, (3)-(4) is the time fixed effect, (5)-(6) the first differenced effect (7)-(9) short-run results of the DFE model (8)-(10) long-run results of the DFE model Clustered t-stats are in parenthesis for (1),(2),(3),(4),(7),(8),(9),(10) and bootstrap z-stats in parenthesis for (5),(6) *, ** and *** indicate 10%, 5% and 1% significance, respectively.

As to the medium skilled migration share ***Table 2.18*** presents the results for medium skilled EU, non-EU, and total migration share. The OLS results –that is ***Model (1)-(2)*** show negative yet insignificant effect of medium skilled non-EU and total migration share, and positive but insignificant effect of medium skilled EU migration share, although biased.

We fail to observe any significance of medium skilled EU/non-EU/ total migration share both in the short run – ***Model (7) and (9)*** of ***Table 2.18*** and in the long run –that is ***Model (8) and (10)*** of ***Table 2.18***. Again, we believe that if we were to have sufficient observations, both the short run and long-run DFE - ***Model (7)*** and ***(9)*** and ***Model (8)*** and ***(10)*** of ***Table 2.18*** results would be more satisfactory and factual. The results for time dummy remains same in here, that is positive and significant in the short and positive but insignificant in the long run.

Table2.18 Value added regressions for Medium Skilled Germany

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\log VA_{it}$	**OLS**	**OLS**	**FE**	**FE**	**FD**	**FD**	**DFE-SR**	**DFE-LR**	**DFE-SR**	**DFE-LR**
$\log HRS_{it}$	0.484*** (0.0533)	0.480*** (0.0517)	0.901*** (0.0138)	0.908*** (0.0129)	0.943 (1.444)	0.941 (1.563)	0.921*** (0.0331)	0.797*** (0.0790)	0.922*** (0.0289)	0.795*** (0.0687)
$\log Cap_{it}$	0.352*** (0.0322)	0.351*** (0.0334)	0.155*** (0.0240)	0.155*** (0.0237)	0.127* (0.0768)	0.127 (0.0783)	0.112*** (0.0423)	0.203** (0.0790)	0.117*** (0.0360)	0.205*** (0.0687)
$EUMigShr_{it}$	0.922 (4.668)		0.764** (0.355)		-0.507 (3.823)		0.397 (0.638)	0.2050 (0.2387)		
$NEUMigShr_{it}$	-0.2483 (0.2444)		0.289 (0.274)		-0.302 (1.145)		-0.0507 (0.309)	0.0385 (0.581)		
$MigShr_{it}$		-1.151 (0.970)		0.413 (0.306)		-0.351 (0.635)			0.117 (0.432)	0.1072 (0.1229)
$D2007$	0.029 (0.068)	0.026 (0.088)	0.021** (0.033)	0.069** (0.031)	0.021* (0.015)	0.019* (0.015)	0.013 (0.015)	0.012 (0.013)	0.029 (0.019)	0.031 (0.019)
Constant	4.301*** (0.281)	4.345*** (0.270)	2.876*** (0.152)	2.831*** (0.154)	0.0135 (0.0247)	0.0135 (0.0203)	1.135 (0.710)	-0.327** (0.147)	1.070 (0.681)	-0.320** (0.153)
N	105	105	105	105	90	90	90	90	90	90
R^2	0.861	0.860	0.977	0.977						

(1)-(2) present OLS results, (3)-(4) is the time fixed effect, (5)-(6) the first differenced effect (7)-(9) short-run results of the DFE model (8)-(10) long-run results of the DFE model Clustered t-stats are in parenthesis for (1),(2),(3),(4),(7),(8),(9),(10) and bootstrap z-stats in parenthesis for (5),(6) *, ** and *** indicate 10%, 5% and 1% significance, respectively.

Finally, ***Table 2.19*** presents the results with low skilled EU/ non-EU and total migration share. The OLS results –***Model (1)-(2)*** of the low skilled migration share as presented in ***Table 2.19***, apart from the EU migrant share, neither the non-EU nor total migration share seem to affect productivity, although the coefficient of non-EU and total migration share is negative. No significance of the low skilled migration share is observed for the EU/non-EU/total migration share in either the short run- ***Model (7)*** and ***(9)*** of ***Table 2.19*** and in the long run- ***Model (8)*** and ***(10)*** of ***Table 2.19***. Repeatedly, labour input seems to be always positive and significant apart from in FD – ***Model (5)-(6).***. The results for time dummy remains same in here as well, that is positive and significant in the short and positive but insignificant in the long run.

Table2.19 Value added regressions for Low Skilled Germany

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\log VA_{it}$	**OLS**	**OLS**	**FE**	**FE**	**FD**	**FD**	**DFE-SR**	**DFE-LR**	**DFE-SR**	**DFE-LR**
$\log HRS_{it}$	0.473*** (0.0554)	0.472*** (0.0540)	0.911*** (0.0114)	0.918*** (0.00850)	0.933 (1.845)	0.935 (1.630)	0.916*** (0.0323)	0.796*** (0.0798)	0.919*** (0.0264)	0.793*** (0.0691)
$\log Cap_{it}$	0.352*** (0.0329)	0.351*** (0.0338)	0.155*** (0.0238)	0.154*** (0.0234)	0.129 (0.0975)	0.128* (0.0766)	0.117*** (0.0416)	0.204** (0.0798)	0.120*** (0.0381)	0.207*** (0.0691)
$EUMigShr_{it}$	0.1236 (0.145)		1.231 (1.112)		-0.261 (19.92)		0.1482 (0.2368)	0.3342 (0.5056)		
$NEUMigShr_{it}$	-0.2962 (0.7842)		-0.267 (0.420)		-0.235 (3.748)		0.0867 (0.436)	0.1227 (0.1242)		
$MigShr_{it}$		-1.483 (1.712)		0.0601 (0.464)		-0.305 (2.851)			0.464 (0.736)	0.2304 (0.1932)
$D2007$	0.024 (0.080)	0.023 (0.085)	0.067** (0.031)	0.070** (0.029)	0.025* (0.017)	0.016* (0.019)	0.015* (0.019)	0.014 (0.017)	0.030* (0.014)	0.028 (0.015)
Constant	4.360*** (0.283)	4.372*** (0.274)	2.821*** (0.156)	2.772*** (0.165)	0.0124 (0.0263)	0.0126 (0.0206)	1.101* (0.654)	-0.319** (0.137)	1.072 (0.652)	-0.320** (0.147)
N	105	105	105	105	90	90	90	90	90	90
R^2	0.860	0.860	0.977	0.977						

(1)-(2) present OLS results, (3)-(4) is the time fixed effect, (5)-(6) the first differenced effect (7)-(9) short-run results of the DFE model (8)-(10) long-run results of the DFE model Clustered t-stats are in parenthesis for (1),(2),(3),(4),(7),(8),(9),(10) and bootstrap z-stats in parenthesis for (5),(6) *, ** and *** indicate 10%, 5% and 1% significance, respectively.

2.4.3. Robustness Checks

We run all robustness check separately for each individual country. As a first robustness check, we calculate the multi-factor productivity (thereafter MFP) based on MFP measurement in Timmer *et al*. (2007b) and Gullickson and Harper (1999), that is the gross value added minus both capital and labour input. The necessary element for this calculation is taken from the 2008 MArch release of the EU KLEMS database.

In order to see how EU and non-EU migration share affects multi-factor productivity, we run the following regression:

$$\Delta MFP_{it} = \beta_0 + \beta_1 EUMigShr_{it} + \beta_2 NEUMigShr_{it} + \varepsilon_{it} \qquad \textbf{(2.8)}$$

The results are as follows:

2.4.3.1 Robustness Check: Multi-factor Productivity

<u>The UK and MFP:</u> ***Model (1)*** of ***Table 2.20*** presents the OLS results for total migration share regardless of skill level. ***Models (2), (3)*** and ***(4)*** are disaggregated models of high, medium and low skilled migration shares respectively. Across all models, the sign of the coefficients remains the same as the OLS result for the EU and non-EU migration share. In fact, for the medium skilled EU migration shares and low skilled non-EU migration share, the results improve in significance. However, the coefficients of the low skilled EU migration share seem to be insignificant here, though positive.

Table2.20 MFP Regression Results for EU and non-EU immigrants in the UK

Dep var: *MFP*	**(1)**	**(2)**	**(3)**	**(4)**
$EUMigShr_{it}$	0.314* (0.109)	0.578** (0.196)	0.479** (0.173)	0.437 (0.591)
$NEUMigShr_{it}$	0.296* (0.142)	0.344* (0.287)	-0.331* (0.291)	0.221* (0.153)
Constant	5.168*** (0.201)	6.101*** (0.159)	6.028*** (0.201)	5.767*** (0.186)
R^2	0.09	0.07	0.08	0.05
N	208	208	208	208

(1)Total EU and non-EU Migrants (2) High Educated EU and non-EU Migrants (3) Medium Educated EU and non-EU Migrants (4) Low educated EU and non-EU Migrants. Clustered t-stats in parenthesis.*, ** and *** indicate 10%, 5% and 1% significance, respectively.

<u>Spain and MFP:</u> As for Spain, ***Table 2.21*** illustrates the OLS results with all migrant shares without distinction of skill- ***Model (1),*** and high, medium and low skilled migration shares in ***Models (2), (3)*** and ***(4)***, respectively. In all models presented below, the sign of the coefficients remains the same as the OLS model results with the EU and non-EU migration share. Some coefficients lose significance while others improve.

Table2.21 MFP Regression Results for EU and non-EU immigrants in Spain

Dep var: *MFP*	**(1)**	**(2)**	**(3)**	**(4)**
$EUMigShr_{it}$	0.478** (0.114)	-0.112 (0.110)	0.231** (0.481)	0.173* (0.054)
$NEUMigShr_{it}$	0.121* (0.116)	0.131* (1.012)	0.115** (0.514)	0.301 (1.462)
Constant	-3.039*** (0.131)	-3.894*** (0.186)	-3.101*** (0.119)	-3.796*** (0.134)
R^2	0.05	0.03	0.05	0.04
N	210	210	210	210

(1)Total EU and non-EU Migrants (2) High Educated EU and non-EU Migrants (3) Medium Educated EU and non-EU Migrants (4) Low educated EU and non-EU Migrants. Clustered t-stats in parenthesis.*, ** and *** indicate 10%, 5% and 1% significance, respectively.

<u>The Netherlands and MFP:</u> As can be seen from ***Table 2.22***, the signs of the coefficients remain the same as the OLS results of Netherlands with the EU and non-EU migrant share as well as high-medium-low skilled migrants, although it loses significance in most cases.

Table2.22 MFP Regression Results for EU and non-EU immigrants in Netherlands

Dep var: *MFP*	**(1)**	**(2)**	**(3)**	**(4)**
$EUMigShr_{it}$	0.713 (0.567)	0.174 (0.500)	0.162 (0.149)	0.141 (0.578)
$NEUMigShr_{it}$	0.457** (0.173)	0.601 (0.782)	-0.764** (0.294)	-0.403 (0.876)
Constant	5.197*** (0.124)	5.124*** (0.111)	5.201*** (0.146)	5.024*** (0.121)
R^2	0.05	0.03	0.03	0.03
N	206	206	206	206

(1)Total EU and non-EU Migrants (2) High Educated EU and non-EU Migrants (3) Medium Educated EU and non-EU Migrants (4) Low educated EU and non-EU Migrants. Clustered t-stats in parenthesis.*, *, ** and *** indicate 10%, 5% and 1% significance, respectively.

<u>Germany and MFP:</u> Similar to other countries, the sign of the coefficients remains the same for Germany when comparing the OLS results of Germany with EU and non-EU migration shares as well as the results with high, medium and low skilled migration shares, as can be seen from ***Table 2.23*** below, while the significance of the coefficients loses power.

Table2.23 MFP Regression Results for EU and non-EU immigrants in Germany

Dep var: *MFP*	**(1)**	**(2)**	**(3)**	**(4)**
$EUMigShr_{it}$	0.116 (0.118)	0.224** (0.091)	0.242* (0.261)	0.316* (0.654)
$NEUMigShr_{it}$	-0.658 (0.905)	-0.119 (0.127)	-0.141 (0.208)	-0.647 (0.469)
Constant	5.591*** (0.102)	5.573*** (0.112)	5.607*** (0.108)	5.586*** (0.104)
R^2	0.01	0.01	0.01	0.02
N	95	95	95	95

(1)Total EU and non-EU Migrant (2)High Educated EU and non-EU Migrant (3)Medium Educated EU and non-EU Migrant (4)Low educated EU and non-EU Migrant. Clustered t-stats in parenthesis.*, **, and *** indicate 10%, 5% and 1% significance, respectively.

As another robustness check, we also check the short run of the DFE results for the UK, Spain and Netherlands to see how it differs from FE results. In other words, we aim to see how the short and long run DFE results vary from FE models when industries are assumed to be identical. Find the ***Table 2.28-2.35*** in ***Appendix I****.* As explained in ***Section 2.4***, for Germany we already applied DFE in replacement of PMG. Thus, we discuss about DFE and FE results for Germany from the ***Tables 2.16-2.19,*** in the end of this section.

<u>The UK and short-run DFE;</u> ***Model (1)*** of ***Table 2.28*** in ***Appendix I*** presents the results with EU and non-EU migrant share, ***Models (2), (3)*** and ***(4)*** are with the high, medium and low skilled EU and non-EU migrant share in the UK, respectively. As can be seen from ***Model (1)*** of ***Table 2.28***, the coefficient of short run DEF results remain same as regular FE which is presented in ***Model (3)*** of ***Table2.4***.In fact, the significance improves for capital input variable. As to high skilled EU and non-EU migration share, ***Model (2)*** of ***Table 2.28*** shows that the sign of the coefficients remains same with regular FE results. However, the EU migration share loses its significance while non-EU migration share becomes stronger in significance. The coefficients for the medium skilled EU and non-EU migration share- ***Model (3)*** of ***Table 2.28*** remains same with regular FE results, in fact most variables improves in significance. As can be seen from ***Model(4)*** of ***Table 2.28***, when comparing regular FE with DFE results for low skilled EU and non-EU migration share, as well as the coefficients remain same, it in fact improves in terms of significance. . ***Table 2.29*** present the same models for total migration share. ***Model (1),*** presents the model with total migration share without distinction of skill level, and ***Model (2), (3), (4)*** presents the models with high, medium and low skilled total migration share, respectively. As can be seen from ***Model (1)*** of ***Table2.29*** the coefficients of all series of DFE results remain same as regular FE which is presented in ***Table 2.4-2.7***. In fact, the significance improves much more for the capital and labour input variable, while still no significance is present for migration share. As to the high skilled total migration share ,***Models (2)*** in ***Table 2.29*** present the results where the capital and labour input variable as well as migration share variable becomes more significant compared to regular FE models – that is, ***Model (4)*** of ***Tables 2.4- 2.7***. The short run DFE results for medium skilled migration share- ***Model (3)*** of ***Table 2.29***, is not much different from regular FE- ***Model (3)*** of ***Table 2.4-2.7***. As to the results for low skilled migration rate-

Model (4) - ***Table 2.29***, the coefficients for the input variables remain same and improve in significance. However, the sign for low skilled migration changes from positive to negative while remaining insignificant.

Spain and short-run DFE: ***Model (1)*** of ***Table 2.30*** presents the results with EU and non-EU migration share, ***Models (2), (3)*** and ***(4)*** with the high, medium and low skilled EU and non-EU migration share in Spain. The regular FE results with industry distinction in Spain, presented in ***Model (3)*** of ***Tables 2.8,*** in *Section 2.4.2.2.,* suggest no significance for non-EU migration share. However, the DFE results - which assume all firms are identical - provide significant results, as can be seen in ***Models (1)*** in ***Table 2.30,*** while the sign of all coefficients and significance for other variables remains the same. ***Model (2)*** of ***Table 2.30*** presents the models with high skilled EU and non-EU migration share. Here, although the sign of the coefficients of short run DFE remain same as regular FE- which is presented in ***Model (3)*** of ***Table 2.9***, we see that high skilled EU and non-EU migration share variables lose their significance. Similarly, the short run DFE results for medium skilled EU and non-EU migration share- ***Model (3)*** of ***Table 2.30*** provides us that apart from the coefficients remaining the same, the significance for migration share variables improves in comparison to regular FE. We observe the same pattern for the low skilled EU and non-EU migration share- ***Model (4)*** of ***Table 2.30***

Furthermore, ***Model (1)*** of ***Table 2.31*** presents the results with total migration share, ***Model (2), (3)*** and ***(4)*** presents the short run DFE results of high, medium and low skilled total migration share. The pattern is same across all ***Models (1)-(4)***, that the sign of the coefficient remains same. In fact, the migration shares across models become significant in short run DFE results in comparison to regular FE. This might be due to the fact that the firms are assumed to be identical, because migrants have different effects across different firms, and one should take this difference into account when analysing the actual effects.

<u>The Netherlands and short-run DFE:</u> ***Table 2.32*** present the short run DFE results for EU and non-EU migration share- ***Model (1),*** high skilled EU and non-EU migration share- ***Model (2),*** medium skilled EU and non-EU migration share- ***Model (3)*** , and finally low skilled EU and non-EU migration share- ***Model (4)***. Labour input variable becomes significant in the short run DFE, comparing to FE in all ***Models (1)-(4)***. EU migration share becomes significant, while non-EU migration share lose significance ***Model (1)-(2***), although the sign of them remains same. Both medium skilled EU and non-EU migration share becomes stronger in terms of significant as can be seen from ***Model (3),*** however the still no significance is observed for low skilled EU and non-EU migration share- ***Model (4)***,although the sign of the coefficients remain same.

Table 2.33 presents models with total migration share- ***Model (1)*** as well as high, medium and low skilled total migration share, ***Model (1), (2)*** and ***(3),*** respectively. In all cases, labour input variables improves in significance in short run DFE models in comparison to regular FE results. Apart from the model with low skilled migration share- ***Model (4)***, total migration share becomes significant in the short run DFE models when comparing to FE results.

<u>Germany and short-run DFE:</u> ***Table 2.34*** presents the short run DFE models with EU and non-EU migration share- ***Model (1),*** and high, medium, low skilled EU and non-EU migration share- ***Model (2), (3),*** and ***(4),*** respectively. Labour input variables, are almost identical in all ***Models (1)-(4).*** Same applies for capital inputs variables in most cases. The sign of the coefficients remain same for each variable, although some loses significance in the short run DFE models.

Table 2.35 present the short run DFE models with total migration share- ***Model (1)***, high, medium and low skilled total migration share- ***Model (2), (3),*** and ***(4).*** Both capital and labour input variables keeps the significance in the short run DFE models as in FE results. Also, time dummy appears to be stronger in DFE results in comparison to FE results.

In general, our results for the UK, Spain, the Netherlands and Germany suggest robustness to many specifications

2.5. Conclusion

The effect of migration on productivity at industrial level varies in the UK, Spain, the Netherlands and Germany. Investigating productivity effects led us to divide this effect into short- and long-run periods, as productivity changes from migration share might take several years to play out thus short run and long run results might act differently. Also, in order to investigate whether EU and non-EU migrants have dissimilar productivity effects, we disaggregated total migration into EU and non-EU migrants. Similarly, in order to investigate whether the skill level of migrants would have similar effects, we disaggregated all migrants as low, medium and high skilled.

The results for the UK showed that migration has a positive and significant effect on the productivity of industries in the long run, particularly those who are highly educated non-EU migrants. The effect of EU migrants, however, appears to be negative both in the short run and long run, although insignificant. When disaggregating migrants by skill level both high and low skilled migrants have a positive and significant correlation with value added. When it comes to medium skilled migrants, this effect seems to be quite the opposite both for EU and non-EU migrants. This might be the fact that, migrants in medium skilled do upgrade their jobs to high skilled ones once they gain enough experience. When it comes to Spain, the effect of migration on the productivity of firms in the short run seems to be positive and significant, only for high and medium skilled non-EU migrants. In the long run, we still observe the significant contribution of non-EU migration to productivity. However, the impact of EU migration share on productivity operates in opposite direction, and still significant. The different effect of skilled migrants from EU and non-EU might be the results of labour market requirements in Spain. Moreover, as an EU member country, Spain might have similar technology to other EU countries, thus EU migrants might not have difficulty adapting to the Spanish labour market, but this enable them to be more mobile comparing to non-EU migrants, so the effect of the EU migrant share is observed rather negative.. Although the catching up process for technology for non-EU migrants might take longer than the EU migrants, the positive and significant results of non-EU migrants might suggest that they have more restrictions in terms of moving from one job to another, thus they start making progress to secure the job they have.

The results for both the UK and Spain suggested that labour inputs is always a significant and positive determinant of value added, this is varying for capital inputs.

As to the Netherlands, the effect of migration on productivity in the short run is positive and significant for EU migrants only. In the long run, the effects of EU and total migrants have a significant effect on the productivity of firms in the Netherlands. Only non-EU migrants seem to have negative and significant effect on productivity. From the descriptive statistics presented in ***Table 2.26*** in ***Appendix H***, some of the industries might have up to 62% of their employees from EU; this has never exceeded 17% for non-EU migrants. Thus, this may be explained that the labour market is more prone to EU migrants than non-EU so the effect is rather positive.

Finally for Germany, there are several cautions to be considered when interpreting the results. Neither a short-run nor a long-run effect of migration on the productivity of firms was found to be significant, although mostly positive. This is interesting, particularly because of the change in labour composition after 2007. The time dummy seem to have positive and significant effect on the value added, but this does not reflected to the migration share effect on productivity. We believe, this is mostly due to the fact that the number of observations is not enough to carry out such analysis. As the number of observations is already low, we were not able to take the lag length suggested by AIC. For the long-run analysis, we were not able we applied long run DFE instead of PMG.

All in all, the Netherlands appears to be the only country that shows significance of EU migration share on productivity of firms in the short run. Splitting the EU and non-migration share allow us to see that the direction of their effect on productivity is opposite in most cases. The coefficient of the total migration share appears to be less than EU and non-EU migration share when splitting up, although significance remains same. The fact that the results for the impact of high educated migration share is always positive and significant, apart from Germany, might be result of high skilled migration prone migration laws across developed countries. In Germany, although we found no significance, having positive sign for total migration share without distinction of education make us consider that if we had more observations, we could have seen more accurate figure

APPENDIX H

Table2.24 Descriptive Statistics for UK

Variable	Obs	Mean	Std.Dev.	Min	Max
Value added	210	61478.4	37213.41	7915	152849
Hours worked	210	3212.264	2443.395	121.6678	8712.018
Capital	210	19528.21	18972.77	12.66508	102573.1
EU-migrants	210	0.023848	0.023989	0.003891	0.139535
Non-EU migrants	210	0.062036	0.124581	0.001957	0.6875
Total migrants	210	0.082979	0.141953	0.007035	0.75
Low educated migrants	210	0.010601	0.014055	0.00077	0.0816
Medium educated migrants	210	0.047956	0.080574	0.003494	0.443857
High educated migrants	210	0.026687	0.058106	0.000943	0.34375

Table2.25 Descriptive Statistics for Spain

Variable	Obs	Mean	Std.Dev.	Min	Max
Value added	210	42509.75	29711.62	1611.217	138178
Hours worked	210	1839.057	1518.152	64.3178	5656.352
Capital	210	16174.35	13819.44	342.7132	62841
EU-migrants	210	0.011755	0.04093	0.000211	0.34512
Non-EU migrants	210	0.029464	0.054349	0.000238	0.346273
Total Migrants	210	0.039789	0.070103	0.000476	0.5
Low educated migrants	210	0.022199	0.037284	0.000157	0.243553
Medium educated migrants	210	0.008022	0.014803	0.000124	0.099349
High educated migrants	210	0.000503	0.002074	0.000001	0.01241

Table2.26 Descriptive Statistics for Netherlands

Variable	Obs	Mean	Std.Dev.	Min	Max
Value added	210	25877.83	16004.87	5113	67700
Hours worked	210	727.8724	570.5508	11.8857	2011.965
Capital	210	9008.549	7699.71	574.2202	38544.41
EU-migrants	210	0.025972	0.0765	0.001553	0.625
Non-EU migrants	210	0.033497	0.037757	0.007529	0.166667
Total migrants	210	0.055612	0.105593	0.002356	0.777314
Low educated migrants	210	0.014463	0.022634	0.001045	0.247722
Medium educated migrants	210	0.023832	0.045637	0.001189	0.366302
High educated migrants	210	0.004848	0.015611	0.000052	0.117382

Table2.27 Descriptive Statistics for Germany

Variable	Obs	Mean	Std.Dev.	Min	Max
Value added	105	131694.3	110911.1	3840	502420
Hours worked	105	3577.8	2882.071	135	11101
Capital	105	44609.67	60848.47	33.54986	253428.3
EU-migrants	105	0.026607	0.03068	0.002897	0.191
Non-EU migrants	105	0.048563	0.039976	0.004089	0.224299
Total migrants	105	0.074408	0.061702	0.008762	0.333333
Low educated migrants	105	0.015297	0.017273	0.000645	0.069473
Medium educated migrants	105	0.043025	0.032406	0.005179	0.140726
High educated migrants	105	0.004994	0.003971	0.000673	0.023846

APPENDIX I

Table2.28 EU and non-EU migration share in the UK

	(1)	(2)	(3)	(4)
$\log VA_{it}$	DFE-SR	DFE-SR	DFE-SR	DFE-SR
$\log HRS_{it}$	0.437***	0.464***	0.451***	0.420**
	(0.162)	(0.153)	(0.166)	(0.173)
$\log Cap_{it}$	0.274***	0.280***	0.270***	0.291***
	(0.0470)	(0.0514)	(0.0489)	(0.0473)
$EUMigShr_{it}$	0.254	0.361	0.428**	-3.175***
	(0.207)	(0.192)	(0.177)	(0.825)
$NEUMigShr_{it}$	0.0914	0.190**	0.104	0.640***
	(0.0628)	(0.0967)	(0.0931)	(0.143)
Constant	1.021***	1.026***	1.050***	1.127***
	(0.277)	(0.280)	(0.272)	(0.248)

Model (1)-(4) presents the short run DFE model. Model (1), (2), and (3) is high, medium and low skilled with EU and non-EU migration share, respectively. Clustered t-stats are in parenthesis.
*, ** and *** indicate 10%, 5% and 1% significance, respectively.

Table2.29 Total migration share in the UK

	(1)	(2)	(3)	(4)
$\log VA_{it}$	DFE-SR	DFE-SR	DFE-SR	DFE-SR
$\log HRS_{it}$	0.456***	0.466***	0.462***	0.455***
	(0.153)	(0.153)	(0.153)	(0.153)
$\log Cap_{it}$	0.278***	0.281***	0.269***	0.271***
	(0.0489)	(0.0512)	(0.0506)	(0.0511)
$MigShr_{it}$	0.0845	0.174**	0.0727	0.203
	(0.0543)	(0.0817)	(0.0827)	(0.404)
Constant	1.043***	1.036***	1.048***	1.111***
	(0.272)	(0.277)	(0.266)	(0.253)

Model (1)-(4) presents the short run DFE model. Model (1), (2), and (3) is high, medium and low skilled with total migration share, respectively. Clustered t-stats are in parenthesis.
*, ** and *** indicate 10%, 5% and 1% significance, respectively.

Table2.30 EU and non-EU migration share in Spain

	(1)	(2)	(3)	(4)
$\log VA_{it}$	DFE-SR	DFE-SR	DFE-SR	DFE-SR
$\log HRS_{it}$	0.468***	0.438***	0.470***	0.462***
	(0.0808)	(0.0871)	(0.0800)	(0.0821)
$\log Cap_{it}$	0.152***	0.149***	0.150***	0.153***
	(0.0480)	(0.0494)	(0.0477)	(0.0480)
$EUMigShr_{it}$	0.514**	-0.233	0.217**	0.453**
	(0.227)	(0.546)	(0.0899)	(0.742)
$NEUMigShr_{it}$	0.259*	0.443	0.202*	0.509
	(0.236)	(0.638)	(0.116)	(0.120)
Constant	-0.223*	-0.293**	-0.241**	-0.222*
	(0.123)	(0.142)	(0.123)	(0.120)

Model (1)-(4) presents the short run DFE models. Model (1), (2), and (3) is high, medium and low skilled with EU and non-EU migration share, respectively. Clustered t-stats are in parenthesis.
*, ** and *** indicate 10%, 5% and 1% significance, respectively.

Table2.31 Total migration share in Spain

	(1)	(2)	(3)	(4)
$\log VA_{it}$	DFE-SR	DFE-SR	DFE-SR	DFE-SR
$\log HRS_{it}$	0.388***	0.454***	0.477***	0.463***
	(0.0632)	(0.0823)	(0.0794)	(0.0790)
$\log Cap_{it}$	0.162***	0.146***	0.147***	0.151***
	(0.0471)	(0.0486)	(0.0469)	(0.0474)
$MigShr_{it}$	0.429*	0.724***	0.194*	0.0321*
	(0.0236)	(0.827)	(0.115)	(0.723)
Constant	-0.126	-0.276**	0.245**	0.209*
	(0.0857)	(0.127)	(0.121)	(0.114)

Model (1)-(4) presents the short run DFE models. Model (1), (2), and (3) is high, medium and low skilled with total migration share, respectively. Clustered t-stats are in parenthesis.
*, ** and *** indicate 10%, 5% and 1% significance, respectively.

Table2.32 EU and non-EU migration share in the Netherlands

	(1)	(2)	(3)	(4)
$\log VA_{it}$	DFE-SR	DFE-SR	DFE-SR	DFE-SR
$\log HRS_{it}$	0.924***	0.924***	0.931***	0.970***
	(0.296)	(0.296)	(0.293)	(0.311)
$\log Cap_{it}$	0.375***	0.375***	0.372***	0.364***
	(0.0924)	(0.0924)	(0.0940)	(0.0921)
$EUMigShr_{it}$	0.0391***	0.0391***	0.127***	0.0876
	(0.00895)	(0.00895)	(0.0263)	(0.147)
$NEUMigShr_{it}$	0.289	0.289	1.136*	-0.159
	(0.275)	(0.275)	(0.688)	(0.402)
Constant	0.192	0.192	0.183	0.196
	(0.173)	(0.173)	(0.187)	(0.219)

Model (1)-(4) presents the short run DFE models. Model (1), (2), and (3) is high, medium and low skilled with total migration share, respectively. Clustered t-stats are in parenthesis.
*, ** and *** indicate 10%, 5% and 1% significance, respectively.

Table2.33 Total migration share in the Netherlands

	(1)	(2)	(3)	(4)
$\log VA_{it}$	DFE-SR	DFE-SR	DFE-SR	FE
$\log HRS_{it}$	0.919***	0.908***	0.932***	DFE-SR
	(0.296)	(0.287)	(0.301)	0.975***
$\log Cap_{it}$	0.376***	0.379***	0.374***	(0.321)
	(0.0906)	(0.0911)	(0.0914)	0.360***
$MigShr_{it}$	0.0337***	0.382***	0.0402**	
	(0.00922)	(0.115)	(0.0184)	0.0372
Constant	0.193	0.197	0.193	(0.114)
	(0.163)	(0.145)	(0.177)	0.209

Model (1)-(4) presents the short run DFE models. Model (1), (2), and (3) is high, medium and low skilled with total migration share, respectively. Clustered t-stats are in parenthesis.
*, ** and *** indicate 10%, 5% and 1% significance, respectively.

Table2.34 EU and non-EU migration share in Germany

	(1)	(2)	(3)	(4)
$\log VA_{it}$	DFE-SR	DFE-SR	DFE-SR	DFE-SR
$\log HRS_{it}$	0.920***	0.917***	0.921***	0.916***
	(0.0318)	(0.0386)	(0.0331)	(0.0323)
$\log Cap_{it}$	0.113***	0.110**	0.112***	0.117***
	(0.0417)	(0.0464)	(0.0423)	(0.0416)
$EUMigShr_{it}$	0.161	2.926	0.397	1.482
	(0.242)	(4.606)	(0.638)	(2.368)
$NEUMigShr_{it}$	-0.0302	-1.930	-0.0507	0.0867
	(0.118)	(1.925)	(0.309)	(0.436)
$D2007$	0.128*	0.127*	0.103*	0.101*
	(0.101)	(0.089)	(0.098)	(0.115)
Constant	1.142	1.205	1.135	1.101*
	(0.704)	(0.769)	(0.710)	(0.654)

Model (1)-(4) presents the short run DFE models. Model (1), (2), and (3) is high, medium and low skilled with total migration share, respectively. Clustered t-stats are in parenthesis.
*, ** and *** indicate 10%, 5% and 1% significance, respectively.

Table2.35 Total migration share in Germany

	(1)	(2)	(3)	(4)
$\log VA_{it}$	DFE-SR	DFE-SR	DFE-SR	DFE-SR
$\log HRS_{it}$	0.922***	0.923***	0.922***	0.919***
	(0.0295)	(0.0301)	(0.0289)	(0.0264)
$\log Cap_{it}$	0.116***	0.118***	0.117***	0.120***
	(0.0376)	(0.0344)	(0.0360)	(0.0381)
$MigShr_{it}$	0.0712	0.125	0.117	0.464
	(0.185)	(2.214)	(0.432)	(0.736)
$D2007$	0.108*	0.135*	0.117*	0.117*
	(0.094)	(0.076)	(0.064)	(0.015)
Constant	1.093	1.060	1.070	1.072
	(0.687)	(0.708)	(0.681)	(0.652)

Model (1)-(4) presents the short run DFE models. Model (1), (2), and (3) is high, medium and low skilled with total migration share, respectively. Clustered t-stats are in parenthesis.
*, ** and *** indicate 10%, 5% and 1% significance, respectively.

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Chapter 3

Migration and Human Capital: Costs and Benefits, A Panel Data Analysis

3.1. Introduction

In the migration literature, the impact of emigration - due to the decrease in labour, particularly skilled labour - on the labour market in origin countries has been paid little attention. In fact, according to Clemens' (2011) extensive survey of the economics of emigration, only less than a quarter of the research on the effects of international migration has been on aspects related to origin countries rather than host countries.

The link between emigration and human capital gained wide publicity in the late 1960s due to an increase in skilled emigrants rather than in general emigration, according to Commander et al.' (2004) survey. This is a result of pro-skilled migration laws across the world. Questions remain open to be explored in more detail, for instance, on how remittances by emigrants in host countries contribute to origin countries' economies; how return migration helps to form human capital which has been improved by the host country; or how the decrease in the number of high skilled emigrants stimulates the skilled population level in the origin country.

In order to be able to measure such relationships between skilled emigration and its direct and indirect consequences on human capital level in the origin country, we need to have a database presenting emigration flows by educational attainment. Alternatively, proxy variables should be investigated for emigration rate and emigrants' educational attainment. For instance, Beine *et al*. (2001) used gross migration rates to proxy high skilled workers who emigrated. However, it does not provide us the full picture of such relationship.

Numerous theories have been presented on this matter but very few empirical papers exist. One reason is the fact that databases on emigration flows by educational attainment have been available for only a few decades and is based on estimated figures.

For instance, Kyriacou (1991) constructed panel data in the form of a human capital database from 1970 to 1985 for total labour force in the origin country based on years of schooling as a proxy for human capital level and school enrolment rate in origin country as a proxy for high skilled population . Carrington and Enrica (1998) estimated the stock of emigrants by their educational attainment for 61 developing countries to the USA and OECD countries. Adams (2003) constructed a dataset that includes information on the estimated educational attainment of emigrants from 24 most labour origin countries to the USA and some OECD countries.

Data on human capital for extended origin countries were available only after 2004 (Docquier and Marfouk, 2004), sponsored by the World Bank. Their dataset provides a time series of human capital levels and emigration rate for 170 countries in 1990 and 190 countries in 2000. In addition to census and register data, Docquier and Marfouk (2006) (from now on referred to as D&M) also used survey data from all the OECD countries and organised their previous dataset for a cross-section of 174 countries in 1990 and 195 countries in 2000: this has been used by many scholars for cross-sectional analysis (Beine *et al*., 2008, 2010; Di Maria and Lazarova, 2011; Docquier *et al*., 2005; Docquier and Marfouk 2004, 2006). Moreover, Dumont and Lemaître (2005) constructed a similar database to D&M, but included far fewer countries, and also defined migration differently.

Based on the D&M database, Docquier *et al*. (2007) controlled it for age of entry and extended the database. This was followed by Docquier *et al*. (2009) who built up a more insightful database which enables gender distinction in addition to educational attainment of emigrants. Clearly, looking at a relationship between high skilled emigration and human capital formation in origin countries requires a longer time dimension so that one can explore the possible dynamic effects.

Such panel data analysis was conceivable only after Defoort (2008) collected such a dataset sponsored by the World Bank. She used the census and registry databases of the host countries where information on migrants and their educational attainments was available from 1975 to 2000 with a five-year frequency. Evidently, collecting such data is demanding, as some data is unavailable for some host countries. Thus, Defoort only focused on six main host countries: Australia, Canada, France, Germany, the UK and the USA. .

With such a dataset available, the first panel data analysis was generated by Beine *et al*. (2011) for 147 origin countries from 1975 to 2000 with a five-year frequency. One advantage of this paper is that it delivers a general picture of high skilled emigration rates and human capital aspects for developing and developed countries from 1975 to 2000 with a five-year frequency. Nevertheless, it only controls for the change in human capital level for the *ex-ante* human capital and high skilled emigration rate for developing and rich countries. Clearly, change in human capital does not depend only on *ex-ante* human capital or high skilled emigration rate, but on multiple other factors, such as public expenditure, remittance and population density, which are used elsewhere (Beine *et al*., 2008, 2010; Di Maria and Lazarova, 2011; Docquier *et al*., 2005; Docquier and Marfouk, 2004, 2006). For instance, public expenditure might have a significant effect on human capital, as it has a direct relation to it. Remittance might play a crucial role in easing the constraints on human capital investment for individuals in the origin country (Docquier et al., 2012; Siegel, 2010; Kaczmerczyk and Okólski, 2008). Furthermore, consistent with the literature on the gravity models of migration, we use population density as a proxy for the cost of acquiring education, because the more people there are per specified area in the origin, the lower the education cost. Finally, we have regional dummies for sub-Saharan and Latin American countries. Thus, overall we believe that it would be too simplistic too take only a very few control variables into account.

In this chapter, we look at the impact of high skilled emigration rate on human capital level in origin countries. To conduct our panel data analysis, we use as the dependent variable the five-year growth rate of human capital defined as the five-year change in the logarithm of the human capital stock. All the explanatory variables are lagged by five years (i.e. *ex-ante*) and include the log of human capital, the high-skilled emigration rate, and interaction variable -for a possible non-linearity in the relationship between emigration rate and human capital-we interact the log of high-skilled emigration with GDPpc. Unlike Beine *et al*. (2011) we mainly interested in poor countries. To do this we set dummy variable $D15$ that is equal to 1 if the country has GDPpc less than 15 % of the average GDPpc of the G7 countries which are poor countries. We also narrow down the countries sampled by selecting countries which are even poorer- that are countries with $D10$ that is equal to 1 if the country has GDPpc less than 10% of the average GDPpc of the G7 countries, as we wanted to check if our results for countries with D15=1 is robust to findings when we narrow down the countries sampled

The selection of origin countries is mainly based on the availability of data. The data is restricted mostly on countries where migration rate is low, so we focused on countries where emigration rate is high. Thus, we end up with 74 origin countries from 1980 to 2000 with a 5-year frequency. For the list of sampled origin countries see ***Table 3.9*** of ***Appendix J***.

The chapter proceeds as follows. Section 3.2 reviews the literature. Section 3.3 describes the data capture, regression model and concerns about reverse causality. Section 3.4 empirically analyses the data and presents the results. Section 3.5 concludes and summarises the results. ***Appendix J***, presents the list of origin countries sampled. Finally, ***Appendix K*** presents the additional cross-section results.

3.2. Literature Review

What is brain drain? Several definitions can be accepted in this regard. For instance, Kwok and Leland (1982) described it as skill transfer by professionals to the countries where the benefit of migration is highest. What is more, in Giannoccolo (2006)'s extensive survey, brain drain was defined as the emigration of highly skilled workers to more developed countries or technologically better off countries, or the emigration of particular professionals such as doctors, surgeons, physicians, etc. In general, regardless of its beneficial or detrimental effect, brain drain is a phenomenon where high skilled emigration occurs. What are the consequences of such emigration? Do origin countries benefit from it, or quite the opposite? Do individuals with high skills return to their origin countries with additional skills acquired from the host countries, or do they indirectly support individuals who are left behind by lessening the constraint on liquidity via remittances? Or, in contrast, do they only attract more individuals to acquire higher skills in the origin country in order to be able to emigrate using the same channels? The paradox between the limited number of skilled residents in potential origin countries and yet the large number of skilled migrants in well-developed economies from those potential countries makes it important to investigate the brain drain effect (Carrington and Enrica, 1999).

As stated before, not many empirical studies are available on the link between emigration and human capital. For the sake of understanding the empirical interpretation, it might be beneficial to outline some of the theory behind it. To begin with early studies, Grubel and

Scott (1966, 1968) found that although the emigration of the highly skilled affects the social capital of the origin country negatively, the lessening numbers of skilled workers most likely to encourage individuals- who stay behind- to acquire higher education so the optimal level of skilled workers in origin country remains stable. By distinguishing between general skilled and technical skilled emigrants, Di Maria and Stryszowski (2009) claimed that the skill level of the remaining individuals is affected negatively in line with economic incentives as a result of skilled emigration, and this effect is even stronger when origin countries are further from the technological frontier. Mountford (1997) argued that although the probability of high skilled immigration is uncertain, due to restrictions from the origin and/or receiving country, it is still most likely to increase the average growth rate of the origin country in the long run. This is because an individual requires a higher education to be able to emigrate under high skill emigration schemes (unlike general emigration), thus this reduces the level of low skilled people in the origin country, which leads to an increase in the growth rate in the long run. The ratio of high skilled emigration in the origin country might depend on the labour market composition in the host countries. For instance, McCulloch and Yellen (1977) stated that if the cost of skilled labour migration is lower in host countries then the ratio of skilled labour (natives and migrants) is higher. High skilled emigration does not only affect the skill composition of origin countries, but also the wage distribution. Bhagwati and Hamada (1974) assessed multiple possible scenarios around high skilled emigration labours' effect on wages in the origin country. Firstly, they claimed that high skilled emigrants can eventually increase the wages at home after integrating the high skilled labours of host countries: secondly, following from the first potential increase in the wages of skilled workers, those of unskilled workers wages may increase, too: thirdly, having experienced higher salaries in host countries may lead to an increase in expected wages in the origin country: and finally, a potential increase may be present after high skilled emigration as it may imply the integration into the international market of the origin country.

Although not many empirical studies available, some findings can be discussed. Using the Polish LFS database, Kaczmarczyk (2010) showed an extensive loss of skilled population caused by a high emigration rate of skilled to mostly EU15 countries and some OECD countries between 1994 and 2007. Seemingly, the long stay of the high skilled in host countries causes shortages of leading groups of workers (professionals) across firms in Poland. Stark and Wang (2002) and Stark (2004) proposed that individuals from closed or small open economies underinvest in human capital in the absence of migration, but choose to increase their human capital level if migration is present. Thus, it might be stated that the decision on high education is related to the probability of migration in origin countries. Vidal (1998) claimed that high skilled migration may eventually affect the origin country's growth level positively by providing incentives for human capital formation. According to Dustmann et al. (2011), brain gain is experienced when the skilled emigrants eventually return to their home countries with additional skills acquired in the host countries, but brain drain occurs if they choose not to return, owing to the loss of the lifetime earnings that would have stayed in the origin country as well as the proportion of skilled workers that is lessened due to emigration. Stark *et al*. (1997, 1998), however, claimed that brain gain can arise regardless of emigrants returning with acquired skills from host countries, since the high skilled emigration eventually affects human capital investments positively and accordingly the human capital level, Thus, even if they do not return, there may still be an indirect brain gain.

Beine *et al*. (2003) found evidence of brain gain using Carrington and Detragiache's (1998) dataset for a cross-section of 50 developing origin countries to the USA. The last decade of international migration featured more skilled migration due to pro-skilled labour migration laws in developed countries. Based on 37 developing origin countries, Beine *et al*. (2001) showed that emigration patterns play a crucial role in the education decisions of individuals because the expected return is high. This is firstly because skilled emigrants can move to developed countries, and also individuals staying in the origin country would be in a good position due to the lack of skilled individuals. Following this, Beine *et al*. (2007) controlled emigrants by their age of entry to the host country – this is a proxy for determining where emigrants gain their education – and found that although brain drain effects are slightly negative after controlling by the age of entry, there is still a significant variation across other control variables. Beine *et al*. (2008) exploited the new D&M dataset for a cross-section of 127 countries in 1990 and 2000, and showed that although some sub-Saharan and Central American countries experienced brain drain, the overall effect of skilled emigration seemed to be beneficial for origin countries, because the skilled emigration ended up increasing the skill level of the origin countries sampled. The robustness of these findings was assessed by Beine *et al*. (2010) by distinguishing whether emigrants acquired their education in the origin or host country (similar to Beine *et al*., 2007), as well as using a relative measure for migration propensity rather than an absolute figure. They confirmed the robustness of all findings in Beine *et al*. (2008).

A gender distinction was taken into account by Docquier *et al*. (2009), suggesting that the high skilled emigration rate is almost 17% more for woman in comparison to men. They found that women - particularly those from undeveloped regions - affect the highly skilled population much more than low skilled women or high skilled men, in 1990 and 2000. Noticeably, such analysis would have been more reliable if a longer time dimension had been available. Bein *et al*. (2011) were the first to overcome such limitations by utilising a new dataset created by Defoort (2008) who constructed panel data for 147 origin countries for

1975 to 2000 with a five-year frequency. They found a significant brain gain effect on the sampled countries if the level of skilled emigration is not higher than 0.30%. They focused on the direct effect of the skilled migration rate from developing and rich countries and *ex-ante* human capital level on the change in human capital level. However, there remained other essential factors that might directly or indirectly affect the human capital level through skilled emigration such as remittance and the relationship between high skilled outsourcing and human capital investment in the origin country. In Section 3.3.2, we will address these issues, and then we will compare some results in Section 3.4**.** Moreover, using the D&M database, Di Maria and Lazarova (2011) investigated the impact of high skilled emigration on the human capital level and composition as well as growth effect of the origin countries. Their cross-section analysis suggested that the high skilled emigration rate significantly affects the human capital level and composition of the skill level in the origin country as well as the growth level of the country. Both effects are mostly present in countries which are technologically less sophisticated.

Batista *et al*. (2012) assessed whether there is a substantial brain drain effect of emigration in Cape Verde by using unique household survey data from December 2005 to March 2006 which included 1066 resident households. They concluded that on the contrary to the general belief in Cape Verde, a high rate of skilled emigration increased the human capital level. Also, an increase in the probability of emigration raises the probability of getting educated by around 45%.

McKenzie and Rapoport (2006) examined the impact of emigration on educational levels in rural Mexico, and found that a high number of emigrants to the United States lowers the number of educated girls aged 16 to 18 and boys aged 12 to 18, significantly. Heuer (2011) also detected a significant negative effect of high skilled emigration on human capital level in developing countries from OECD in 2000, and found that this effect is even stronger for more professional emigrants, using Carrington and Detragiache (1998)'s database. Niimi *et al*. (2010) also proposed that high skilled emigrants remit less than unskilled ones using a combination of the D&M, IMF and World Bank databases for 2000. Sanromá and Ramos (2008), by applying the LFS and Population Census of Spain in 2001, explained that the human capital of migrants from countries that have similar economic and social backgrounds is transferable, whereas migrants from countries with no similarities to Spain show negligible transferability of skills.

Friedberg (2000) looked at human capital evaluation from the host country's viewpoint and showed that individuals who have acquired skills abroad are less valued than those who have acquired them in Israel, using Israeli Censuses of Population and Housing data in 1974 and 1985. This is due to the earning difference between migrants and natives.

According to Herbst and Rok (2013), in their extensive human capital and migration survey, most empirical studies showed that high skilled emigration negatively affects the origin country's human capital level. Adams (2003) found that international migration from 24 popular origin countries to the USA and some OECD countries involved approximately 10% of the best educated population, yet some origin countries were faced with an extensive brain drain effect of losing the best educated population of the country, based on estimations of 2000 census data. Docquier *et al*. (2005) focused on global migration rates and the selection bias of emigrants when examining the human capital effect using the D&M database. They suggested that a negative brain drain effect is observed only if there is a high emigration rate from the sampled origin countries, or if there is a high selection bias amongst emigrants, not both. They also found that the countries most affected by brain drain were in the Caribbean, most regions in Africa and Central America. These are the same regions which were found to experience a strong and negative brain drain effect in Docquier and Morfouk (2004) and Carrington and Enrica (1998).

Faini (2003) argued that undeveloped countries may not benefit from brain drain, and object to the common belief that high skilled migrants remit more. Applying Docquier and Marfouk's (2004) dataset, Faini (2007) showed that although skilled migrants earn more and are thus expected to remit more; this is less likely to be the case. Because, in order for them to attain the life standards they have hoped for, they utilize most of earning for themselves.

3.3. Data and Model

3.3.1. Data and Descriptive Statistics

Before estimating the regression models, we should first describe the data sources. The main database for human capital and the educational attainment of emigrants is - as mentioned earlier - obtained from Defoort (2008). We analyse 74 migrant origin countries for which data on human capital, educational attainment and number of emigrants are available. Defoort (2008) focused on six main individual OECD host countries, Australia, Canada, France, Germany, the UK and the USA, as well as these as one aggregate group. The other control variables that we use, such as public expenditure, remittances, population density, population size and GDP per capita are obtained other databases. ***Table 3.1*** shows the notation, variable names, data sources and the units of analysis for these variables.

Table3.1 Data and Sources

Notation	Variable	Unit	Source
EDU	Public expenditure on education	% of GDP	UN Database, World Bank WDI
REM	Remittance	Constant in current US Dollar price	World bank WDI
p	High skilled emigration rate by country of birth	The emigration of skilled workers in the origin country	Panel Data on International Migration by Defoort (2008)
H_{α}	Human Capital	Initial (i.e. at time t-5) level of *ex ante* human capital. Residents + emigrants with post-secondary education	Panel Data on International Migration by Defoort (2008)
STOCK	Immigration Stock by country of birth	The number of immigrants living in the OECD area	Panel Data on International Migration by Defoort (2008)
DENS	Population Density	Midyear population divided by land area in square kilometres	World Bank, WDI
POP	Population size in the origin	Total	ITU Communication database
GDPD	Gross Domestic Product	Constant in current US Dollar price	CEPII

Table 3.2 presents the descriptive statistics of these variables. Our dependent variable is the five year growth rate of human capital and is summarized in row 1 of ***Table 3.2.*** As can be seen from these descriptive statistics this growth rate lays approximately between -2% and 10%. The negative growth in human capital indicates that in some periods the number of people with post-secondary education in these origin countries fell. In order to investigate the potential catching up effect, we control the change in human capital level with the *ex-ante* human capital level summarized in row 2 of ***Table 3.2***. From this we can see that the maximum level of individuals with post-secondary education or with more than 13 years of schooling - approximately 676 million - is almost half of the maximum level of population of 1,200 million. Note that population only captures residents, whereas the human capital level captures both residents and emigrated individuals. Moreover, to be able to observe the

migration incentive effect we use the rate of skilled emigrant, row 3 of ***Table 3.2*** as one of the control variables. The skill rate of the origin countries lies from approximately 1% to 85% of the population in the origin country.

To address potential non-linear relation between high skilled emigration rate and human capital, we interact high skilled emigration rate with $\log GDPpc$. Estimations carried out for two sub-samples of origin countries based on dummy variables: $D15$ and $D10$ which are defined as D10=1 and D15=1 if the country has GDPpc less than 10% and 15% of the average GDPpc of the G7, respectively. Thus our interaction variables for each sub-sample of countries can be written as $\log(p_{t-5}) \times D15$ and $\log(p_{t-5}) \times D10$**,** as in row 4 and 5 of **Table 3.2.** From the descriptive statistics, we lose a number of observations from $D15$ to $D10$, based on the GDP per capita of origin country. Seemingly, the number of countries with GDP per capita that is less than15% the average GDP per capita of the G7 countries is 207, whereas the number of countries where the GDP per capita is 10% lower than the average GDP per capita in the G7 countries is 177. Through the literature, population density, that is row 6 of ***Table 3.2*** , is found to be a decreasing factor for education cost, so we control for this variable. Thus, when midyear population of origin countries divided by land area in square kilometres across origin countries the population density varies from 1.2 to 1157.6. Additionally, public expenditure on education, that is row 7 of ***Table 3.2***, is also considered a factor that affects education cost, is given as % of GDP and lies between 5% and 17 % approximately. Decreasing the liquidity constrains, remittance-row 8 of ***Table 3.2*** is considered a control variable at a constant in current US dollar price. This varies from 21,310.16 to 6,220 million US dollars. We also present the descriptive statistics for the instrumental variables in ***Table 3.2*** which is to be covered in ***Section 3.3.2.1***. Variables in row 9 and 10 of ***Table 2.3*** are the number of individuals in the origin country and the number of migrants in the host countries.

Finally, variables in row 11 and 12 of ***Table 3.2*** are dummy variables for sub-Saharan countries and Latin American countries, and take values of 0 and 1.

Table3.2 Descriptive statistics for five-year interval data

No	Variable	Obs	Mean	Std Dev	Min	Max
1	$\Delta_5 \log H_{\alpha,t}$	300	0.0587106	0.0171546	-0.0243697	0.0978335
2	$H_{\alpha,t-5}$	300	1.99E+07	7.60E+07	17025.11	6.76E+08
3	p_{t-5}	300	0.2032383	0.2268437	0.0075913	0.8520139
4	$\log(p_{t-5})\times D15$	207	-15.53329	8.869384	-38.05195	-1.183644
5	$\log(p_{t-5})\times D10$	177	-15.65798	8.412883	-38.05195	-1.183644
6	$DENS_{t-5}$	300	108.6069	182.8187	1.230139	1157.603
7	EDU_{t-5}	300	3.854615	2.010898	0.045755	17.38824
8	REM_{t-5}	300	4.41E+08	9.44E+08	21310.16	6.22E+09
9	POP_{t-5}	300	4.49E+07	1.57E+08	61906	1.20E+09
10	$STOCK_{t-5}$	300	170382	396208	105.5	4558347
11	$SSAD$	300	0.36	0.480802	0	1
12	$LATD$	300	0.2266667	0.4193747	0	1

Note: The five year lags (*t*-5) actually represent a one-time interval lag because the data are recorded at five year intervals.

3.3.2. Model

We will be applying $\beta - convergence$ that has been used elsewhere in human capital literature (Beine *et al*.:2007, Beine *et al*.:2008, Beine *et al*.:2010, Beine *et al*.:2011, Docquier *et al*.:2009, Di Maria and Lazarova: 2011). This model suggests that poorer or developing economies grow faster than those rich ones. Since that is consistent with human capital and migration theories, that is, (1) poorer countries are more prone to acquire high skills than rich ones so that they can emigrate, or (2) they are more prone to acquire high skills than rich ones so the level of human capital in the origin countries holds around the same level even after high skilled emigration (Kaczmarczyk: 2010, Stark and Wang: 2002, Stark: 2004, Vidal 1998). Using the $\beta - convergence$ model we regress the five-year growth rate of human capital, defined as $\Delta_5 \log(H_{\alpha,t}) \equiv \log(H_{\alpha,t}) - \log(H_{\alpha,t-5})$, on a set of explanatory variables. To begin with, we control the five year growth rate of human capital with the level of human capital at $t-5$, that is $H_{\alpha,t-5}$ to capture the potential catching-up effect. The number of high skilled emigrants is also expected to have a direct impact on the five-year change in human capital so we also control for this by including its lagged value p_{t-5}. In addition, to control for possible non-linearities we include two dummy variables that are interacted with the log of the high-skilled emigration rate, see rows 4 and 5 of Table 3.2. These two dummy variables, $D15$ and $D10$ are used to indicate origin countries whose GDP per capita frontier is substantially below that of the average G7 countries. Moreover, we control the log of change in human capital for public expenditure - (EDU_{t-5}) which we believe has a positive effect on human capital formation. In addition to the direct effect of high skilled emigration, the remittances from workers abroad would give the most relevant definition of human capital. Because, remittance- REM_{t-5} might play a crucial role in easing the constraints on human capital investment for individuals in origin countries and it is to control for return high skilled emigration. We also include population density in the model as a proxy for the cost of acquiring education, because the more people per specified area in the origin country means the lower the education cost. Finally, we have regional dummies for sub-Saharan and Latin American countries $SSAD$ and $LATD$, respectively.

Thus, our estimation model is:

$$\begin{aligned}\Delta_5 \log(H_{\alpha,t}) = {} & \beta_0 + \beta_1 \log(H_{\alpha,t-5}) + \beta_2 \log(p_{t-5}) + \beta_3 \log(p_{t-5}) \times GDPpc_{t-5} \\ & + \beta_4 DENS_{t-5} + \beta_5 \log(EDU_{t-5}) + \beta_6 \log REM_{t-5} + \beta_7 SSAD \\ & + \beta_8 LATD + \varepsilon\end{aligned} \qquad \textbf{(3.1)}$$

where t takes the value of 2000, 1995, 1990 and 1985, respectively. The dataset we obtained is a product of the World Bank Development Research Group, collected by Defoort (2008) in which most data for migration stocks and their educational attainments are based on six major OECD countries as host countries: Australia, Canada, France, Germany, the UK and the USA.

Thus, one should be cautious about interpreting the regression results as all of the origin countries in the sample are not necessarily origin emigrants only to those six major host countries. To be able to compare the results with Beine *et al* (2011)'s findings, we provide their model as following:

$$\Delta_5 \log\left(H_{\alpha,t}\right) = \beta_0 + \beta_1 \log(H_{\alpha,t-5}) + \beta_2 \log(p_{t-5})_D + \beta_3 \log(p_{t-5})_R \qquad \textbf{(3.2)}$$

where, $(p_{t-5})_D$ and $(p_{t-5})_R$ presents the skilled emigration rate in developing and rich countries at time t-5, respectively.

3.3.2.1. Endogeneity

Before we carry out the estimation, we should first address some concerns of endogeneity. Since we are looking at the impact of the emigration rate of skilled individuals on the change in the level of education that is gained by individuals in the origin countries, one should be cautious about reverse causality, because, the rate of high skilled emigration directly affects the human capital level in the origin, or on the other hand a higher level of human capital may lead to a higher skilled migration since there will be a reduction on the skill premium in local labour market in the origin countries. To address such a reverse causality issue, we adopted instrumental variables, population size in the origin and migration stock in OECD countries, which were also used by Beine *et al*. (2008:2011), and Di Maria and Emiliya (2011).

Up until the existing of such panel data in regards of human capital and educational attainment of emigrants, the existing literature had difficulty to deal with omitted variables, unobserved heterogeneity or endogeneity issues. Since the data enables us to do so, we provided both fixed effect and first difference models in addition to our main estimation IV models. We run OLS, fixed effect and first differenced regressions as well as IV-fixed effect and IV-first differenced regressions. The essential features of instrumental variables are, firstly, that the instrumental variable has to be correlated with the endogenous variable skilled migration rate- p_{t-5}, and secondly, that it should be uncorrelated with an error term in the main estimation model (Baum, 2009). To begin with, the migration stock in the OECD area undoubtedly stimulates the future migration so is correlated with skilled migration rate- p_{t-5}. Population size is also directly related to the ratio of the skilled migration rate. Thus, we guarantee the first feature of the instrumental variable.

In order to see if the second feature of the instrumental variables is applied, in other words if the instruments are valid, we should see whether population size and migration stocks might have an independent direct effect on the independent variable, the log of change in human capital level. To do this, we perform a number of tests. Firstly, we perform the Kleibergen-Paap Wald F-statistic for identification, where the null hypothesis states that the instruments are strong. Secondly, we perform the Hansen J-statistics for the over-identification test where the null hypothesis states that the instruments are over-identified, and finally, we perform the endogeneity test where the null hypothesis states that the endogenous variable is exogenous after being instrumented. The F values for the Kleibergen-Paap Wald and Hansen J statistics and the p-values for endogeneity test are provided in the results tables.

3.4 Results of the Panel Analysis

The panel analysis results are presented in ***Tables 3.3 to 3.8***. ***Models (1), (2)*** and ***(3)*** of ***Table 3.3*** present the results of the OLS, fixed effects (FE) and first difference (FD) regressions for poor countries, respectively, whereas models ***(4)*** and ***(5)*** of ***Table 3.3*** present the IV-fixed effect and IV-first differenced results.

We found a significant divergence in native human capital levels among the countries sampled, as the coefficient for the log of *ex-ante* human capital is positive across the main regressions ranging from 50% to 88%. This is coherent with the negative and significant brain drain affect that we find. The negative coefficient for the log of high skilled varies from 1% to 4% per year across all regressions, suggesting that it takes approximately 3 years for each country to diverge long run level of human capital. In other words the negative sign- ranging from 1% to 4% per year- for the percentage of skilled population means that there is a decrease in the human capital level in origin countries sampled in the model after high skilled emigration in as short as 3 years' time, approximately. A negative and significant result for the interaction variable of high skilled emigrants with $D15$ suggests a weak incentive effect in poor countries. As expected, remittance and public expenditure are found to be positively related with a change in human capital level. Although the coefficient of public expenditure and remittance are small, they are mostly found to be significant at around 1%. Population density is also found to be positive and significant at around 0.11 to 0.20, suggesting that the more population density the less distance to schools so the less cost of acquiring education which results in an increase in the human capital level. The dummy variables for sub-Saharan and Latin American countries are dropped from the models due to collinearity – apart from the OLS model – and only origin countries from Latin America found to positively and significantly affect the log change of human capital level, but the OLS results might be biased due to the endogeneity issue.

As can be seen from columns **(4)** and **(5)** of ***Table 3.3***, the Kleibergen-Paap Wald F-statistic for identifying the instrumental variables does not reject the hypothesis that the instruments are strong, since the F-test is greater than the critical value of 10%. The Hansen J-statistics for the over-identification test where the null hypothesis states that the instruments are over-identified is also not rejected, as the p-values are far above the critical value of 5%, and finally, the endogeneity test does not reject the exogeneity of the instrumented variable, since the F-test is above the critical value of 10%.

Table3.3 Regression analysis for countries with D15 : 1980-2000

	(1)	(2)	(3)	(4)	(5)
Regression method:	***OLS***	***F.E.***	***F.D.***	***F.E. I.V.***[a]	***F.D. I.V.***[a]
$\log H_{\alpha,t-5}$	-0.0013* (0.0008)	0.8815*** (0.0261)	0.6163*** (0.1098)	0.8652*** (0.0428)	0.5018** (0.2148)
$\log p_{t-5}$	-0.0272*** (0.0051)	-0.0159 (0.0183)	-0.0417 (0.0273)	-0.0136 (0.0186)	-0.0439** (0.0196)
$\log p_{t-5} \times \log GDPpc_{t-5} \times D$	-0.0034*** (0.0007)	-0.0015 (0.0022)	-0.0048* (0.0028)	-0.0012 (0.0022)	-0.0050** (0.0023)
$\log DENS_{t-5}$	-0.0031*** (0.0011)	0.1059*** (0.0339)	0.1482** (0.0743)	0.1251** (0.0523)	0.1950** (0.0975)
$\log EDU_{t-5}$	0.0052*** (0.0018)	0.0035 (0.0042)	0.0065** (0.0030)	0.0033 (0.0041)	0.0066 (0.0042)
$\log REM_{t-5}$	0.0010* (0.0006)	0.0039* (0.0021)	0.0001 (0.0015)	0.0041* (0.0021)	0.0001 (0.0021)
$SSAD$	-0.0038 (0.0038)				
$LATD$	0.0079*** (0.0024)				
$Cons$	0.0594*** (0.0110)	1.3840*** (0.2658)	0.0372*** (0.0122)		0.0488** (0.0222)
R^2	0.26	0.98	0.63	0.98	0.62
N	203	197	140	193	140
Hansen J-Stat				0.12	0.33
Endogeneity				0.63	0.57
K-P Wald F-Stat				10.726	10.725

(1)-(2) and (3) present the OLS, fixed effect and first difference results, (4) presents the fixed effect IV results and finally (5) presents the first differenced IV results. P-vals for Hansen J statistics of over-identification and endogeneity and the test for an endogenous regressor are reported. The F-test of the K-P Wald F-statistics is a weak identification test. Robust t-statistics are reported in parenthesis. SSAD and LATD are omitted from (2)-(5) due to collinearity. The stata command for IV – fixed effect and first difference results is xtivreg2. *, ** and *** indicate 10%, 5% and 1% significance, respectively.

[a] Stock of migrants in OECD and population size is used as instrumental variables.

As to the countries with $D10$ in ***Table 3.4***, the results do not appear to be very different in terms of the sign of the coefficient than those in developing countries shown in ***Table 3.3***. However, the main differences are that the divergence effect appears to be much stronger in undeveloped countries (***Table 3.3***) as the coefficients are quite larger than the ones in ***Table 3.4***. The ratio of the skilled population seems to be decreasing in undeveloped countries almost twice as much as in developing countries. These two findings may suggest us that undeveloped countries are experiencing more detrimental brain drain effects than developing ones. As to incentive effects, undeveloped countries show weak incentives, although smaller than the developing ones. As can be seen from ***Models (4)*** and ***(5)*** of ***Table 3.4***, tests for post estimation suggest the strong and good identification of instruments as well as the exogeneity of the instrumented variable. SSAD and LATD are omitted due to collinearity. The IV- fixed effect results is not provided by the command (Stata 13- xtivreg2) used, so is not available in ***Model (4)***.

Table3.4 Regression analysis for countries with D10: 1980-2000

	(1)	(2)	(3)	(4)	(5)
Regression method:	***OLS***	***F.E.***	***F.D.***	***F.E. I.V.***[a]	***F.D. I.V***[a]
$\log H_{\alpha,t-5}$	0.996*** (0.0021)	0.6200*** (0.1110)	0.8870*** (0.0278)	0.9340*** (0.0434)	0.8610*** (0.1800)
$\log p_{t-5}$	-0.0915*** (0.0121)	-0.0796** (0.0378)	-0.0484** (0.0230)	-0.0571** (0.0235)	-0.0765*** (0.0263)
$\log p_{t-5} \times \log GDPpc_{t-5} \times D$	0.0113*** (0.0016)	-0.0085** (0.0035)	-0.0047* (0.0025)	-0.0056** (0.0026)	-0.0083*** (0.0028)
$\log DENS_{t-5}$	-0.0074*** (0.0025)	0.1520* (0.0791)	0.1010** (0.0399)	0.0409 (0.0582)	0.0488 (0.0917)
$\log EDU_{t-5}$	0.0151*** (0.0047)	0.0062*** (0.0020)	0.0039 (0.0045)	0.0042 (0.0045)	0.0050 (0.0049)
$\log REM_{t-5}$	0.0023* (0.0014)	0.0006 (0.0018)	0.0046* (0.0026)	0.0045* (0.0026)	0.0012 (0.0026)
$SSAD$	-0.0030 (0.0101)				
$LATD$	0.0191*** (0.0062)				
$Cons$	0.1380*** (0.0260)	0.0374*** (0.0126)	1.2800*** (0.2770)		0.0132 (0.0189)
R^2	0.98	0.67	0.99	0.99	0.63
N	172	116	172	168	116
Hansen J-Stat				0.11	0.38
Endogeneity				0.87	0.88
K-P Wald F-Stat				10.180	10.976

(1)-(2) and (3) present the OLS, fixed effect and first difference results, (4) presents the fixed effect IV results and finally (5) presents the first differenced IV results. The P-vals for Hansen J statistics of over-identification and endogeneity the test for endogenous regressor are reported. The F-test of K-P Wald F-statistics is a weak identification test. The robust t-statistics are reported in parenthesis. SSAD and LATD are omitted from (2)-(5) due to collinearity. The stata command for IV – fixed effect and first difference results is xtivreg2. *, ** and *** indicate 10%, 5% and 1% significance, respectively.

[a] Stock of migrants in OECD and population size is used as instrumental variables.

In comparison to Beine *et al*.'s (2011), panel data analysis, they showed a net brain gain effect of skilled emigration rates on human capital levels when the emigration rate does not exceed 20 -30%. However, the descriptive statistics of high skilled emigrants in our work suggests that 235 out of 296 observations for high skilled emigration are less than 30 %, and 209 out of 296 observations are less than 20%. In general, only 61 out of 296 figures are over 30%. Yet, we observe a significant brain drain effect across the sampled origin countries. One explanation to this could be the origin countries that are sampled. Also, we have more independent variables in comparison Beine *et al*. (2011)'s.

Since migration stocks in the OECD area and population size in the origin are confirmed to be valid and strong instruments, we applied the IV-fixed effect and IV-first differenced models for six individual host countries, as Defoort's (2008) database also provides migration stock in those individual host countries. However, the stock of migration in those individual countries can only capture the migration network of these six host countries, and therefore caution should be used in interpreting the results. ***Tables 3.5*** and ***3.6*** present the country specific results of IV fixed effect results for developing and undeveloped countries, ***Tables 3.7*** and ***3.8*** present the country specific results of IV- first difference results for developing and undeveloped countries where the instrumental variables- stock of migrants and populations size- are measured for an individual host countries. ***Models (1), (2), (3), (4), (5)*** and ***(6)*** of ***Tables 3.5- 3.8*** present the results for Australia, Canada, France, Germany, the UK and the USA. As expected, the K-P Wald F-statistics of the weak identification test in ***Table 3.5*** reject the null hypothesis of being strong instruments as the F statistic is lower than the critical value of 10% for each country. Intuitively, this reflects the results by weakening the significance of the brain drain effect and incentive effect of the human capital level, although the level of *ex-ante* human capital is still quite significant and suggests a strong divergence in native human capital in developing origin countries. For undeveloped countries - as can be seen from ***Table 3.6*** – the weak identification test is even poorer, suggesting the weakness of the instruments again. However, there is a negative and significant brain drain effect for emigration to Canada, the UK and the US for undeveloped countries.

Table3.5 Panel data analysis of IV-fixed effect for countries with D15 : 1980-2000

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Host countries	**Australia[a]**	**Canada[a]**	**France[a]**	**Germany[a]**	**UK[a]**	**USA[a]**
$\log H_{\alpha,t-5}$	0.7663*** (0.1047)	0.7863*** (0.1082)	0.8156*** (0.0726)	0.7591*** (0.1049)	0.7641*** (0.1069)	0.8413*** (0.0713)
$\log p_{t-5}$	0.0005 (0.0241)	-0.0023 (0.0217)	-0.0065 (0.0246)	0.0016 (0.0242)	0.0009 (0.0244)	-0.0102 (0.0233)
$\log p_{t-5} \times \log GDPpc_{t-5} \times D$	-0.0061 (0.0026)	-0.0002 (0.0025)	0.0003 (00025)	-0.0007 (0.0026)	-0.0006 (0.0027)	-0.0007 (0.0024)
$\log DENS_{t-5}$	0.2417** (0.1235)	0.2181* (0.1286)	0.1836** (0.0848)	0.2502** (0.1238)	0.2443* (0.1261)	0.1533* (0.0846)
$\log EDU_{t-5}$	0.0022 (0.0045)	0.0024 (0.0045)	0.0028 (0.0042)	0.0021 (0.0045)	0.0022 (0.0045)	0.0031 (0.0041)
$\log REM_{t-5}$	0.0052** (0.0025)	0.0051** (0.0024)	0.0046** (0.0022)	0.0053 (0.0025)	0.0052** (0.0025)	0.0043** (0.0021)
$SSAD$	0.98	0.98	0.98	0.98	0.98	0.98
$LATD$	193	193	193	193	193	193
Hansen J-Stat	0.46	0.58	0.32	0.78	0.39	0.24
Endogeneity	0.29	0.22	0.37	0.17	0.17	0.49
K-P Wald F-Stat	6.111	6.320	6.442	6.267	6.129	6.789

Models (1), (2), (3), (4), (5) and (6) present the results for Australia, Canada, France, Germany, the UK and the USA respectively. The P-vals for the Hansen J statistics of over-identification and endogeneity and the test for the endogenous regressor are reported. The F-test of K-P Wald F-statistics is a weak identification test. The robust t-statistics are reported in parenthesis. The stata command for IV – fixed effect and first difference results is xtivreg2. *, ** and *** indicate 10%, 5% and 1% significance, respectively.
[a]Stock of migrants in individual host countries and population size are used as instrumental variables

Table3.6 Panel data analysis of IV-fixed effect for countries with D10: 1980-2000

	(1)	(2)	(3)	(4)	(5)	(6)
Host countries	**Australia[a]**	**Canada[a]**	**France[a]**	**Germany[a]**	**UK[a]**	**USA[a]**
$\log H_{\alpha,t-5}$	0.8610*** (0.0730)	0.9030*** (0.0838)	0.8980*** (0.0502)	0.8640*** (0.0731)	0.8780*** (0.0708)	0.9450*** (0.0398)
$\log p_{t-5}$	-0.0437 (0.0276)	-0.0514** (0.0238)	-0.0505 (0.0327)	-0.0441 (0.0277)	-0.0468* (0.0278)	-0.0592* (0.0310)
$\log p_{t-5} \times \log GDPpc_{t-5} \times D$	-0.0042* (0.0023)	-0.0050** (0.0023)	-0.0049* (0.0028)	-0.0043* (0.0024)	-0.0045* (0.0024)	-0.0058** (0.0027)
$\log DENS_{t-5}$	0.1330 (0.0951)	0.0800 (0.107)	0.0861 (0.0651)	0.1300 (0.0951)	0.1120 (0.0924)	0.0264 (0.0520)
$\log EDU_{t-5}$	0.0037 (0.0039)	0.0040 (0.0040)	0.0041 (0.0038)	0.0037 (0.0039)	0.0038 (0.0039)	0.0043 (0.0039)
$\log REM_{t-5}$	0.0047* (0.0024)	0.0046* (0.0025)	0.0046* (0.0024)	0.0047* (0.0024)	0.0047* (0.0024)	0.0045* (0.0025)
$SSAD$	0.98	0.98	0.98	0.98	0.98	0.98
$LATD$	168	168	168	168	168	168
Hansen J-Stat	0.44	0.42	0.51	0.46	0.13	0.18
Endogeneity	0.72	0.80	0.93	0.57	0.94	0.11
K-P Wald F-Stat	3.207	3.747	3.560	3.269	3.356	10.750

Models (1),(2),(3),(4),(5) and (6) present the results for Australia, Canada, France, Germany, the UK and the USA respectively. The P-vals for the Hansen J statistics of over-identification and endogeneity and the test for the endogenous regressor are reported. The F-test of K-P Wald F-statistics is a weak identification test. The robust t-statistics are reported in parenthesis. The stata command for IV – fixed effect and first difference results is xtivreg2. *, ** and *** indicate 10%, 5% and 1% significance, respectively.

[a] Stock of migrants in individual host countries and population size are used as instrumental variables

Tables 3.7 and ***3.8*** present the IV-first difference models for developing and undeveloped countries respectively. Although the instruments are weak as the K-P Wald F-statistics suggest, the significance of the main variables hold both for developing and undeveloped countries. In fact, the results for undeveloped countries are much better than those for developing countries in respect of significance.

Table3.7 Panel data analysis of IV-first differenced for countries with D15: 1980-2000

	(1)	(2)	(3)	(4)	(5)	(6)
Host countries	**Australia[a]**	**Canada[a]**	**France[a]**	**Germany[a]**	**UK[a]**	**USA[a]**
$\log H_{\alpha,t-5}$	0.1603 (0.6323)	0.3451 (0.4757)	0.4054 (0.4835)	0.1061 (0.5156)	-0.1651 (0.6313)	0.3672 (0.3351)
$\log p_{t-5}$	-0.0507** (0.0249)	-0.0470* (0.0258)	-0.0458* (0.0241)	-0.0518** (0.0241)	-0.0506** (0.0249)	-0.0466** (0.0233)
$\log p_{t-5} \times \log GDPpc_{t-5} \times D$	-0.0056** (0.0028)	-0.0052* (0.0028)	-0.0051** (0.0026)	-0.0056** (0.0028)	-0.0055** (0.0028)	-0.0052** (0.0025)
$\log DENS_{t-5}$	0.3345 (0.2606)	0.2590 (0.2038)	0.2344 (0.1982)	0.3567 (0.2195)	0.3326 (0.2602)	0.2500 (0.1542)
$\log EDU_{t-5}$	0.0068* (0.0041)	0.0067** (0.0032)	0.0067** (0.0031)	0.0069 (0.0045)	0.0068* (0.0041)	0.0067** (0.0032)
$\log REM_{t-5}$	0.0001 (0.0019)	0.0001 (0.0017)	0.0001 (0.0016)	0.0001 (0.0021)	0.0001 (0.0019)	0.0001 (0.0017)
$Cons$	0.0833 (0.0659)	0.0647 (0.0494)	0.0586 (0.0503)	0.0888 (0.0541)	0.0828 (0.0658)	0.0624* (0.0344)
R^2	0.47	0.57	0.60	0.43	0.47	0.58
N	140	140	140	140	140	140
Hansen J-Stat	0.51	0.55	0.33	0.79	0.89	0.66
Endogeneity	0.40	0.51	0.69	0.11	0.41	0.42
K-P Wald F-Stat	1.219	1.642	1.606	1.635	1.221	5.689

Models (1), (2), (3), (4), (5) and (6) present the results for Australia, Canada, France, Germany, the UK and the USA respectively. The P-vals for the Hansen J statistics of over-identification and endogeneity and the test for the endogenous regressor are reported. The F-test of K-P Wald F-statistics is a weak identification test. The robust t-statistics are reported in parenthesis. The stata command for IV – fixed effect and first difference results is xtivreg2. *, ** and *** indicate 10%, 5% and 1% significance, respectively.
[a]Stock of migrants in individual host countries and population size are used as instrumental variables

Table3.8 Panel data analysis of IV-first differenced for countries with D10: 1980-2000

	(1)	(2)	(3)	(4)	(5)	(6)
Host countries	**Australia[a]**	**Canada[a]**	**France[a]**	**Germany[a]**	**UK[a]**	**USA[a]**
$\log H_{\alpha,t-5}$	0.5300* (0.2710)	0.6580** (0.3180)	0.7210*** (0.1880)	0.4460* (0.2540)	0.5240* (0.2710)	0.7850*** (0.1980)
$\log p_{t-5}$	-0.0808** (0.0362)	-0.0791** (0.0398)	-0.0783** (0.0391)	-0.0819** (0.0346)	-0.0809** (0.0361)	-0.0775* (0.0413)
$\log p_{t-5} \times \log GDPpc_{t-5} \times D$	-0.0085** (0.0033)	-0.0084** (0.0036)	-0.0084** (0.0036)	-0.0086*** (0.0032)	-0.0085** (0.0033)	-0.0083** (0.0038)
$\log DENS_{t-5}$	0.1910 (0.1230)	0.1360 (0.1440)	0.1090 (0.0808)	0.2270* (0.1190)	0.1940 (0.1230)	0.0812 (0.0890)
$\log EDU_{t-5}$	0.0067*** (0.0025)	0.0060** (0.0026)	0.0057*** (0.0022)	0.0071*** (0.0027)	0.0067*** (0.0025)	0.0054** (0.0024)
$\log REM_{t-5}$	0.0004 (0.0017)	0.0007 (0.0017)	0.0009 (0.0018)	0.00014 (0.0017)	0.0003 (0.0017)	0.0010 (0.0019)
$Cons$	0.0465 (0.0296)	0.0336 (0.0338)	0.0273 (0.0208)	0.0550* (0.0282)	0.0472 (0.0298)	0.0208 (0.0214)
R^2	0.66	0.67	0.66	0.65	0.66	0.65
N	116	116	116	116	116	116
Hansen J-Stat	0.33	0.16	0.32	0.08	0.29	0.17
Endogeneity	0.85	0.57	0.81	0.19	0.84	0.36
K-P Wald F-Stat	3.274	3.261	4.208	3.417	3.291	7.473

Models (1), (2), (3), (4), (5) and (6) present the results for Australia, Canada, France, Germany, the UK and the USA respectively. The P-vals for the Hansen J statistics of over-identification and endogeneity and the test for the endogenous regressor are reported. The F-test of K-P Wald F-statistics is a weak identification test. The robust t-statistics are reported in parenthesis. The stata command for IV – fixed effect and first difference results is xtivreg2. *, ** and *** indicate 10%, 5% and 1% significance, respectively.
[a]Stock of migrants in individual host countries and population size are used as instrumental variables

In order to check whether the panel data analysis results would differ from cross-section analysis, we provide additional regressions of cross-section analysis for each time interval (i.e. 1980-1985, 1985-1990, 1990-1995, 1995-2000) both for country groups with $D15$ and $D10$ and present them in ***Tables 3.10-3.25*** in ***Appendix K.*** One reason to this is that, up until the use of panel data on migration and human capital, for the analysis on human capital and migration, only cross-section analysis were available. (Beine *et al*., 2001:2003; 2007:2008, Di Maria and Lazarova, 2011). Thus, we would like to see whether the results would deviate much. Cross-section analyses are carried out as follows:

For the 1980-1985 time interval, the dependent variable is the log change of the human capital as $\Delta \log H_{\alpha,85-80}$ regressed on the log of *ex-ante* human capital - $\log H_{\alpha,80}$ and the other control variables are just as in equation **(3.1)**. The dependent variable repeats for the 1985-1990, 1990-1995 and 1995-2000 time intervals as $\Delta \log H_{\alpha,90-85}$, $\Delta \log H_{\alpha,95-90}$, $\Delta \log H_{\alpha,00-95}$ respectively. Intuitively, all dependent variables are regressed on the log of *ex-ante* human capital level $\log H_{\alpha,85}, \log H_{\alpha,90}, \log H_{\alpha,95}$, and other corresponding control variables.

Tables 3.10 and ***3.11*** present the OLS results of the cross-section analyses for countries with $D15$ and countries with $D10$ thresholds. ***Tables 3.12, 3. 14, 3.16, 3.18, 3.20, 3.22, 3.24*** present the IV results for countries with $D15$ thresholds where migration stock as the instrumental variable is taken as the stock of immigrants in OECD, Australia, Canada, France, Germany, the UK and the US respectively. Finally, ***Tables 3.13,3. 15, 3. 17, 3. 19, 3. 21,3. 23 and 3.25*** present the IV results of countries with $D10$ where migration stock as the instrumental variable is taken as the stock of immigrants in OECD, Australia, Canada, France, Germany, the UK and the USA respectively. ***Models (1), (2), (3)*** and ***(4)*** of each table from

Table 3.10-3***.25*** present the results for the 1980-1985: 1985-1990; 1990-1995; and 1995-2000 time intervals.

To start with, since we are dealing with the cross-section of individual host countries per 5-year time interval, the number of observations for each analysis is quite large, varying from 40 to 50. However, as can be seen from ***Tables 3.10*** and ***3.11***, the OLS results suggest that a negative and significant brain drain effect (the coefficient of $\log \rho_{j-5}$) for each time period: 1980-1985, 1985-1990, 1990-1995 and 1995-2000, for countries with $D15$ and $D10$ thresholds, respectively. The estimation carried out is based on all aggregated OECD countries. We observe convergence (i.e. negative coefficient for $\log H_{\alpha,t-5}$) in native human capital in origin countries and for countries with $D10$ it is more significant. This finding is completely opposite of what we found in panel data analysis. The reason to this could be the very few observation in each cross-section analysis. ***Table 3.10*** and ***3.11***. ***Tables 3.12*** and ***3.13*** present the IV results for countries with $D15$ and $D10$ where population size and migration stocks in OECD are considered as an instrument. A negative brain drain effect (coefficient of $\log \rho_{t-5}$) still holds very significant both for countries with $D15$ and $D10$, with the effect a little stronger in countries with $D10$. This suggests that countries- whose GDP per capita is bottom half of the GDP per capita distribution of G7 countries- experience more negative brain drain effects. This may suggest that the poorer the country the more emigration of high skilled and the less incentive to go back to origin countries after emigrating better countries. Public expenditure on education found to affect changes in human capital levels positively and significantly. For ***Tables 3.14-3. 15***, 3.***16-3.17***, ***3.18-3.19, 3.20-3.21, 3.22-3.23*** and ***3.24-3.25***, in addition to population size, migration stock in Australia, Canada, France, Germany, the UK and the US is considered, respectively. The significance of the negative brain drain effect holds across all specifications both for countries with $D15$ and $D10$. For the cross section analysis for each individual host countries, not much evidence is found for the significance of human capital convergence in natives in origin countries. This could be due to the fact that the number of observations is limited (varying from 40 to 50), and also the instrumental variable for the stock of migration based on in individual countries may not be a strong instrument. The Hansen J-statistics reject the hypothesis that the endogenous variable - high skilled emigration - is over-identified, across all specifications.

3.5. Conclusion

We found a significant negative brain drain impact of high skilled emigration across 74 origin countries by applying panel data on international migration by Defoort (2008) from 1980 to 2000 with a five-year frequency, where most data for migration stocks and their educational attainments are based on six major OECD countries as host countries: Australia, Canada, France, Germany, the UK and the USA.

Our IV-fixed effect and IV-first difference models showed a significant and negative brain drain effect of high skilled emigration across countries sampled. This suggests that origin countries in the sample lose their skilled population rather than gaining them *ex-post* emigration. Our findings for two sub-sample countries - D10 and D15- are not much different in terms of the signs of the coefficients, but the significance improves much more for countries with D10. In general, we found a divergence in native human capital levels among the countries sampled. A negative and significant result for the interaction variables of high skilled emigrants for countries with $D15$ and $D10$ suggests a weak incentive effect in both sub-sampled countries; it is more deficient for countries with D10. As expected, remittance and public expenditure are found to be positively related with a change in human capital level.

Although the coefficient of public expenditure and remittance are small and mostly insignificant, they are all found to be positive. It confirms our findings where the incentive effects do not operate, meaning that there is a brain drain rather than a brain gain effect of high skilled emigration for the countries sampled. The coefficient of REM_{t-5} is found to be around 0.1%, which is quite low, may suggest that once high skilled people emigrate to developed/rich countries, they settle down quickly and hold their earnings for their high standard life. Population density is also found to be positive and significant, suggesting that the less the cost of acquiring education, the more the increase in human capital level. We found a negative effect for sub-Saharan origin countries, although insignificant, but a positive and significant affect for Latin American origin countries. We only see these results by OLS estimation, as they are dropped from the fixed effect and first differenced estimations due to collinearity.

The selection of instrumental variables, just as used elsewhere (Beine *et al*., 2008, 2011; Di Maria and Emiliya, 2011), are shown to be valid and strong instruments, as confirmed by the Hansen J-statistics, endogeneity test and K-P Wald F statistics. The value for each statistic is above the critical value suggesting the exogeneity of the instrumented variable, not to mention being strong and over-identified.

The IV-fixed effect and IV-first differenced results for both country groups based on the instrument - migration stock in individual host countries - holds the significance of the negative brain drain effect. The instrument of migration stocks in individual host countries - Australia, Canada, France, Germany, the UK and the USA - may not be as strong instruments as migration stock in OECD. This can be seen by the fail of Hansen J-statistics of over-identification test. This could also be the result of the limited number of observations, varying from 40 to 50 for each cross-section analysis.

In general, our panel data analysis delivers a negative brain drain effect across the countries sampled. This effect is much stronger in countries with D10 specification in comparison to countries with D15 specification, suggesting more detrimental brain drain for even poorer countries. This chapter contributes a more insightful panel data analysis of human capital and high skilled emigration. The results of the IV-fixed effect and IV-first difference are quite robust, and the number of tests for post-estimations assures that the possible reverse causality concern is addressed. In addition to Beine *et al*.'s (2011) procedure, we controlled remittance, as a soothing effect of liquidity constraint, public expenditure on education as an intensifier of the decision to gain higher education, and population density as a proxy for cost of acquiring education, and indeed found them to be significant factors in most cases. In general, in contrast to Beine *et al*. (2011), we found a significant and negative brain drain effect. This could be the fact that the origin countries sampled are different from ours as well as additional variables we used.

APPENDIX J

Table3.9 List of Origin Countries in data sample

Algeria	**Dominican Republic**	**Madagascar**
Antigua and Barbuda	**Ecuador**	**Malaysia**
Argentina	**Egypt**	**Maldives**
Bangladesh	**El Salvador**	**Mali**
Barbados	**Ethiopia**	**Malta**
Belize	**Fiji**	**Mauritania**
Benin	**Gabon**	**Mexico**
Bolivia	**Ghana**	**Morocco**
Botswana	**Greece**	**Mozambique**
Brazil	**Grenada**	**Namibia**
Burkina Faso	**Guatemala**	**New Zealand**
Cameroon	**Guinea**	**Niger**
Central African Republic	**Guinea-Bissau**	**Nigeria**
Chile	**Haiti**	**Pakistan**
China	**Honduras**	**Panama**
Colombia	**India**	**Papua New Guinea**
Comoros	**Indonesia**	
Costa Rica	**Jamaica**	
Cote d'Ivoire	**Kenya**	
Dominica	**Lesotho**	

APPENDIX K

Table3.10 Cross-section analysis of OLS for countries with D15[a] : OECD[b]

	(1)	(2)	(3)	(4)
Time intervals	**1980-1985**	**1985-1990**	**1990-1995**	**1995-2000**
$\log H_{\alpha,t-5}$	-0.0017 (0.0017)	-0.0011 (0.0015)	-0.0023 (0.0016)	-0.0009 (0.0014)
$\log p_{t-5}$	-0.0307* (0.0153)	-0.0287* (0.0147)	-0.0281** (0.0107)	-0.0253** (0.0097)
$\log p_{t-5} \times \log GDPpc_{t-5} \times D$	-0.0014 (0.0030)	-0.0035 (0.0022)	-0.0036 (0.0024)	-0.0038** (0.0017)
$\log DENS_{t-5}$	-0.0005 (0.0031)	-0.0028 (0.0019)	-0.0020 (0.0022)	-0.0052*** (0.0016)
$\log EDU_{t-5}$	0.0114* (0.0058)	0.0101** (0.0045)	0.0065 (0.0051)	0.0005 (0.0021)
$\log REM_{t-5}$	0.0010 (0.0014)	0.0011 (0.0011)	0.0016 (0.0011)	0.0011 (0.0011)
$SSAD$	-0.0036 (0.0083)	0.0056 (0.0063)	-0.0019 (0.0065)	-0.0116 (0.0074)
$LATD$	0.0080 (0.0053)	0.0095* (0.0056)	0.0098** (0.0047)	0.0078* (0.0045)
$Cons$	0.0479* (0.0240)	0.0458** (0.0225)	0.0511* (0.0299)	0.0641*** (0.0171)
R^2	0.21	0.34	0.31	0.38
N	50	49	51	53

Models (1), (2), (3) and (4) present the results for 1980-1985: 1985-1990; 1990-1995; and 1995-2000 time intervals. Robust t-statistics are reported in parenthesis *, ** and *** indicate 10%, 5% and 1% significance, respectively.
[a] Countries in the bottom two-thirds of the GDP per capita distribution
[b] Stock of migrants in OECD and population size are used as instrumental variables.

Table3.11 Cross-section analysis of OLS for countries with D10 [a] : OECD[b]

	(1)	(2)	(3)	(4)
Time intervals	**1980-1985**	**1985-1990**	**1990-1995**	**1995-2000**
$\log H_{\alpha,t-5}$	-0.0532*** (0.0153)	-0.0476*** (0.0142)	-0.0337*** (0.0119)	-0.0323*** (0.0107)
$\log p_{t-5}$	-0.0069*** (0.0021)	-0.0061*** (0.0020)	-0.0041** (0.0016)	-0.0041*** (0.0014)
$\log p_{t-5} \times \log GDPpc_{t-5} \times D$	-0.0038* (0.0021)	-0.0035 (0.0021)	-0.0032** (0.0015)	-0.0032*** (0.0012)
$\log DENS_{t-5}$	0.0155** (0.0065)	0.0157*** (0.0056)	0.0036 (0.0059)	0.0024 (0.0015)
$\log EDU_{t-5}$	0.0155** (0.0065)	0.0157*** (0.0056)	0.0036 (0.0059)	0.0024 (0.0015)
$\log REM_{t-5}$	0.0005 (0.00114)	0.0001 (0.0012)	0.0004 (0.0010)	0.0006 (0.0007)
$SSAD$	-0.0073 (0.0104)	0.0031 (0.0076)	-0.0041 (0.0076)	-0.0031 (0.0093)
$LATD$	0.0084 (0.0068)	0.0101 (0.0061)	0.0027 (0.0064)	0.0077* (0.0045)
$Cons$	0.0436* (0.0226)	0.0441* (0.0257)	0.0545* (0.0283)	0.0533*** (0.0171)
R^2	0.34	0.47	0.32	0.45
N	44	40	47	46

Models (1), (2), (3) and (4) present the results for 1980-1985: 1985-1990; 1990-1995; and 1995-2000 time intervals. Robust t-statistics are reported in parenthesis *, ** and *** indicate 10%, 5% and 1% significance, respectively.
[a] Countries in the bottom half of the GDP per capita distribution
[b] Stock of migrants in OECD and population size are used as instrumental variables.

Table3.12 Cross-section analysis of IV for countries with D15 [a] : OECD[b]

	(1)	(2)	(3)	(4)
Time intervals	**1980-1985**	**1985-1990**	**1990-1995**	**1995-2000**
$\log H_{\alpha,t-5}$	-0.0017 (0.0015)	-0.0010 (0.0013)	-0.0023 (0.0015)	-0.0009 (0.0013)
$\log p_{t-5}$	-0.0306** (0.0137)	-0.0287** (0.0133)	-0.0281*** (0.0097)	-0.0253*** (0.0088)
$\log p_{t-5} \times \log GDPpc_{t-5} \times D$	-0.0038** (0.0019)	-0.0035* (0.0019)	-0.0032** (0.0013)	-0.0032*** (0.0011)
$\log DENS_{t-5}$	-0.0005 (0.0028)	-0.0028 (0.0018)	-0.0020 (0.0020)	-0.0052*** (0.0014)
$\log EDU_{t-5}$	0.0114** (0.0052)	0.0101** (0.0041)	0.0065 (0.0046)	0.0005 (0.0019)
$\log REM_{t-5}$	0.0010 (0.0012)	0.0010 (0.0010)	0.0016* (0.0010)	0.0011 (0.0010)
$SSAD$	-0.0036 (0.0075)	0.0055 (0.0057)	-0.0019 (0.0059)	-0.0115* (0.0067)
$LATD$	0.0080* (0.0048)	0.0095* (0.0050)	0.0098** (0.0042)	0.0078* (0.0041)
$Cons$	0.0475** (0.0214)	0.0455** (0.0202)	0.0511* (0.0271)	0.0643*** (0.0156)
R^2	0.21	0.34	0.31	0.38
N	50	49	51	53
Hansen J-Stat	0.26	0.18	0.15	0.41
Endogeneity	0.74	0.53	0.93	0.79
K-P Wald F-Stat	779.952	1227.069	708.806	946.731

Models (1), (2), (3) and (4) present the results for 1980-1985: 1985-1990; 1990-1995; and 1995-2000 time intervals. The P-vals for Hansen J statistics of over-identification and endogeneity and the test for the endogenous regressor are reported. The F-test of K-P Wald F-statistics is a weak identification test. Robust t-statistics are reported in parenthesis. The stata command for IV – fixed effect and first difference results is xtivreg2. *, ** and *** indicate 10%, 5% and 1% significance, respectively.

[a] Countries in the bottom two-thirds of the GDP per capita distribution

[b] Stock of migrants in OECD and population size are used as instrumental variables.

Table3.13 Cross-section analysis of IV for countries with D10 [a] : OECD[b]

	(1)	(2)	(3)	(4)
Time intervals	**1980-1985**	**1985-1990**	**1990-1995**	**1995-2000**
$\log H_{\alpha,t-5}$	-0.0017 (0.0020)	-0.0019 (0.0026)	-0.0028* (0.0015)	-0.0021* (0.0012)
$\log p_{t-5}$	-0.0527*** (0.0139)	-0.0469*** (0.0126)	-0.0354*** (0.0109)	-0.0322*** (0.0097)
$\log p_{t-5} \times \log GDPpc_{t-5} \times D$	-0.0066*** (0.0019)	-0.0057*** (0.0018)	-0.0041*** (0.0015)	-0.0041*** (0.0012)
$\log DENS_{t-5}$	-0.0011 (0.0026)	-0.0028 (0.0024)	-0.0039* (0.0020)	-0.0037** (0.0015)
$\log EDU_{t-5}$	0.0160*** (0.0060)	0.0159*** (0.0049)	0.0024 (0.0049)	0.0024* (0.0013)
$\log REM_{t-5}$	0.0007 (0.00141)	0.0009 (0.0011)	0.00170* (0.0010)	0.0005 (0.0010)
$SSAD$	-0.0052 (0.0108)	0.0056 (0.0077)	-0.0027 (0.0069)	-0.0031 (0.0084)
$LATD$	0.0104 (0.0073)	0.0124** (0.0062)	0.0055 (0.0053)	0.0076* (0.0042)
$Cons$	0.0491** (0.0210)	0.0489* (0.0251)	0.0691** (0.0282)	0.0531*** (0.0152)
R^2	0.36	0.48	0.36	0.45
N	44	40	47	46
Hansen J-Stat	0.91	0.44	0.46	0.90
Endogeneity	0.35	0.93	0.68	0.39
K-P Wald F-Stat	803.843	580.489	691.542	1240.333

Models (1), (2), (3) and (4) present the results for 1980-1985: 1985-1990; 1990-1995; and 1995-2000 time intervals. The P-vals for Hansen J statistics of over-identification and endogeneity and the test for the endogenous regressor are reported. The F-test of K-P Wald F-statistics is a weak identification test. Robust t-statistics are reported in parenthesis. The stata command for IV – fixed effect and first difference results is xtivreg2. *, ** and *** indicate 10%, 5% and 1% significance, respectively.

[a] Countries in the bottom half of the GDP per capita distribution

[b] Stock of migrants in OECD and population size are used as instrumental variables.

Table3.14 Cross-section analysis of IV for countries with D15 [a] : Australia[b]

	(1)	(2)	(3)	(4)
Time intervals	**1980-1985**	**1985-1990**	**1990-1995**	**1995-2000**
$\log H_{\alpha,t-5}$	-0.0018 (0.0016)	-0.0011 (0.0013)	-0.0023 (0.0015)	-0.0009 (0.0013)
$\log p_{t-5}$	-0.0308** (0.0138)	-0.0287** (0.0133)	-0.0281*** (0.0097)	-0.0254*** (0.0088)
$\log p_{t-5} \times \log GDPpc_{t-5} \times D$	-0.0038** (0.0019)	-0.0035* (0.0019)	-0.0032** (0.0013)	-0.0032*** (0.0011)
$\log DENS_{t-5}$	-0.0005 (0.0028)	-0.0028 (0.0018)	-0.0020 (0.0020)	-0.0052*** (0.0015)
$\log EDU_{t-5}$	0.0114** (0.0052)	0.0101** (0.0041)	0.0065 (0.0046)	0.0005 (0.0019)
$\log REM_{t-5}$	0.0010 (0.0012)	0.0011 (0.0010)	0.0016* (0.0010)	0.0011 (0.0010)
$SSAD$	-0.0036 (0.0076)	0.0055 (0.0057)	-0.0019 (0.0059)	-0.0115* (0.0067)
$LATD$	0.0080* (0.0048)	0.0095* (0.0050)	0.0098** (0.0042)	0.0078* (0.0041)
$Cons$	0.0481** (0.0215)	0.0457** (0.0202)	0.0511* (0.0271)	0.0644*** (0.0156)
R^2	0.21	0.34	0.31	0.38
N	50	49	51	53
Hansen J-Stat	0.02	0.01	0.01	0.11
Endogeneity	0.71	0.73	0.95	0.75
K-P Wald F-Stat	1021.297	1397.544	787.979	1115.850

Models (1), (2), (3) and (4) present the results for 1980-1985: 1985-1990; 1990-1995; and 1995-2000 time intervals. The P-vals for Hansen J statistics of over-identification and endogeneity and the test for the endogenous regressor are reported. The F-test of K-P Wald F-statistics is a weak identification test. Robust t-statistics are reported in parenthesis. The stata command for IV – fixed effect and first difference results is xtivreg2. *, ** and *** indicate 10%, 5% and 1% significance, respectively.
[a] Countries in the bottom two-thirds of the GDP per capita distribution
[b] Stock of migrants in Australia and population size are used as instrumental variables.

Table3.15 Cross-section analysis of IV for countries with D10 [a]: Australia[b]

	(1)	(2)	(3)	(4)
Time intervals	**1980-1985**	**1985-1990**	**1990-1995**	**1995-2000**
$\log H_{\alpha,t-5}$	-0.0019 (0.0020)	-0.0021 (0.0025)	-0.0028* (0.0015)	-0.0024* (0.0012)
$\log p_{t-5}$	-0.0526*** (0.0139)	-0.0468*** (0.0126)	-0.0354*** (0.0109)	-0.0322*** (0.0097)
$\log p_{t-5} \times \log GDPpc_{t-5} \times D$	-0.0066*** (0.0019)	-0.0056*** (0.0018)	-0.0041*** (0.0014)	-0.0041*** (0.0012)
$\log DENS_{t-5}$	-0.0010 (0.0026)	-0.0028 (0.0024)	-0.0039* (0.0020)	-0.0037** (0.0015)
$\log EDU_{t-5}$	0.0160*** (0.0060)	0.0159*** (0.0049)	0.0024 (0.0049)	0.0024* (0.0013)
$\log REM_{t-5}$	0.0007 (0.0014)	0.0011 (0.0011)	0.0017* (0.0010)	0.00056 (0.0010)
$SSAD$	-0.0050 (0.0108)	0.0058 (0.0077)	-0.0027 (0.0069)	-0.0031 (0.0084)
$LATD$	0.0105 (0.0073)	0.0127** (0.0062)	0.0055 (0.0053)	0.0076* (0.0042)
$Cons$	0.0497** (0.0211)	0.0494** (0.0251)	0.0692** (0.0282)	0.0532*** (0.0152)
R^2	0.36	0.48	0.36	0.45
N	44	40	47	46
Hansen J-Stat	0.02	0.01	0.01	0.15
Endogeneity	0.87	0.35	0.73	0.49
K-P Wald F-Stat	1007.500	686.070	797.186	1127.540

Models (1), (2), (3) and (4) present the results for 1980-1985: 1985-1990; 1990-1995; and 1995-2000 time intervals. The P-vals for Hansen J statistics of over-identification and endogeneity and the test for the endogenous regressor are reported. The F-test of K-P Wald F-statistics is a weak identification test. Robust t-statistics are reported in parenthesis. The stata command for IV – fixed effect and first difference results is xtivreg2. *, ** and *** indicate 10%, 5% and 1% significance, respectively.
[a] Countries in the bottom half of the GDP per capita distribution
[b] Stock of migrants in Australia and population size are used as instrumental variables.

Table3.16 Cross-section analysis of IV for countries with D15 [a]: Canada [b]

	(1)	(2)	(3)	(4)
Time intervals	**1980-1985**	**1985-1990**	**1990-1995**	**1995-2000**
$\log H_{\alpha,t-5}$	-0.0016 (0.0016)	-0.0011 (0.0013)	-0.0022 (0.0015)	-0.0009 (0.0013)
$\log p_{t-5}$	-0.0305** (0.0138)	-0.0287** (0.0133)	-0.0280*** (0.0097)	-0.0255*** (0.0088)
$\log p_{t-5} \times \log GDPpc_{t-5} \times D$	-0.0038** (0.0019)	-0.0035* (0.0019)	-0.0032** (0.0013)	-0.0032*** (0.0011)
$\log DENS_{t-5}$	-0.0005 (0.0028)	-0.0028 (0.0018)	-0.0020 (0.0020)	-0.0052*** (0.0014)
$\log EDU_{t-5}$	0.0115** (0.0052)	0.0101** (0.0041)	0.0066 (0.0046)	0.0005 (0.0019)
$\log REM_{t-5}$	0.0010 (0.0012)	0.0010 (0.0010)	0.0016 (0.0011)	0.0011 (0.0010)
$SSAD$	-0.0036 (0.0075)	0.0054 (0.0057)	-0.0019 (0.0059)	-0.0115* (0.0067)
$LATD$	0.0080* (0.0048)	0.0094* (0.0050)	0.0097** (0.0042)	0.0078* (0.0041)
$Cons$	0.0471** (0.0215)	0.0453** (0.0202)	0.0505* (0.0271)	0.0644*** (0.0156)
R^2	0.21	0.34	0.30	0.38
N	50	49	51	53
Hansen J-Stat	0.07	0.06	0.01	0.03
Endogeneity	0.56	0.45	0.36	0.93
K-P Wald F-Stat	719.896	1240.188	815.529	958.589

Models (1), (2), (3) and (4) present the results for 1980-1985: 1985-1990; 1990-1995; and 1995-2000 time intervals. The P-vals for Hansen J statistics of over-identification and endogeneity and the test for the endogenous regressor are reported. The F-test of K-P Wald F-statistics is a weak identification test. Robust t-statistics are reported in parenthesis. The stata command for IV – fixed effect and first difference results is xtivreg2. *, ** and *** indicate 10%, 5% and 1% significance, respectively.

[a] Countries in the bottom two-thirdsof the GDP per capita distribution

[b] Stock of migrants in Canada and population size are used as instrumental variables.

Table3 .17 Cross-section analysis of IV for countries with D10 [a] : Canada[b]

	(1)	(2)	(3)	(4)
Time intervals	**1980-1985**	**1985-1990**	**1990-1995**	**1995-2000**
$\log H_{\alpha,t-5}$	-0.0017 (0.0020)	-0.0019 (0.0025)	-0.0027* (0.0015)	-0.0023* (0.0012)
$\log p_{t-5}$	-0.0526*** (0.0139)	-0.0469*** (0.0126)	-0.0354*** (0.0109)	-0.0322*** (0.0097)
$\log p_{t-5} \times \log GDPpc_{t-5} \times D$	-0.0066*** (0.0019)	-0.0057*** (0.0018)	-0.0041*** (0.0015)	-0.0041*** (0.0012)
$\log DENS_{t-5}$	-0.0011 (0.0026)	-0.0028 (0.0024)	-0.0039* (0.0020)	-0.0037** (0.0015)
$\log EDU_{t-5}$	0.0160*** (0.0060)	0.0159*** (0.0049)	0.0024 (0.0050)	0.0024* (0.0013)
$\log REM_{t-5}$	0.0007 (0.0014)	0.0009 (0.0011)	0.0017* (0.0011)	0.0005 (0.0010)
$SSAD$	-0.0051 (0.0108)	0.0055 (0.0076)	-0.0028 (0.0069)	-0.0031 (0.0084)
$LATD$	0.0104 (0.0073)	0.0124** (0.0062)	0.0054 (0.0053)	0.0076* (0.0042)
$Cons$	0.0492** (0.0210)	0.0488* (0.0251)	0.0687** (0.0282)	0.0531*** (0.0152)
R^2	0.36	0.48	0.36	0.45
N	44	40	47	46
Hansen J-Stat	0.21	0.04	0.01	0.01
Endogeneity	0.61	0.92	0.24	0.13
K-P Wald F-Stat	788.712	609.579	805.087	1143.481

Models (1), (2), (3) and (4) present the results for 1980-1985: 1985-1990; 1990-1995; and 1995-2000 time intervals. The P-vals for Hansen J statistics of over-identification and endogeneity and the test for the endogenous regressor are reported. The F-test of K-P Wald F-statistics is a weak identification test. Robust t-statistics are reported in parenthesis. The stata command for IV – fixed effect and first difference results is xtivreg2. *, ** and *** indicate 10%, 5% and 1% significance, respectively.

[a] Countries in the bottom half of the GDP per capita distribution

[b] Stock of migrants in Canada and population size are used as instrumental variables.

Table3.18 Cross-section analysis of IV for countries with D15 [a] : France[b]

	(1)	(2)	(3)	(4)
Time intervals	**1980-1985**	**1985-1990**	**1990-1995**	**1995-2000**
$\log H_{\alpha,t-5}$	-0.0016 (0.0016)	-0.0010 (0.0013)	-0.0024 (0.0015)	-0.0009 (0.0013)
$\log p_{t-5}$	-0.0306** (0.0138)	-0.0287** (0.0133)	-0.0281*** (0.0097)	-0.0255*** (0.0088)
$\log p_{t-5} \times \log GDPpc_{t-5} \times D$	-0.0038** (0.0019)	-0.0035* (0.0019)	-0.0032** (0.0013)	-0.0032*** (0.0011)
$\log DENS_{t-5}$	-0.0005 (0.0028)	-0.0028 (0.0018)	-0.0020 (0.0020)	-0.0052*** (0.0014)
$\log EDU_{t-5}$	0.0114** (0.0052)	0.0101** (0.0041)	0.0065 (0.0046)	0.0005 (0.0019)
$\log REM_{t-5}$	0.0010 (0.0013)	0.0010 (0.0011)	0.0017* (0.0010)	0.0011 (0.0010)
$SSAD$	-0.0036 (0.0076)	0.0055 (0.0057)	-0.0019 (0.0059)	-0.0115* (0.0067)
$LATD$	0.0080* (0.0048)	0.0095* (0.0050)	0.0098** (0.0043)	0.0078* (0.0041)
$Cons$	0.0473** (0.0215)	0.0455** (0.0202)	0.0514* (0.0272)	0.0645*** (0.0156)
R^2	0.21	0.34	0.31	0.38
N	50	49	51	53
Hansen J-Stat	0.71	0.42	0.14	0.77
Endogeneity	0.61	0.51	0.97	0.68
K-P Wald F-Stat	921.598	1346.506	1095.559	1179.773

Models (1), (2), (3) and (4) present the results for 1980-1985: 1985-1990; 1990-1995; and 1995-2000 time intervals. The P-vals for Hansen J statistics of over-identification and endogeneity and the test for the endogenous regressor are reported. The F-test of K-P Wald F-statistics is a weak identification test. Robust t-statistics are reported in parenthesis. The stata command for IV – fixed effect and first difference results is xtivreg2. *, ** and *** indicate 10%, 5% and 1% significance, respectively.

[a] Countries in the bottom two-thirds of the GDP per capita distribution

[b] Stock of migrants in France and population size are used as instrumental variables.

Table3.19 Cross-section analysis of IV for countries with D10 [a] :France[b]

	(1)	(2)	(3)	(4)
Time intervals	**1980-1985**	**1985-1990**	**1990-1995**	**1995-2000**
$\log H_{\alpha,t-5}$	-0.0017 (0.0020)	-0.0019 (0.0025)	-0.0028* (0.0015)	-0.0023* (0.0012)
$\log p_{t-5}$	-0.0527*** (0.0139)	-0.0469*** (0.0126)	-0.0355*** (0.0109)	-0.0323*** (0.0097)
$\log p_{t-5} \times \log GDPpc_{t-5} \times D$	-0.0066*** (0.0019)	-0.0056*** (0.0018)	-0.0041*** (0.0015)	-0.0041*** (0.0012)
$\log DENS_{t-5}$	-0.0011 (0.0026)	-0.0028 (0.0024)	-0.0039* (0.0020)	-0.0038** (0.0015)
$\log EDU_{t-5}$	0.0160*** (0.0060)	0.0159*** (0.0049)	0.0024 (0.0049)	0.0024* (0.0013)
$\log REM_{t-5}$	0.0007 (0.0014)	0.0009 (0.0011)	0.0017* (0.0010)	0.0006 (0.0010)
$SSAD$	-0.0052 (0.0108)	0.0056 (0.0076)	-0.0027 (0.0069)	-0.0031 (0.0084)
$LATD$	0.0103 (0.0073)	0.0125** (0.0062)	0.0055 (0.0053)	0.0077* (0.0042)
$Cons$	0.0491** (0.0210)	0.0490* (0.0251)	0.0695** (0.0283)	0.0533*** (0.0153)
R^2	0.36	0.48	0.36	0.45
N	44	40	47	46
Hansen J-Stat	0.50	0.91	0.15	0.31
Endogeneity	0.43	0.90	0.79	0.48
K-P Wald F-Stat	1024.172	832.633	1127.586	1407.195

Models (1), (2), (3) and (4) present the results for 1980-1985: 1985-1990; 1990-1995; and 1995-2000 time intervals. The P-vals for Hansen J statistics of over-identification and endogeneity and the test for the endogenous regressor are reported. The F-test of K-P Wald F-statistics is a weak identification test. Robust t-statistics are reported in parenthesis. The stata command for IV – fixed effect and first difference results is xtivreg2. *, ** and *** indicate 10%, 5% and 1% significance, respectively.

[a] Countries in the bottom half of the GDP per capita distribution

[b] Stock of migrants in France and population size are used as instrumental variables.

Table3.20 Cross-section analysis of IV for countries with D15 [a]: Germany[b]

	(1)	(2)	(3)	(4)
Time intervals	**1980-1985**	**1985-1990**	**1990-1995**	**1995-2000**
$\log H_{\alpha,t-5}$	-0.00160 (0.00155)	-0.000992 (0.00127)	-0.00230 (0.00149)	-0.000903 (0.00125)
$\log p_{t-5}$	-0.0016 (0.00155)	-0.0010 (0.00127)	-0.0023 (0.00149)	-0.0009 (0.00125)
$\log p_{t-5} \times \log GDPpc_{t-5} \times D$	-0.0038** (0.00186)	-0.0035* (0.00191)	-0.0032** (0.00132)	-0.0032*** (0.00107)
$\log DENS_{t-5}$	-0.0005 (0.00280)	-0.0028 (0.00175)	-0.0020 (0.00202)	-0.0052*** (0.00145)
$\log EDU_{t-5}$	0.0114** (0.0052)	0.0101** (0.0041)	0.0065 (0.0046)	0.0005 (0.0019)
$\log REM_{t-5}$	0.0010 (0.00125)	0.00103 (0.000960)	0.00161* (0.000956)	0.0011 (0.0010)
$SSAD$	-0.0036 (0.0075)	0.0055 (0.0057)	-0.0019 (0.0059)	-0.0115* (0.0067)
$LATD$	0.0080* (0.0048)	0.0094* (0.0050)	0.0098** (0.0042)	0.0078* (0.0041)
$Cons$	0.0472** (0.0214)	0.0454** (0.0202)	0.0509* (0.0272)	0.0644*** (0.0156)
R^2	0.21	0.34	0.31	0.38
N	50	49	51	53
Hansen J-Stat	0.83	0.88	0.74	0.81
Endogeneity	0.59	0.55	0.85	0.72
K-P Wald F-Stat	704.871	1211.072	1196.491	1396.524

Models (1), (2), (3) and (4) present the results for 1980-1985: 1985-1990; 1990-1995; and 1995-2000 time intervals. The P-vals for Hansen J statistics of over-identification and endogeneity and the test for the endogenous regressor are reported. The F-test of K-P Wald F-statistics is a weak identification test. Robust t-statistics are reported in parenthesis. The stata command for IV – fixed effect and first difference results is xtivreg2. *, ** and *** indicate 10%, 5% and 1% significance, respectively.

[a] Countries in the bottom two-thirds of the GDP per capita distribution

[b] Stock of migrants in Germany and population size are used as instrumental variables.

Table3.21 Cross-section analysis of IV for countries with D10 [a] :Germany[b]

	(1)	(2)	(3)	(4)
Time intervals	**1980-1985**	**1985-1990**	**1990-1995**	**1995-2000**
$\log H_{\alpha,t-5}$	-0.0017 (0.0020)	-0.0019 (0.0025)	-0.0027* (0.0015)	-0.0018* (0.00125)
$\log p_{t-5}$	-0.0527*** (0.0139)	-0.0469*** (0.0126)	-0.0354*** (0.0109)	-0.0322*** (0.0097)
$\log p_{t-5} \times \log GDPpc_{t-5} \times D$	-0.0066*** (0.0019)	-0.0057*** (0.0018)	-0.0041*** (0.0015)	-0.0041*** (0.0013)
$\log DENS_{t-5}$	-0.0011 (0.0026)	-0.0028 (0.0024)	-0.0039* (0.0020)	-0.0037** (0.0015)
$\log EDU_{t-5}$	0.0160*** (0.0060)	0.0159*** (0.0049)	0.0024 (0.0050)	0.0024* (0.0013)
$\log REM_{t-5}$	0.0007 (0.0014)	0.0009 (0.0011)	0.0017* (0.0010)	0.0006 (0.0011)
$SSAD$	-0.0052 (0.0108)	0.0056 (0.0076)	-0.0027 (0.0069)	-0.0031 (0.0084)
$LATD$	0.0103 (0.0073)	0.0125** (0.0062)	0.0055 (0.0053)	0.0076* (0.0042)
$Cons$	0.0491** (0.0210)	0.0489* (0.0251)	0.0690** (0.0283)	0.0532*** (0.0152)
R^2	0.36	0.48	0.36	0.45
N	44	40	47	46
Hansen J-Stat	0.36	0.33	0.90	0.67
Endogeneity	0.40	0.90	0.59	0.40
K-P Wald F-Stat	746.254	587.051	1142.368	1462.187

Models (1), (2), (3) and (4) present the results for 1980-1985: 1985-1990; 1990-1995; and 1995-2000 time intervals. The P-vals for Hansen J statistics of over-identification and endogeneity and the test for the endogenous regressor are reported. The F-test of K-P Wald F-statistics is a weak identification test. Robust t-statistics are reported in parenthesis. The stata command for IV – fixed effect and first difference results is xtivreg2. *, ** and *** indicate 10%, 5% and 1% significance, respectively.

[a] Countries in the bottom half of the GDP per capita distribution

[b] Stock of migrants in Germany and population size are used as instrumental variables.

Table3.22 Cross-section analysis of IV for countries with D15 [a]: UK[b]

	(1)	(2)	(3)	(4)
Time intervals	**1980-1985**	**1985-1990**	**1990-1995**	**1995-2000**
$\log H_{\alpha,t-5}$	-0.0015 (0.0016)	-0.0009 (0.0013)	-0.0022 (0.0015)	-0.0009 (0.0013)
$\log p_{t-5}$	-0.0305** (0.0138)	-0.0287** (0.0133)	-0.0280*** (0.0097)	-0.0254*** (0.0088)
$\log p_{t-5} \times \log GDPpc_{t-5} \times D$	-0.0038** (0.0019)	-0.0035* (0.0019)	-0.0032** (0.0013)	-0.0032*** (0.0011)
$\log DENS_{t-5}$	-0.0005 (0.0028)	-0.0028 (0.0018)	-0.0020 (0.0020)	-0.0052*** (0.0015)
$\log EDU_{t-5}$	0.0115** (0.0052)	0.0101** (0.0041)	0.0066 (0.0046)	0.0005 (0.0019)
$\log REM_{t-5}$	0.0009 (0.0012)	0.0011 (0.0010)	0.0016 (0.0010)	0.0011 (0.0010)
$SSAD$	-0.0036 (0.0075)	0.0054 (0.0057)	-0.0019 (0.0059)	-0.0116* (0.0067)
$LATD$	0.0081* (0.0048)	0.0093* (0.0050)	0.0097** (0.0042)	0.0078* (0.0041)
$Cons$	0.0467** (0.0216)	0.0450** (0.0203)	0.0503* (0.0272)	0.0642*** (0.0156)
R^2	0.21	0.34	0.31	0.38
N	50	49	51	53
Hansen J-Stat	0.32	0.16	0.05	0.02
Endogeneity	0.39	0.20	0.35	0.79
K-P Wald F-Stat	873.501	1454.507	919.764	1078.235

Models (1), (2), (3) and (4) present the results for 1980-1985: 1985-1990; 1990-1995; and 1995-2000 time intervals. The P-vals for Hansen J statistics of over-identification and endogeneity and the test for the endogenous regressor are reported. The F-test of K-P Wald F-statistics is a weak identification test. Robust t-statistics are reported in parenthesis. The stata command for IV – fixed effect and first difference results is xtivreg2. *, ** and *** indicate 10%, 5% and 1% significance, respectively.

[a] Countries in the bottom two-thirds of the GDP per capita distribution

[b]Stock of migrants in the UK and population size are used as instrumental variables.

Table3.23 Cross-section analysis of IV for countries with D10 [a] :UK[b]

	(1)	(2)	(3)	(4)
Time intervals	**1980-1985**	**1985-1990**	**1990-1995**	**1995-2000**
$\log H_{\alpha,t-5}$	-0.0017 (0.0020)	-0.0018 (0.0025)	-0.0026* (0.0015)	-0.0019* (0.0012)
$\log p_{t-5}$	-0.0527*** (0.0139)	-0.0469*** (0.0126)	-0.0353*** (0.0109)	-0.0322*** (0.0097)
$\log p_{t-5} \times \log GDPpc_{t-5} \times D$	-0.0066*** (0.0019)	-0.0057*** (0.0019)	-0.0041*** (0.0015)	-0.0041*** (0.0012)
$\log DENS_{t-5}$	-0.0011 (0.0026)	-0.0029 (0.0024)	-0.0039* (0.0020)	-0.0037** (0.0015)
$\log EDU_{t-5}$	0.0160*** (0.0060)	0.0159*** (0.0049)	0.0025 (0.0050)	0.0024* (0.0013)
$\log REM_{t-5}$	0.0007 (0.0014)	0.0009 (0.0011)	0.0017* (0.0010)	0.0005 (0.0010)
$SSAD$	-0.0052 (0.0109)	0.0054 (0.0076)	-0.0028 (0.0069)	-0.0031 (0.0084)
$LATD$	0.0103 (0.0073)	0.0123** (0.0062)	0.0053 (0.0053)	0.0076* (0.0042)
$Cons$	0.0490** (0.0210)	0.0485* (0.0252)	0.0685** (0.0283)	0.0531*** (0.0152)
R^2	0.36	0.48	0.36	0.45
N	44	40	47	46
Hansen J-Stat	0.72	0.18	0.12	0.01
Endogeneity	0.37	0.31	0.20	0.21
K-P Wald F-Stat	830.343	841.212	928.513	1293.225

Models (1), (2), (3) and (4) present the results for 1980-1985: 1985-1990; 1990-1995; and 1995-2000 time intervals. The P-vals for Hansen J statistics of over-identification and endogeneity and the test for the endogenous regressor are reported. The F-test of K-P Wald F-statistics is a weak identification test. Robust t-statistics are reported in parenthesis. The stata command for IV – fixed effect and first difference results is xtivreg2. *, ** and *** indicate 10%, 5% and 1% significance, respectively.

[a] Countries in the bottom half of the GDP per capita distribution

[b] Stock of migrants in the UK and population size are used as instrumental variables.

Table3.24 Cross-section analysis of IV for countries with D15 [a] :USA[b]

	(1)	(2)	(3)	(4)
Time intervals	**1980-1985**	**1985-1990**	**1990-1995**	**1995-2000**
$\log H_{\alpha,t-5}$	-0.0016 (0.0016)	-0.0010 (0.0013)	-0.0023 (0.0015)	-0.0009 (0.0013)
$\log p_{t-5}$	-0.0306** (0.0138)	-0.0287** (0.0133)	-0.0281*** (0.0097)	-0.0255*** (0.0088)
$\log p_{t-5} \times \log GDPpc_{t-5} \times D$	-0.0038** (0.0019)	-0.0035* (0.0019)	-0.0032** (0.0013)	-0.0032*** (0.0011)
$\log DENS_{t-5}$	-0.0005 (0.0028)	-0.0028 (0.0018)	-0.0020 (0.0020)	-0.0052*** (0.0014)
$\log EDU_{t-5}$	0.0114** (0.00524)	0.0101** (0.00406)	0.0065 (0.0046)	0.0005 (0.0019)
$\log REM_{t-5}$	0.00010 (0.0012)	0.0010 (0.0010)	0.00160* (0.0010)	0.0011 (0.0010)
$SSAD$	-0.0036 (0.0075)	0.0054 (0.0057)	-0.0019 (0.0059)	-0.0115* (0.0067)
$LATD$	0.0080* (0.0048)	0.0094* (0.0050)	0.0098** (0.0042)	0.0078* (0.0041)
$Cons$	0.0472** (0.0215)	0.0452** (0.0203)	0.0508* (0.0272)	0.0645*** (0.0156)
R^2	0.21	0.34	0.31	0.38
N	50	49	51	53
Hansen J-Stat				
Endogeneity				
K-P Wald F-Stat				

Models (1), (2), (3) and (4) present the results for 1980-1985: 1985-1990; 1990-1995; and 1995-2000 time intervals. The P-vals for Hansen J statistics of over-identification and endogeneity and the test for the endogenous regressor are reported. The F-test of K-P Wald F-statistics is a weak identification test. Robust t-statistics are reported in parenthesis. The stata command for IV – fixed effect and first difference results is xtivreg2. *, ** and *** indicate 10%, 5% and 1% significance, respectively.

[a] Countries in the bottom two-thirds of the GDP per capita distribution

[b] Stock of migrants in the USA and population size are used as instrumental variables.

Table3.25 Cross-section analysis of IV for countries with D10 [a] :USA[b]

	(1)	(2)	(3)	(4)
Time intervals	**1980-1985**	**1985-1990**	**1990-1995**	**1995-2000**
$\log H_{\alpha,t-5}$	-0.0017 (0.0020)	-0.0019 (0.0026)	-0.0027* (0.0015)	-0.0023* (0.0012)
$\log p_{t-5}$	-0.0527*** (0.0139)	-0.0469*** (0.0126)	-0.0354*** (0.0109)	-0.0322*** (0.0097)
$\log p_{t-5} \times \log GDPpc_{t-5} \times D$	-0.0066*** (0.0019)	-0.0057*** (0.0019)	-0.0041*** (0.0015)	-0.0041*** (0.0012)
$\log DENS_{t-5}$	-0.0011 (0.0026)	-0.0029 (0.0024)	-0.0039* (0.0020)	-0.0037** (0.0015)
$\log EDU_{t-5}$	0.0160*** (0.0060)	0.0159*** (0.0049)	0.0024 (0.0050)	0.0023* (0.0013)
$\log REM_{t-5}$	0.0007 (0.0014)	0.0009 (0.0012)	0.0017* (0.0011)	0.0005 (0.0010)
$SSAD$	-0.0052 (0.0108)	0.0055 (0.0077)	-0.0027 (0.0068)	-0.0031 (0.0084)
$LATD$	0.0103 (0.0073)	0.0124** (0.0062)	0.0054 (0.0053)	0.0076* (0.0042)
$Cons$	0.0491** (0.0210)	0.0487* (0.0252)	0.0690** (0.0283)	0.0532*** (0.0153)
R^2	0.36	0.48	0.36	0.45
N	44	40	47	46
Hansen J-Stat	0.48	0.23	0.88	0.92
Endogeneity	0.29	0.84	0.53	0.38
K-P Wald F-Stat	736.011	605.643	958.951	1323.661

Models (1), (2), (3) and (4) present the results for 1980-1985: 1985-1990; 1990-1995; and 1995-2000 time intervals. The P-vals for Hansen J statistics of over-identification and endogeneity and the test for the endogenous regressor are reported. The F-test of K-P Wald F-statistics is a weak identification test. Robust t-statistics are reported in parenthesis. The stata command for IV – fixed effect and first difference results is xtivreg2. *, ** and *** indicate 10%, 5% and 1% significance, respectively.

[a] Countries in the bottom half of the GDP per capita distribution

[b] Stock of migrants in the USA and population size are used as instrumental variables.

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