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# Knowledge Remittances: Does Emigration Foster Innovation?

## Abstract

Does the emigration of skilled individuals necessarily result in losses for source countries due to the brain drain? Combining industry-level patenting and migration data from 32 European countries, we show that emigration in fact positively contributes to innovation in source countries. We use changes in the labour mobility legislation within Europe as exogenous variation to establish causality. By analysing patent citation data, we further provide evidence that these positive effects are driven by knowledge flows that are triggered by emigrants. While skilled migrants are not inventing in their home country anymore, they contribute to cross-border knowledge and technology diffusion and thus help less advanced countries to catch up to the technology frontier.

JEL-Codes: F220, J610, O330, O310, O520.

Keywords: migration, innovation, knowledge spillovers, patent citations, EU enlargement.

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# 1 Introduction

Remittances, the money international migrant workers are sending back from the country of employment to their home country, represent an important source of income for developing countries and hence constitute a direct benefit of emigration.[1] Furthermore, apart from financial contributions, skilled migrants can "send" back the knowledge they have acquired while working in other countries. This remittance of knowledge has the potential to increase innovation in the origin countries and bring them closer to the technology frontier, thus mitigating the negative effects of the loss of human capital due to emigration.

The number of highly educated foreigners in the OECD area now exceeds 31 million, accounting for 45 percent of the increase in the foreign born population over the last decade (OECD Database on Immigrants in OECD Countries, 2016). The number of skilled migrants has especially increased within Europe since many members of the European Union (EU) and the European Free Trade Association (EFTA) have introduced free movement for citizens of the partner countries. Given the strong increase in labour mobility and raising concerns in countries experiencing net outflows of skilled people, it is important to understand the consequences of migration. Should firms and policy-makers think and act in the context of a "global war for talent" or can the international mobility of skilled individuals make everyone better off, in particular, by stimulating cross-border knowledge flows?

In this project, we establish a causal link between labour mobility, knowledge flows, and innovation activities. By exploiting changes in the European labour mobility legislation as a quasi-experimental setting, we evaluate the effect of skilled emigration on innovation. We find that the emigration of skilled individuals increases patenting in source countries and argue that knowledge remittances can explain this positive effect. Using data on patent citations and migration flows from 32 European countries, we find that emigration increases cross-border knowledge flows. Industries that are exposed to a higher mobility of their workers start to cite patents from the emigrants' destinations more frequently than before. The international mobility of skilled workers seems to enlarge R&D networks and

[1] Russell (1986).

promote the transfer of tacit knowledge. In this way, migration enables a faster diffusion of knowledge from more to less technologically advanced countries and helps the latter to catch up.

We embed these results within the following conceptual framework. We assume a knowledge production function, where innovation (here, for instance, measured by the number of patents) is produced with the inputs of capital and labour and a certain production technology. Emigration leads to a reduction in labour and thus has a direct negative effect on innovation production. However, there might also be an indirect effect, which has often been overlooked in this discussion. International migration can increase the flow of ideas and knowledge across borders. Migrants might share knowledge about new technologies, processes, and products with their former colleagues and friends at home. This increases the stock of knowledge in the source countries and, through the recombination of ideas, positively affects innovation. The production technology thus improves and patent production can grow even if the available skilled labour is reduced. Our conceptual considerations thus suggest that migration has a negative direct and a positive indirect effect on patenting levels in source countries. Although we cannot disentangle these effects with our data, we provide empirical evidence on the total effect.

The main challenge in the empirical analysis is the endogeneity of migration flows. This could be due to reverse causality or omitted variables. To establish causality, we construct an instrumental variable (IV) for migration, using changes in labour mobility laws within Europe. These laws are adopted and enforced by the destination countries and hence can be treated as exogenous to economic conditions in migrants' source countries.

The aim of our estimations are twofold. Combining several data sources, we do not only establish a link between emigration and innovation in the source country, but also shed light on the effect on knowledge remittances, potentially driving innovation. We start by analysing the effects of international labour mobility on total patenting activity in source countries. The IV estimate suggests that a one percent increase in the number of emigrants increases patent applications by 0.64 percent in the following two years. This result is statistically significant at the one percent level and robust to controls, fixed effects, and varying lags. The effect is quantitatively more pronounced when we consider only the flows of migrants with patenting potential.

We complement the analysis of innovation activity by looking at the convergence in patenting between migrants' origin and destination industries. We limit the sample to pairs where the destination is more technologically advanced than the origin and analyse whether the difference in patenting levels changes with migration flows. This is a highly policy-relevant question, especially in the context of the European Union: Some countries may block the initiatives aimed at enhancing within-EU labour mobility by arguing that the outflow of skilled people will further augment the asymmetries between richer and poorer member states. Contrary to this argument, though, our results show that patenting differences between origins and destinations decrease in the number of emigrants. Hence, emigration can promote convergence to the innovation level of more advanced economies.

To establish the channel for the positive impact of emigration on innovation, we link emigration to reverse knowledge flows, that is the transfer of knowledge from migrants' destinations back to their origins. While skilled emigrants do not patent in their home country anymore, they can stimulate knowledge and technology diffusion, thus improving the production technology in the origin country. Common to the innovation literature, we use cross-border patent citations as a proxy for knowledge flows. The regression analysis relates the number of citations to a particular destination country with the number of migrants that currently work there. We find evidence that knowledge flows from destination to origin indeed increase with migration: the 2SLS regressions yield an elasticity of knowledge flows to emigration equal to 0.59.

Our project relates to two broad strands of the literature. The first one investigates the effects of labour mobility on innovation. Several papers have established a positive effect of migration on patenting in destination countries. Kerr and Lincoln (2010) use random visa allocations to find causal effects for the US. Bosetti et al. (2015), Parrotta et al. (2014), Ozgen et al. (2014) and Niebuhr (2010) focus on European countries and establish cultural diversity as one of the main channels to generate new ideas and innovation. The effect of migration on source countries received less attention. Kerr (2008) and Choudhury (2015) find that source countries benefit from knowledge flows and return migration and consequently increase patenting and innovation. Kaiser et al. (2015) provide firm-level evidence by looking at worker mobility within Denmark. They find that hiring new knowledge workers increases a firm's patenting activity. Interestingly, the former employers of these workers also increase patenting, which can be explained by reverse knowledge flows. Braunerhjelm et al. (2015) conduct a similar analysis with a matched employer-employee dataset from Sweden and also show that both the receiving and the sending firms benefit from the mobility of knowledge workers. The effects are stronger for interregional mobility. We contribute to this literature by providing causal evidence that emigration leads to an increase in patenting. We thereby confirm what Kerr (2008) and Choudhury (2015) showed for China and India in a very different context and using another methodology. As we have comparable patenting data for source and destination countries, we can extend this result and show that emigration leads to a catch-up process.

The second strand of the literature analyses the determinants of knowledge flows. Starting with the seminal contribution by Jaffe et al. (1993), these studies have established that knowledge is localised beyond the effects of agglomeration. Later studies focused on international knowledge spillovers (Hu and Jaffe 2003; Jaffe and Trajtenberg 1999), showing that knowledge takes time to cross country borders. Thompson and Fox-Kean (2005) challenge the approach by Jaffe et al. (1993) and point out that intra-national localization effects are not robust to a finer technology classification. However, even with their more conservative estimations, the international localization remains significant. Singh and Marx (2013) investigate whether advances in communication technologies and lower costs of travelling reduce the localisation of knowledge over time. While they find evidence for a reduction in the significance of state borders in the US, their results show that the effect of international borders has even strengthened over time. Few studies so far analysed the impact of international migration on cross-border knowledge flows.[2] Kerr (2008), for instance, studies the role of skilled immigrants in the U.S. and finds that immigrants form ethnic scientific networks that enhance the technology transfer to source countries.

We extend this literature on knowledge flows to the European context using

[2]Prior literature on the international knowledge flows has focused on trade, foreign direct investment and R&D accessibility (MacGarvie 2005, 2006; Peri 2005).

an identification strategy that allows for a causal interpretation. We build a unique dataset by merging comparable migration data for 32 European countries with European patent data and find evidence for knowledge flows. Due to our unique European enlargement setting, we are able to estimate causal effects of labour mobility independently of other integration events by exploiting different opening times for trade, FDI and migration. We find that the positive effect of mobility on knowledge remittances is particularly high for migrants with patenting potential and is robust to a variety of specifications and samples.

The paper is organised as follows. The next section describes a conceptual framework to guide our empirical analysis. Section 3 outlines the data, followed by Section 4 that presents the empirical specification and describes the instrument. Section 5 discusses the results. Section 6 suggests knowledge flows as the channel. Section 7 provides robustness checks and Section 8 concludes.

## 2 Conceptual Considerations

This paper analyses the effects of emigration on innovation in source countries. As there are two opposing effects, our storyline becomes clearer if we support it with some conceptual considerations. The considerations are based on a classical knowledge production function as introduced by Griliches (1979) and further developed by Jaffe (1986) and Jaffe (1989). We augment the knowledge production function with emigration. The concept illustrates two opposing effects: a reduction in knowledge production due to a decreasing skilled labour force vs. an increase due to a better production technology induced by knowledge flows and technological spillovers.

We assume a simplified knowledge production function of the form

$$Y = Af(K, L_s). \tag{1}$$

$K$ is a measure of relevant capital available for research and development such as laboratories and equipment. $L_s$ stands for skilled labour and $A$ measures total factor productivity (efficiency of knowledge production). In our case $A$ describes how well labour and capital can be combined to produce the knowledge output $Y$

and captures factors that are not explicitly modelled, such as the knowledge stock on which researchers can build. To measure the output $Y$, we refer to patents, as is common to the literature.

The direct effect of emigration, in this setting, is a reduction in $L_s$. Due to the outmigration of skilled people, less workers are available for the production of innovation in the source country. The innovation output $Y$ should thus decrease.

However, there is a second indirect effect of emigration that works through the total factor productivity $A$. After emigration, workers send back knowledge to their home countries. For instance they may transmit technological information and ideas back to their previous employer through communication with former colleagues. This employer becomes better at producing innovation, which is reflected in an increasing $A$.

Theoretically, it is unclear whether the negative direct or the positive indirect effect prevails. This depends on several other characteristics such as the industry, the technology, and the innovation process. Consequently, it is even more important to gain this knowledge from a rigorous empirical assessment of the question. Using patent data as a measure of innovation output $Y$ and controlling for various other factors corresponding to $K$ and components of $A$ that are unrelated to the stock of knowledge, our empirical specification is able to identify this net effect.

# 3 Data Description

We create a unique dataset by merging comparable migration data for 32 European countries with European patent data. The dataset has four dimensions: origin region[3], destination country, industry (two-digit, NACE Rev. 2), and year. The dependent variables of interest are the number of patent applications (by origin-industry-year) as a proxy for innovation and the number of cross-border citations

[3]Here and in the following text "region" refers to the region to which Eurostat's LFS data aggregate migrants' origin countries: EU15+4 (EU15 and EFTA), NMS10 (new member states in 2004), NMS3 (Bulgaria, Romania and Croatia) and all other countries. The fact that the EU3 region consists of Bulgaria and Romania, which joined the EU in 2007, and Croatia, which followed only in 2013, adds further imprecision, as we cannot tell from the data how many emigrants from this region came from Bulgaria and Romania and were able to take advantage of the EU's right to free movement already.)

(by origin-destination-industry-year) as a proxy for knowledge flows. The main explanatory variable is the annual number of emigrants from a given origin currently employed in a given destination industry.

The ideal migration dataset would contain precise data on migration flows, disaggregated by origin and destination (countries and employing industries), skill level, and occupation. In the absence of such a dataset, we use the second-best data from Eurostat Labour Force Surveys (2000 - 2014). These are harmonised surveys, which take place annually in all EU countries, Iceland, Norway and Switzerland and cover around 5% of national populations. The surveys provide demographic information on individuals, including their current country of residence, region of origin (EU15+4, NMS10, NMS2 or Other), education level, occupation, and currently employing industry.[4] We thus obtain the stock of migrants by year, region of origin, destination country, and destination industry. In addition, we can use the information by education level (university degree, vocational degree, or below) and by occupation (two-digit, ISCO) to identify the stock of migrants with patenting potential.[5] The available dataset has several limitations. We can only observe the region of migrants' origin instead of the country. This means that we cannot differentiate between different 2004 accession countries but have to treat them as one region (NMS10). Similarly we have to treat Romania and Bulgaria as one region (NMS2). Furthermore, as we do not observe the origin industry of a migrant, we assume that it is the same as the current industry at the destination. Besides, we cannot identify flows of return migrants. These limitations result in high observational noise and might bias our estimations towards zero.

To construct the instrument for migration flows we use changes in the European labour mobility legislation. We obtain the relevant information from the Labour Reforms database, prepared by the European Commission, which we com-

[4]EU15+4 include 15 pre-2004 EU member countries (Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, Netherlands, Portugal, Spain, Sweden, United Kingdom) + 4 EFTA countries (Iceland, Liechtenstein, Norway, Switzerland). NMS10 include countries that joined the EU in 2004 (Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Slovakia, Slovenia, Malta, and Cyprus) and NMS2 include countries that joined the EU in 2007 (Bulgaria and Romania).

[5]We assign a dummy called *patenting potential* to migrants working in occupations "Managers" and "Professionals" (ISCO codes: 11, 13, 21, 22, 23, 25, 31, 32, 35).

plement with information from national legislations of the destination countries. Our baseline dataset covers the years from 2000 to 2012, this period encompassed several changes to European labour mobility as described in more detail in Subsection 4.2.

The data on innovative activity and knowledge flows come from the EPO's Worldwide Patent Statistical Database (PATSTAT, 2014 Autumn Edition).[6] We are able to assign patents to industries (two-digit NACE Rev. 2) via the International Patent Classification (IPC) of patents.[7]. We then aggregate patent applications by country, industry, and year and patent citations by patenting country, cited country, industry, and year. In our dataset, *patenting country* corresponds to the origin country of migrants, while cited country corresponds to their current destination. To assign patents to countries, we use the PATSTAT information about the location of patent inventors and applicants, which are usually the organisations employing the inventors. Since a patent can have several inventors, it may be assigned to multiple countries if it is the result of an international collaboration. In these cases, we assign a share of the patent to each country that is proportional to the share of co-inventors from that country. The causes and consequences of such collaborations have been studied by Kerr and Kerr (forthcoming). Through this assignment of patents to the inventors' countries it is possible to link a patent with the location of all the patents that cite it.

Figure 1 motivates the subsequent econometric analysis: cross-border patent citations (a proxy for knowledge flows) significantly increase following the introduction of free labour mobility between a pair of countries. This figure mirrors the response of migration flows to changes in labour mobility regulation within Europe (Figure 3 in the Appendix).

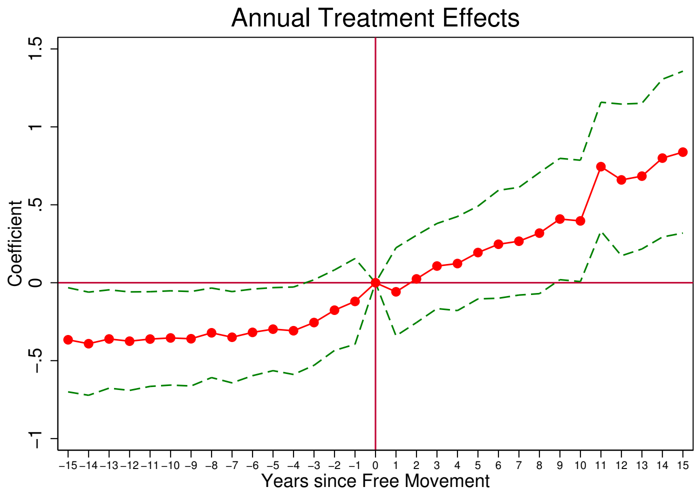
We complement the dataset with several important control variables: bilateral industry-specific FDI flows (provided by Eurostat), GDP and bilateral trade

[6]Patents and patent citations are imperfect measures for innovation and knowledge flows and have been criticised for example by Duguet and MacGarvie (2005). Yet, these are the best proxies, which are available over long periods of time and comparable across the countries we study.

[7]In order to assign four-digit IPC classes to industries, we use the concordance table provided by Eurostat in Appendix 1 of the publication "Patent Statistics: Concordance IPC V8 - NACE REV.2", published in October 2014 and last accessed on 21 November 2016.
https://circabc.europa.eu/sd/a/d1475596-1568-408a-9191-426629047e31/2014-10-16-Final%20IPC_NACE2_2014.pdf

flows (from CEPII). By combining these different data sources, we can draw conclusions about the effects of international migration on patenting in the origin countries and establish reverse knowledge flows as the channel, while controlling for possible fixed and time-varying confounders.

Figure 1: Cross-Border Patent Citations, Annual Treatment Effects of Free Labour Mobility




*Notes:* Annual treatment effects on cross-border citations in patent applications around the introduction of free movement (1965-2014). The regression includes year and country-pair fixed effects. Standard errors are clustered at the citing country level.
Source: PATSTAT, European Commission, own calculations.

# 4 Econometric Specification

In our empirical analysis we first provide causal evidence for the effect of emigration on patenting in origin countries. Second, we link this effect to the increase in knowledge flows. We obtain the elasticities of patenting and cross-border citations to migration using OLS and 2SLS approaches. In the latter, the variation in migration flows is generated only by the exogenous changes in labour mobility laws over 2000-2012. Our baseline regressions include the sample of all patenting European countries. Besides, we provide separate estimates for a sub-sample of Eastern European countries, which were affected the most by the changes in labour mobility over the analysed period.

## 4.1 Baseline Regressions

### Patenting in Origin Countries

We start by analysing the effects of emigration on total patenting in the origin countries. For this, we aggregate the data at the origin, industry, and year level. Because we do not have detailed country-of-origin data, we use the region of migrants' origin: EU15+4, NMS10 and NMS2. The dependent variable is the number of patent application in a specific origin, industry, and year. The explanatory variable is the number of emigrants from a specific region that work in the same industry but in other European countries. We estimate the following fixed-effects regression:

$$Y_{oiy} = \beta_1 M_{oiy-l} + \beta_2 X_{oiy} + \phi_y + \phi_{oi} + \varepsilon_{oiy} \tag{2}$$

where $o$ denotes the region of origin, $i$ the two-digit industry, and $y$ the year. $Y_{oiy}$ is the log number of patent applications in a given region and industry. $M_{oiy-l}$ is the log number of emigrants from an origin region, currently working in a given industry.[8] $l$ stands for the lag between migration and patenting. The coefficient $\beta_1$ captures the elasticity of patenting to migration. $X_{oiy}$ contains time-varying controls: a dummy for EU membership, trade inflows, and FDI inflows. $\phi_y$ and $\phi_{oi}$ denote time and origin-industry fixed effects. $\varepsilon_{oiy}$ is the error term. The identifying variation thus comes from the within origin-industry changes in the number of emigrants and patent applications. To account for a possible endogeneity bias, we complement the OLS estimations with the 2SLS results, where we instrument migration with changes in labour mobility legislation. We describe the instrument in more detail in Section 4.2 below.

### Patenting Asymmetries between More and Less Advanced Countries

We go one step further and analyse whether migration increases or, on the contrary, lowers patenting asymmetries between more and less advanced economies. On the one hand, agglomeration effects and the resources available for research could lead to richer destinations specializing even more on their comparative ad-

[8]Here and in all other specifications, before taking logs we add 1 to each observation. This transformation ensures that we do not lose observations with zero values.

vantage, thus hindering convergence. If we assume that skilled migrants move from less innovative to more innovative places, labour mobility can increase patenting asymmetries despite some positive effects on the origin. On the other hand, through the migrants working abroad, industries at origins can get access to the frontier knowledge from more advanced economies. This can increase innovation efficiency in origin industries and can allow a faster catch-up process with the technology leaders. Hence, patenting asymmetries between destinations and origins of migrants might decrease. We empirically evaluate the effect of migration on patenting asymmetries with the following regression:

$$log(\frac{P_{diy}}{P_{oiy}}) = \beta_1 M_{odiy-l} + \beta_2 X_{1oy} + \beta_3 X_{2dy} + \beta_4 X_{3odiy} + \phi_y + \phi_{odi} + \varepsilon_{odiy} \quad (3)$$

The level of observation is origin-destination ($od$) pair, industry ($i$), and year ($y$). The dependent variable $log(\frac{P_{diy}}{P_{oiy}})$ is the log difference in patent applications between the destination and origin industries. The main explanatory variable is $M_{odiy-l}$ - the log number of migrants from origin $o$ working in industry $i$ in destination $d$. $l$ stands for the lag between migration flows and patenting. The coefficient $\beta_1$ shows whether the patenting asymmetries increase or decrease in migration. In this specification we can also control for time-varying origin- and destination-specific effects ($X_{1oy}, X_{2dy}, X_{3odiy}$): the total number of patents at origin, the total number of patents at destination, the total number of patents in a given industry, a within EU dummy (equals one when both origin and destination are EU members), the ratio of GDP per capita between destination and origin, bilateral industry-level FDI, and trade flows. $\phi_y$ and $\phi_{odi}$ denote time and origin-destination-industry fixed effects. $\varepsilon_{doiy}$ is the error term. The coefficient $\beta_1$ is thus identified solely through the variation in the number of emigrants within an origin-destination-industry. General changes in patenting at origin and destination cannot confound the results. As with specification 2, we estimate OLS and 2SLS regressions.

**Knowledge Flows**

Further, we investigate one potential channel behind the effect of migration on innovation: knowledge flows. One speaks of knowledge flows whenever a researcher or an inventor builds on the work done by others to create ideas or to solve a specific technological problem. A common way to track knowledge flows is to use citations data (Jaffe et al. 1993). This approach assumes that a citation to a particular patent or a publication reflects the usefulness of the knowledge contained therein for further work. To determine the effect of migration on knowledge flows we estimate the following empirical model:

$$Y_{odiy} = \beta_1 M_{odiy-l} + \beta_2 X1_{oiy} + \beta_3 X2_{diy-l} + \beta_4 X3_{odiy} + \phi_y + \phi_{odi} + \varepsilon_{odiy} \quad (4)$$

As in specification 3, the level of observation is origin-destination ($od$) pair, industry ($i$), and year ($y$). The outcome of interest $Y_{odiy}$ represents the log number of cross-border citations. $M_{odiy-l}$ is the log number of migrants from origin $o$ working in industry $i$ at destination $d$. $l$ stands for the lag between migration flows and patenting. We focus on reverse knowledge flows, i.e. knowledge flowing from destination to origin countries of migrants. Hence, $Y_{odiy}$ represents citations to patents from destination countries by new patents at origin.[9] For example, $Y_{PL/BEiy}$ counts citations by Polish patents in industry $i$, filed in year $y$, to existing Belgian patents. It proxies the knowledge flows from Belgium to Poland. $M_{PL/BEiy-l}$ represents the number of Polish migrants in Belgium, currently working in industry $i$. The coefficient $\beta_1$ captures the elasticity of citations to migration. In our example, it shows the percent change in the number of citations from Poland to Belgium if the number of emigrants from Poland to Belgium increased by 1 percent.

To avoid mechanic effects from the general increase in patenting at origin or destination industries, we control for the number of patent applications in the origin industry ($X1_{oiy}$) and for the lagged number of patent applications in a destination industry $X2_{diy-l}$. $X3_{odiy}$ denote other controls: a within EU dummy (equals

[9] We consider citations in patent publications and date patents with their application filing date.

one when both origin and destination countries are EU members), the total number of patents in a given industry, the bilateral FDI, and trade flows. $\phi_y$ and $\phi_{odi}$ denote time and origin-destination-industry fixed effects. $\varepsilon_{doiy}$ is the error term. We again run both OLS and 2SLS regressions.

## 4.2 Instrument for Migration Flows

Even though we control for many observable factors and have a number of fixed effects in the baseline OLS regressions, an endogeneity problem might still arise. Estimates could be biased, for instance, if reduced patenting at the origin forces inventors to leave. To avoid this problem, we use changes in the labour mobility laws in Europe as a source of exogenous variation for migration flows.

The freedom of movement for workers is a policy chapter of the acquis communautaire of the European Union and represents one of the four economic freedoms: free movement of goods, services, labour and capital. According to the Article 45 of the Treaty on the Functioning of the EU, "freedom of movement shall entail the abolition of any discrimination based on nationality between workers of the Member States as regards employment, remuneration and other conditions of work and employment." In practice, it means that there are no restrictions (such as quotas on foreign workers) or additional bureaucratic procedures (such as obtaining a work permit or a permission from the local authorities) related to the employment of foreign citizens. This right primarily concerns the citizens of the EU and EEA member states who, starting from 1958, have gradually introduced free labour mobility towards their partner countries.[10]

In our project, we exploit two episodes of changes in the free labour mobility in Europe. First, in 2004 all EEA countries introduced free movement for the citizens of Switzerland. Switzerland responded with a symmetric measure in 2007.[11] Second, a special scheme has been in force following the EU enlargements in 2004 and 2007. For up to seven years after the accession, old EU members could restrict

[10]Norway and Iceland exert this right since 1994. Liechtenstein exerts this right since 1995, but imposes a permanent quota for all EEA citizens.

[11]However, as a result of the "Against mass immigration" initiative, Switzerland is scheduled to impose permanent quotas on residence/work permits for citizens of all EEA countries except Liechtenstein, starting from 2017.

the access to their labour markets for citizens of new member states. While some countries kept the restrictions for the whole period, some provided easier labour market access only in certain industries, and some opened up their entire labour markets directly upon the accession. When imposing restrictions the countries had to apply them to the whole group of NMS from the same entry year. Therefore, they could not target labour mobility laws at the citizens of some particular states. Iceland, Liechtenstein, Norway, and Switzerland applied the transitional provisions towards the accession countries in the same way. These labour mobility laws created variation in the migration flows between European countries on the country, industry, and year level. Table 5 in the Appendix provides an overview of the precise opening dates of countries and industries. Importantly for the identification, these changes to labour mobility did not coincide with other integration events (free movement of capital and goods).

Figure 2 shows the spikes in migration from NMS during the initial opening in 2004, when countries such as the UK, Sweden, and Ireland opened their labour markets and in 2011 when all transitional provisions for the 2004 accession countries where abolished and Germany, for instance, fully opened its labour market.

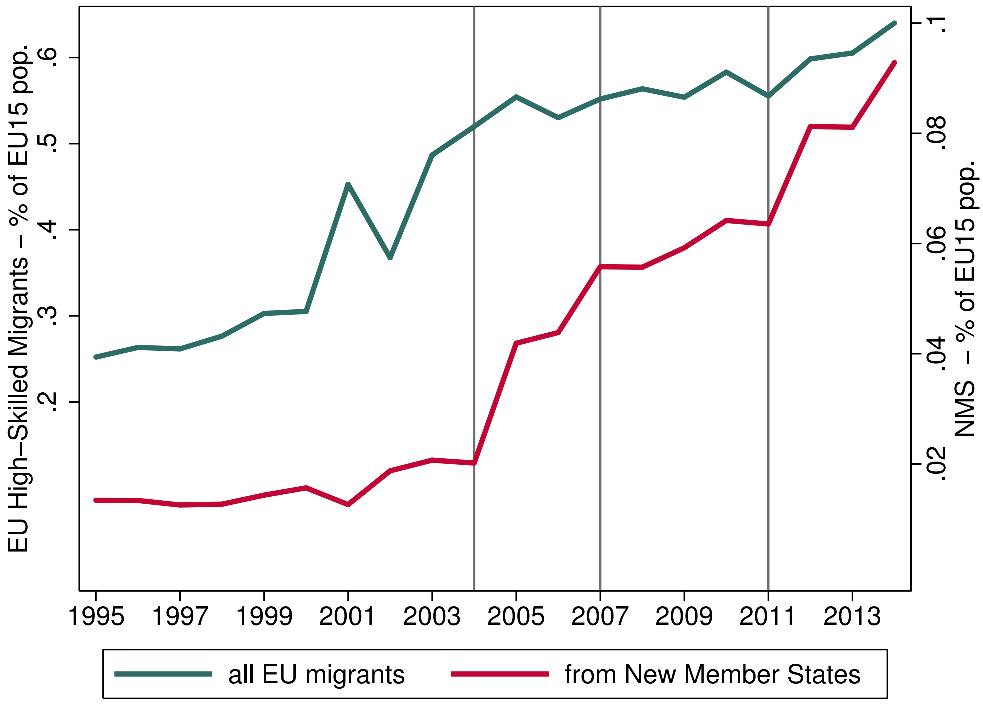
We can thus instrument real migration with exogenous labour mobility legislation. The first-stage regression takes the following form:

$$M_{odiy} = \gamma_1 FM_{odiy-1} + \gamma_2 FM_{odiy-2} + \gamma_3 FM_{odiy-3} + \gamma_4 X_{odiy} + \nu_y + \nu_{odi} + u_{odiy} \quad (5)$$

$FM_{odiy-l}$ is an indicator variable, which is equal to one if a specific industry $i$ in a destination country $d$ is open for labour migrants from a country $o$ in a given year $y$. We include a one, two and three year lag to allow for the delayed effect. In our sample this indicator changes only for origin and destination pairs with either Switzerland or new EU member states. As these migration flows might be different, we show separate results for migration from only Eastern Europe in every case. $X_{odiy}$, $\nu_y$, and $\nu_{odi}$ are the same controls and fixed effects as used in the baseline OLS specifications. When using the instrument for the patenting regressions (specification 2), we aggregate the values of the free movement variable by origin, industry, and year.[12] In this case, the $FM$ variable can be interpreted as the

[12]For each origin region we have 31 free movement indicators corresponding to 31 possible

Figure 2: High-skilled Migration in Europe




*Notes:* The graph shows the share of high-skill migrants (born in other European countries) in the EU15 population. Source: Eurostat.

exposure of a given origin-industry (*oi*) to free labour mobility of its workers.

When constructing the free movement dummies, we take into account the fact that many old EU members did not explicitly specify which industries are open to migrants from the NMS, but rather allowed for special job schemes in sectors that experienced labour shortages. In case of such implicit exceptions, we set the free movement dummy equal to 1 and multiply it by a measure of labour shortages in a given industry of an old EU member state. As such measure, we use the share of firms (in the destination industries) reporting to be constrained by the factor labour. These data are available from the European Commission Business Survey. To account for possible endogeneity (arising, for instance, when labour shortages are reported in industries that grow faster in all EU countries), we control for the overall number of patent applications in a given two-digit industry (aggregate over all European countries).

# 5 Results

In this Section, we first show the effects of migration on total patenting at the origin. Second, we provide evidence that emigration can reduce patenting asymmetries between less and more advanced economies. We show OLS as well as 2SLS results. First-stage and reduced form regressions are provided in the Appendix. Our baseline sample includes all patenting European countries. In addition, we show separate estimations for the sub-sample of Eastern European countries.

## 5.1 Migration and Patenting

This Section shows that the emigration of labour increases overall innovation, measured by the number of patent applications per year in a region. As the migration data only allow us to estimate the effect of emigration at the region level, we aggregate the free movement variable by industry and region of origin: EU15+4, NMS10, and NMS2. The aggregated $FM$ measure approximates the number of countries to whose labour markets an inventor in a certain industry and region of

destinations. We aggregate them to one measure by using proximity weights (the inverse log distances between the two largest cities of two countries.)

Table 1: Patent Applications and Migration, OLS and 2SLS

| | (1) OLS Patents | (2) OLS cit. weighted | (3) OLS Patents | (4) 2SLS Patents | (5) 2SLS cit. weighted | (6) 2SLS Patents |
|---|---|---|---|---|---|---|
| L2.Migrants | 0.0994*** | 0.0949** | | 0.637*** | 0.903*** | |
| | (0.0259) | (0.0420) | | (0.139) | (0.199) | |
| L2.Migr.pat.potential | | | 0.0572 | | | 1.175*** |
| | | | (0.0420) | | | (0.332) |
| in EU | -0.262*** | -0.298*** | -0.296*** | -0.112 | -0.0729 | -0.406** |
| | (0.0903) | (0.0752) | (0.0844) | (0.157) | (0.205) | (0.164) |
| L2.Trade flow | 1.634*** | 2.535*** | 2.124*** | -0.679 | -0.945 | 3.325*** |
| | (0.348) | (0.432) | (0.342) | (0.607) | (0.877) | (0.724) |
| L2.FDI inflow | 2.03e-05** | 3.15e-05** | 2.10e-05** | 1.16e-05 | 1.84e-05 | 2.34e-06 |
| | (9.82e-06) | (1.22e-05) | (8.06e-06) | (2.07e-05) | (2.90e-05) | (1.12e-05) |
| Observations | 383 | 383 | 383 | 383 | 383 | 383 |
| Region industry FE | yes | yes | yes | yes | yes | yes |
| Year FE | yes | yes | yes | yes | yes | yes |
| Clusters | 53 | 53 | 53 | 53 | 53 | 53 |
| F | | | | 6.517 | 11.29 | 7.285 |

*Notes:* The regressions in this table estimate the relationship between the migration flow out of a country and innovation in that country. The first three columns are estimated with OLS and the last three column use a 2SLS estimation with our instrument based on free movement legislation. The dependent variables are the number of patent applications in an industry and origin region in a year or, in columns 2 and 5, the citation-weighted patent applications (i.e. patent applications + forward citations to these patents). Patent application numbers and citation-weighted counts, number of migrants and trade flows are taken in natural logarithms (more precisely, for variable $x$ we use $\log(x+1)$ to include observations where $x = 0$). The sample includes all EU members and countries in the European Free Trade Association. All specifications include year and region-industry fixed effects. Robust standard errors are clustered at the region-industry level.
*** p<0.01, ** p<0.05, * p<0.1
Sources: Patstat, Eurostat, CEPII

origin had access to and is normalised to be between 0 and 1, where 1 corresponds to full access to all EU15+4 countries.

The first three columns of table 1 show the baseline OLS regressions and the last three columns show 2SLS regressions, which use the labour mobility legislation as an instrument for migration.[13] Columns 1 and 4 estimate the relationship between the overall number of emigrants and the number of patent applications from inventors in that region. These regressions show that workers' migration to other EU member states has a significant and positive effect on patenting in the

[13]Note that the right to free movement was not symmetric due to a one-sided transition period, e.g. workers of old EU member states have been able to move to new EU member states as a rule earlier than the other way round. Thus the instrument varies also with the direction of migration and we observe variation in emigration and patenting over time for pairs of origin region and industry. We cluster on the origin-industry level to account for autocorrelation in the regressions in table 1. When we consider asymmetries and citations, there is additional variation depending on the destination country, such that we cluster on the origin-destination-industry level.

regions of origin. As both variables are measured in logarithms, the coefficient can be interpreted as the elasticity: the effect in the IV estimation in column 4 suggests that a one percent increase in the number of emigrants in an industry causes patent applications in the region of origin to increase by 0.6 percent. The 95% confidence interval for the elasticity is between 0.37 and 0.91. If we consider the average number of emigrants in the year 2004 (2459 emigrants) and the average number of patent applications 2 years later (255 applications) for new EU member states per industry, this implies that about 1 to 2 additional applications result from 25 additional emigrants.[14] Note however, that this number only includes migrants in industries that were matched to the patent data, i.e. in which there is patenting. Furthermore, the number of patent applications in 2006 we have used for this calculation already includes the additional applications, such that the number of additional patents is likely to be lower. Despite the noise and the level of aggregation in our data the regressions are able to reject that there is a negative effect.

The second and fifth columns of table 1 use citation-weighted patents as the treatment variable, i.e. the number of patent applications plus the number of citations to these patents in a region, industry, and year. The number of later patents building on and therefore citing a patent is often used as a measure of quality.[15] The citations for more recent cohorts in our sample are subject to truncation, which is controlled for through year fixed effects. As the coefficients are similar, we conclude that the quality of patenting has not deteriorated. Thus, merely a higher propensity of inventors in origin regions to file patents as a result of European integration does not seem to be the driver of the effect. Of course, the number of later patents citing a patent (forward citations) is only a rough measure of quality and may be affected by emigrants spreading information about their home countries' latest technologies abroad as well. Nonetheless, a higher number of forward citations would likely be associated with a greater benefit of source

[14] One percent of 2459 emigrants is about 25 and 0.37% (0.91%) of 255 applications is 0.94 (2.32).

[15] The relationship between citations and the social value of an invention has been documented in a case study on Computed Tomography scanners in Trajtenberg (1990). A more recent study by Moser et al. (2015) finds a robust correlation between citations of hybrid corn patents and the improvement in yield reported in field trial data.

countries' innovations, since they indicate that more follow-on innovation built on them.

Columns 3 and 6 differ from the other regressions in table 1 in the migration variable, which here includes only emigrants with patenting potential. Whereas the OLS regression shows a smaller and insignificant partial correlation, the coefficient in the IV regression is larger than the corresponding coefficient for all migrants in column 4.

The OLS estimate is likely to be downward biased due to omitted variables and reverse causality. If there is an omitted variable bias in the OLS regressions that is negatively correlated with emigration and positively with patenting levels, then the OLS estimate is downward biased. This is very likely and could be driven, for instance, by management quality. A good manager might lead to a good work and research environment. This results both in high patenting levels and low emigration from this firm and consequently biases the OLS estimate downward. Moreover, we might encounter reverse causality in the OLS regressions. If higher patenting levels lead to less migration, then we observe a negative relationship between the two variables that goes in the other direction. As a consequence, the OLS estimator is smaller than it should be and thus downward biased.

Tables 6 and 7 in the Appendix provide the first stage results and the reduced form that complement the 2SLS results analysis. One can see that the instrument is highly relevant in the first stage and that the overall effect of the three lags for the free movement variables sum up to a positive effect.

Table 8 in the Appendix provides the same table with the restricted sample of NMS10 countries (2004 accession years). Due to the level of aggregation in the migration data, the 2SLS effects are not significant. Importantly we find no evidence of a significant negative effect, which would be expected if the loss of human capital dominated.

## 5.2 Migration and Convergence

While the results of the previous Section suggest that emigration can positively affect innovation at the origin, this Section investigates whether this positive effect is enough to reduce patenting asymmetries between less and more advanced economies or whether international migration still benefits knowledge production at destination countries more. This analysis is relevant for policy discussions about benefits and costs of free labour mobility in Europe. Furthermore, the results in this Section serve as a robustness check for the effects found above. When analysing asymmetries we use all four dimensions of our dataset: origin, destination, industry, and year, and can therefore control for unobserved origin- and destination-specific time-varying changes, which could bias our estimates of patenting elasticity to migration in Section 5.1.

To have a clear direction of migration flows from less to more advanced economies, we restrict the sample to the origin-destination pairs, where destinations are EU15+4 countries and origins are new EU member states. In addition, in our baseline sample we consider origin and destination pairs with Switzerland as a destination and other EU15+4 countries as origins. We also show the results for migration from Eastern Europe only, and the results are consistent. For each industry and year, we construct an asymmetry measure as the log difference between the amount of patent applications at destinations and origins.

On average, destination industries file more than three times the amount of patent applications compared to origins. As expected, the patent quality of the former is also higher. We then regress the asymmetry measure on the number of migrants. Table 2 presents OLS (columns 1-3) and 2SLS (columns 4-6) results. The OLS coefficient of migration is slightly positive, but is not statistically significant. This may be caused by the bias due to higher migration outflows from more problematic industries. Another reason is that once we move to the more disaggregated level, we introduce more noise in the migration data (more missing and zero observations). This especially concerns already disaggregated migration data by skill and occupation. 2SLS estimates, however, suggest that emigration allows origin industries to catch up to the patenting level of destinations: a one percent increase in the number of migrants reduces patenting asymmetries by 0.30 percent (column 4 and 5 in 2). The coefficient for migrants with patenting potential is much larger in magnitude, but is imprecisely estimated (see column 6). Overall, the regressions' results fit the framework of a patent production function with decreasing returns to skilled labour: a marginal increase in patent production at destination (due to the immigration of skilled labour) is smaller than the marginal increase in patenting at origins (due to the increase in patenting efficiency).

Table 10 in the Appendix presents the results from the same specifications but estimated on a restricted sample with new EU member states as origins and EU15+4 as destinations (thus excluding emigration from EU15+4 to Switzerland). The obtained coefficients are slightly smaller in magnitude, but still significant. Table 11 in the Appendix shows the reduced form results, where instead of migration figures we use the bilateral free movement dummies. One of the drawbacks of our migration data is the large amount of missing observations, which could be either due to the effective absence of migrants or to misreporting.[16] This raises external validity issues to our estimations in terms of a generalisation to all European countries. Therefore, the most interesting results of Table 11 are in columns 5 and 6 where we present the coefficients from the regressions over the whole sample of origin and destination pairs. The number of observations increases multiple times, yet the coefficients for the free movement dummies are very close to the estimates from the baseline sample. Moreover, most coefficients are more precisely estimated due to improved power: we note that EU membership, higher bilateral trade flows and FDI also help the convergence.

While interpreting the regression coefficients, we implicitly assume that migrants stay within the same industry. This is reasonable, as for skilled migrants the losses associated with changing the industry are substantial. Hence, they are more likely to seek employment in the same sector in the destination countries. If the assumption would not hold for some industries, how would this affect our estimations?[17] Suppose there are two industries: $L$ and $M$ in Poland and Belgium. The Polish migrants from industry $L$ move to Belgium to work in industry $M$. Empirically, we observe $M_{BE/PL/M/y}$ to increase. The inflow of the skilled Polish workers in the Belgian industry $M$ raises its innovation activities (or in the worst case, does not affect them). The performance of the Polish industry $M$ is likely to remain unchanged. The asymmetry measure $log(\frac{P_{BE/M/y}}{P_{PL/M/y}})$ either increases or at

[16]For example, due to missing migration data we have to drop all observations with Germany as a destination country.

[17]There are pairs of NACE industries, between which inventors may indeed be likely to move, for example between “26 Manufacture of computer, electronic and optical products” and “27 Manufacture of electrical equipment”.

Table 2: Convergence in Patenting Levels and Migration, OLS and 2SLS

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | OLS | OLS | OLS | 2SLS | 2SLS | 2SLS |
| | $log(\frac{P_{diy}}{P_{oiy}})$ | $log(\frac{P_{diy}}{P_{oiy}})$ | $log(\frac{P_{diy}}{P_{oiy}})$ | $log(\frac{P_{diy}}{P_{oiy}})$ | $log(\frac{P_{diy}}{P_{oiy}})$ | $log(\frac{P_{diy}}{P_{oiy}})$ |
| | Patents | cit. weighted | Patents | Patents | cit. weighted | Patents |
| L2.Migrants | 0.0319 | 0.0376 | | -0.305** | -0.334** | |
| | (0.0223) | (0.0276) | | (0.146) | (0.158) | |
| L2.Migr.pat.potential | | | 0.117** | | | -1.831 |
| | | | (0.0575) | | | (2.212) |
| Patents, origin | -1.220*** | -1.391*** | -1.206*** | -1.207*** | -1.376*** | -1.419*** |
| | (0.0762) | (0.0817) | (0.0753) | (0.0883) | (0.0946) | (0.281) |
| Patents, dest | 1.066*** | 1.105*** | 1.069*** | 1.058*** | 1.096*** | 1.021*** |
| | (0.0713) | (0.0908) | (0.0717) | (0.0777) | (0.0978) | (0.0894) |
| Within EU | 0.00806 | -0.0884* | 0.0109 | 0.0194 | -0.0759 | -0.0180 |
| | (0.0483) | (0.0531) | (0.0487) | (0.0520) | (0.0572) | (0.0635) |
| $GDP_d/GDP_o$ | -0.173 | 0.400 | -0.197 | -0.188 | 0.384 | 0.173 |
| | (0.316) | (0.367) | (0.319) | (0.338) | (0.394) | (0.530) |
| L3.Trade flow | -0.0791 | -0.0236 | -0.0718 | -0.0281 | 0.0326 | -0.113 |
| | (0.0629) | (0.0799) | (0.0622) | (0.0679) | (0.0867) | (0.0827) |
| L3.FDI flow | 0.000575 | -0.000443 | 0.000380 | -0.000116 | -0.00120 | 0.00254 |
| | (0.00668) | (0.00668) | (0.00671) | (0.00783) | (0.00786) | (0.00926) |
| Observations | 2,946 | 2,946 | 2,946 | 2,864 | 2,864 | 2,864 |
| R-squared | 0.486 | 0.551 | 0.486 | 0.424 | 0.500 | 0.325 |
| Origin-dest-industry FE | yes | yes | yes | yes | yes | yes |
| Year FE | yes | yes | yes | yes | yes | yes |
| Clusters | 582 | 582 | 582 | 500 | 500 | 500 |
| F | | | | 83.92 | 122.8 | 76.50 |

*Notes:* The dependent variable is the natural logarithm of $Patents_{dest}/Patents_{origin}$. Number of migrants, number of patents (in origin and destination countries), GDP ratio between destination and origin, FDI, and trade flows are in natural logarithms. The sample includes all EU and EFTA members. All specifications include year and origin-destination-industry fixed effects. Robust standard errors are clustered at the origin-destination-industry level.
*** p<0.01, ** p<0.05, * p<0.1
Sources: Patstat, Eurostat, CEPII

most stays the same, which goes in the opposite direction of the reported effect. We thus might underestimate the magnitude of the effect.

# 6 The Channel: Knowledge Flows

Having established that emigration leads to an increase in patenting, we want to analyse one potential channel in more detail: knowledge flows. This Section shows that migrants stimulate knowledge flows from their new destinations to their countries of origin.

Table 3 presents the baseline OLS and 2SLS results. The dependent variable is the log count of citations by patents in the origin to the destination country. This dependent variable proxies the knowledge flows due to emigration. In the baseline estimations, we allow for two-year lags between the time of migration and the citations in the patent applications. The results are similar for a one-year lag but slightly weaker. Importantly, given the structure of the dataset, we can account for origin-industry and destination-industry shocks. A possible threat to identifying the coefficient of interest would arise if destination industries, which experienced a positive patenting shock, started to attract more workers from other countries. A higher supply of patents from this destination would also mechanically increase the amount of citations to this country. We can control for such an effect by including the number of patent applications in the destination industry (with a three year lag).[18] In a similar way, we control for the number of patent applications in the source country. The migration effect is identified from the within origin-destination variation in the migration stocks and the count of cross-border citations. Since both dependent and explanatory variables are in natural logs, the coefficient represents the elasticity of cross-border citations to the number of migrants.

In the first column, we regress the citations on the overall number of migrants $M_{odiy}$, year, and origin-destination-industry fixed effects; in column 2 we add additional time-varying controls; in column 3 we use the number of migrants with patenting potential as the main independent variable. OLS results suggest a posi-

[18] As a rule of thumb, it takes about three years for a patent to be granted.

Table 3: Citations to Destination Industries, OLS and 2SLS

| | (1)<br>OLS | (2)<br>OLS | (3)<br>OLS | (4)<br>2SLS | (5)<br>2SLS | (6)<br>2SLS |
|---|---|---|---|---|---|---|
| L2.Migrants | 0.0334* | 0.0269 | | 0.799*** | 0.588*** | |
| | (0.0170) | (0.0167) | | (0.213) | (0.225) | |
| L2.Migr.pat.potential | | | 0.0638* | | | 2.916 |
| | | | (0.0348) | | | (2.302) |
| Patents, origin | | 0.191*** | 0.192*** | | 0.174*** | 0.192*** |
| | | (0.0237) | (0.0238) | | (0.0268) | (0.0310) |
| L3.Patents, dest | | 0.0435*** | 0.0431*** | | 0.0427*** | 0.0219 |
| | | (0.0145) | (0.0145) | | (0.0158) | (0.0236) |
| Within EU | | -0.0501 | -0.0471 | | -0.0698* | 0.0468 |
| | | (0.0378) | (0.0379) | | (0.0416) | (0.0845) |
| L3.Trade flow | | 0.00665 | 0.0119 | | -0.104* | 0.00902 |
| | | (0.0392) | (0.0390) | | (0.0617) | (0.0440) |
| L3.FDI flow | | 0.00780 | 0.00711 | | 0.0126** | -0.0134 |
| | | (0.00493) | (0.00495) | | (0.00570) | (0.0203) |
| Observations | 7,299 | 7,287 | 7,287 | 7,136 | 7,124 | 7,124 |
| R-squared | 0.080 | 0.095 | 0.095 | | | |
| Origin-dest-industry FE | yes | yes | yes | yes | yes | yes |
| Year FE | yes | yes | yes | yes | yes | yes |
| Clusters | 1322 | 1320 | 1320 | 1159 | 1157 | 1157 |
| F | | | | 20.29 | 22.20 | 14.98 |

*Notes:* The dependent variable is number of citations from a region and industry to another country per year. Citation counts, number of migrants, total number of patent application in origin and destination industries, FDI and trade flows are taken in natural logarithms. The sample includes all EU and EFTA members. All specifications include year and origin-destination-industry level fixed effects. Robust standard errors are clustered at the origin-destination-industry level.
*** p<0.01, ** p<0.05, * p<0.1
Sources: Patstat, Eurostat, CEPII

tive association between migration and cross-border citations. The estimated coefficient for migrants with patenting potential is robust to all controls and is twice as large compared to the overall migration stock.

Columns 4 to 6 of table 3 show the 2SLS results that yield quantitatively larger elasticities than the OLS. A one percent increase in emigrants induces a 0.59 percent growth in cross-border citations to their origins. Table 12 in the Appendix summarises the results for the sub-sample where new EU member states are origins and EU15+4 are destinations. Despite the reduction in the sample size, the main 2SLS coefficients remain positive and significant. The reduced form regressions (Table 13 in the Appendix) are also consistent. When we estimate the reduced form for the whole sample of origins and destinations, the free movement coefficients gain significance and quantitatively remain almost identical to those from the baseline sample. This indicates that some of the insignificant results in the baseline regressions (as, for example, the imprecise coefficient for migrants with patenting potential) are mainly due to power problems with noisy migration data.

Previous research has emphasised the role of communication between moving researchers and their former colleagues at the previous employers (e.g. Braunerhjelm et al. 2015; Kaiser et al. 2015). To test whether the channel they have found for inventors moving between firms within a country is also the primary channel of international knowledge flows in our setting, we exclude the inventor's network. To do this, we exclude citations between inventors and all employers (applicants) and other inventors they are listed with on a patent application at any point in time. Table 4 reports the results for the restricted sample. While the coefficients change slightly, they remain positive and significant. Thus only a small part of the effect seems to be driven by the inventors' close network. Knowledge flows that this method could not capture include, for example, if a student at an Eastern European university moves on to work in Western Europe, filing patents for the first time and citing her professors' research. However, the sizable effect that remains suggests that wider spillovers play an important role.

Citations are not always added by the inventor himself but can also be added by the examiner. One worry might thus be that examiners become more aware of research done in other European countries and that they consequently are more likely to add citations from these countries. Alternatively, the effect might be driven by the fact that more patents are filed at the European Patent Office, where examiners may be more likely to add references to foreign patents than at the national offices.[19] This concern is addressed by Table 15, which shows the results only with citations that were added by the applicant (rather than the examiner or a third party) according to PATSTAT and we can see that there are no qualitative changes.[20]

There are a number of ways for the knowledge flows to occur in practice. One possibility is that emigrants increase the awareness of new knowledge or

[19]The latter concern is also addressed in table 14, where only citations among patents filed with the USPTO are included, such that European institutional changes should not affect the results.

[20]In unreported regressions, we limit citations further to only include those that are marked in PATSTAT as applicant-added and, additionally, where citing and cited patents are both priority patents filed at the USPTO. The results are qualitatively similar despite the fact that only less than 1% of citations remain.

Table 4: Citations to Inventor's Network Excluded

| | (1) OLS | (2) OLS | (3) OLS | (4) 2SLS | (5) 2SLS | (6) 2SLS |
|---|---|---|---|---|---|---|
| L2.Migrants | 0.0346** | 0.0276* | | 0.797*** | 0.631*** | |
| | (0.0171) | (0.0167) | | (0.197) | (0.203) | |
| L2.Migr.pat.potential | | | 0.0464 | | | 3.878* |
| | | | (0.0314) | | | (2.355) |
| Patents, origin | | 0.174*** | 0.175*** | | 0.155*** | 0.177*** |
| | | (0.0226) | (0.0226) | | (0.0262) | (0.0358) |
| L3.Patents, dest | | 0.0353*** | 0.0350*** | | 0.0344** | 0.00732 |
| | | (0.0134) | (0.0134) | | (0.0150) | (0.0247) |
| Within EU | | -0.0496 | -0.0471 | | -0.0711* | 0.0787 |
| | | (0.0355) | (0.0356) | | (0.0403) | (0.0867) |
| L3.Trade flow | | 0.0296 | 0.0350 | | -0.0893 | 0.0312 |
| | | (0.0389) | (0.0387) | | (0.0597) | (0.0484) |
| L3.FDI flow | | 0.00982** | 0.00925* | | 0.0150*** | -0.0179 |
| | | (0.00481) | (0.00482) | | (0.00569) | (0.0224) |
| Observations | 7,299 | 7,287 | 7,287 | 7,136 | 7,124 | 7,124 |
| R-squared | 0.077 | 0.091 | 0.091 | | | |
| Origin-dest-industry FE | yes | yes | yes | yes | yes | yes |
| Year FE | yes | yes | yes | yes | yes | yes |
| Clusters | 1322 | 1320 | 1320 | 1159 | 1157 | 1157 |
| F | | | | 19.18 | 19.85 | 10.82 |

*Notes:* In this table, citations within the network of the inventor are excluded, i.e. citations from applicants and inventors with whom the cited inventor has patented at any point in time. The dependent variable is the number of citations from a region and industry to another country in a year. Citation counts, number of migrants, total number of patent application in origin and destination industries, FDI and trade flows are taken in natural logarithms. The sample includes all EU and EFTA members. All specifications include year and origin-destination-industry level. Robust standard errors are clustered at the origin-destination-industry level.
*** p<0.01, ** p<0.05, * p<0.1
Sources: Patstat, Eurostat, CEPII

technologies. This could happen, for example, if emigrants inform their former colleagues or if they meet at conferences. Another possibility is that researchers in the source countries are aware of new knowledge or technologies but need to learn how to use the tacit knowledge embedded in them. A close contact among former colleagues might spur the transfer of tacit knowledge. Additionally return migration can increase innovation in source countries. Often, emigrants return to their home countries after several years abroad and create start-ups or contribute to innovation in other ways.[21]

[21] Our time frame of analysis is more likely to reflect the increasing awareness of new technologies or the transfer of tacit knowledge.

# 7 Robustness

To confirm the validity of the results, we conducted a number of robustness checks. We find that the increase in patenting activities as a result of emigration is not driven by different pre-trends or institutional changes in the European patenting system.

One way to check the validity of the results is to examine pre-trends. If our results are valid, the coefficient of interest should be zero if we regress citation patterns on future labour market openings. Figure 1 in Section 3 shows the annual treatment effects for the regression of cross-border citations on the free movement variable. We look specifically at bilateral citations during the time period 15 years before and 15 years after free movement between two countries has been established. The data we use for this graph are based on patent applications over the 50 year period from 1965 to 2014. The regression includes year dummies and country-pair fixed effects to take out trends. The figure shows that there is no significant change in cross-border citations in the years prior to the establishment of free labour mobility.[22] This is reassuring and increases the credibility of our results. It becomes clear that the effect only starts to gain momentum at the time of the introduction of free movement and builds up over the following years.

One might also worry that the institutional framework of registering patents has changed in the EU, especially in the context of EU enlargement and the European Patent Convention. We thus restrict the sample to patents that have been registered at the United States Patent and Trademark Office (USPTO). Table 14 in the Appendix shows the results. While we have fewer observations, the qualitative results remain the same. The results thus do not seem to be driven by institutional changes in Europe.

[22]Note that this graph uses country-level data, such that the free movement indicator only switches to 1 once all sectors are open. Some of the (insignificant) increase before time 0 may thus be due to the partial openings during the transition periods, which we exploit in the main part of the paper for identification.

# 8 Conclusion and Policy Implications

This paper analyses the effects of emigration on patenting levels in source countries. We find that countries that experience emigration increase their level of patenting. We further suggest that this has led to a catch-up process that brought origin countries closer to the technology frontier. We also find that the international mobility of people has increased technology and knowledge spillovers as evidenced by cross-border patent citation in the respective countries. Specific channels that could have fostered the knowledge spillovers are the transfer of tacit knowledge, the increased and improved network of inventors and return migration.

One policy recommendation that directly follows from these findings is that the EU could benefit from further facilitating migration within Europe. As there are no more legal barriers to free labour mobility, hindering factors are mostly language and administrative barriers. The EU could reduce these barriers by ensuring the recognition of foreign qualifications and the promotion of language courses at all age levels. In this way, the EU can exploit the full potential of migrants both for destination and source countries.

Another policy implication is to ease skilled migration to Europe from outside the European Union. This could be achieved by easing the access to European labour markets and the recruitment of highly qualified foreign workers. While the Blue Card has been a step in this direction, its scope could be increased to obtain a higher impact and administrative barriers should be reduced. For those skilled migrants that are already in Europe, for instance skilled refugees, labour market restrictions should be lifted to ease labour market integration. If these people can be integrated fast into qualified positions without a loss in human capital, the innovation system would greatly benefit.

We have shown in this paper that source countries can benefit from emigration through knowledge flowing back into the country. These benefits of knowledge flows can be maximised by facilitating research networks with emigrated inventors, for example by organising conferences in the origin countries. Furthermore, governments can design programmes to actively keep the diaspora engaged and by encouraging and facilitating return migration. Return migrants bring back the newly gained knowledge and many times create their own start-ups which can foster development in the countries of origin.

While this paper establishes that knowledge flows mitigate the negative consequences of emigration, further research is needed to shed light on the precise way these knowledge flows are created and characterised. Do migrants possess tacit knowledge that flows with people but cannot be transferred by other means? Or do migrants enlarge the R&D network and create better awareness of technologies in other countries? Do migrants have a competitive advantage in negotiating licensing fees with their country of origin? These open questions may guide further research in order to better understand how to increase knowledge flows and maximise their benefits.

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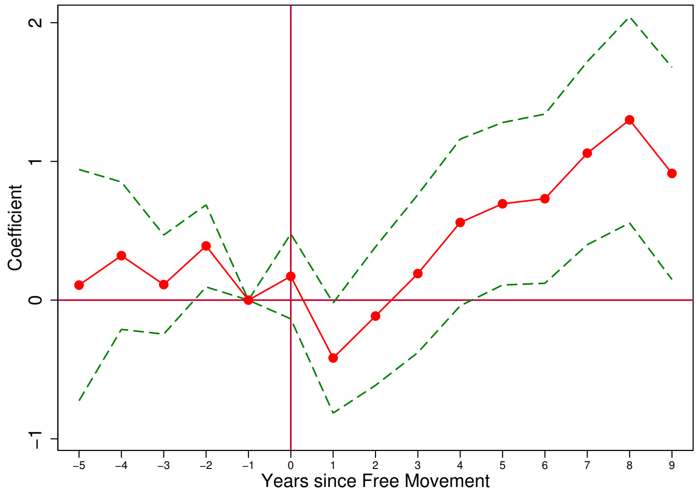
# 9 Appendix

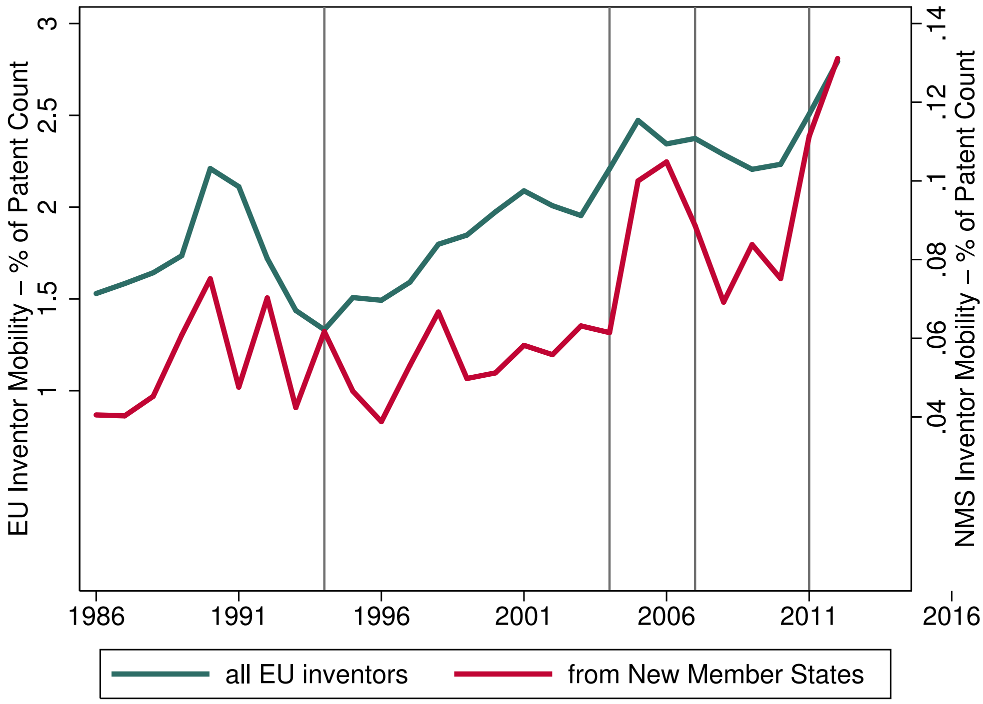
## 9.1 Additional Tables and Graphs

Figure 3: Migration Flows, Annual Treatment Effects of Free Labour Mobility




*Notes:* Annual treatment effects on migration around the introduction of free movement (1986-2012). The regression includes destination-year and country-pair-industry fixed effects. Standard errors are clustered at the country-pair-industry level.
Source: PATSTAT, European Commission, own calculations.

Figure 4: Inventor Mobility in Europe




*Notes:* The graph shows the number of mobile inventors normalised to the total number of patent applications. We count as mobile inventor and inventor who changes his country of residence compared to the previous patent application. Thus migrants can be identified only if they have at least one patent application in each country.
Source: PATSTAT.

Table 5: Overview of the Gradual Opening of the EU15+4 Labour Markets

| Country | NMS8 (2004 entry) | NMS2 (2007 entry) | Sectoral Exceptions |
|---|---|---|---|
| Austria | 2011 | 2014 | NMS8 (2007-2010), NMS2 (2007-2013): Construction, Manufacturing of Electronics and Metals, Food and beverage services (restaurant business), other sectors with labour shortages |
| Belgium | 2009 | 2014 | - |
| Denmark | 2009 | 2009 | - |
| Finland | 2006 | 2007 | - |
| France | 2008 | 2014 | NMS8 (2005-2007), NMS2 (2007-2013): Agriculture, Construction, Accommodation and food services (tourism and catering), other sectors with labour shortages |
| Germany | 2011 | 2014 | NMS8 (2004-2010), NMS2 (2007-2013): sectors with labour shortages |
| Greece | 2006 | 2009 | - |
| Iceland | 2006 | 2012 | - |
| Ireland | 2004 | 2012 | - |
| Italy | 2006 | 2012 | NMS8 (2004-2005): sectors with labour shortages; NMS2 (2007-2011): Agriculture, Construction, Engineering, Accommodation and food services (tourism and catering), Domestic work and care services, other sectors with labour shortages; Occupations: Managerial and professional occupations |
| Luxembourg | 2008 | 2014 | NMS2 (2007 - 2013): Agriculture, Viticulture, Accommodation and food services (tourism and catering) |
| Netherlands | 2007 | 2014 | NMS8 (2004-2006), NMS2 (2007-2013): International transport, Inland shipping, Health, Slaugther-house/meet-packaging, other sectors with labour shortages |
| Norway | 2009 | 2012 | NMS8 (2004-2008), NMS2 (2007-2011): sectors with labour shortages |
| Portugal | 2006 | 2009 | - |
| Spain | 2006 | 2009 | Reintroduction of restrictions for Romanians: 11/08/2011 - 31/12/2013 |
| Sweden | 2004 | 2007 | - |
| United Kingdom | 2004 | 2014 | NMS2 (2007-2013): Agriculture, Food manufacturing |

*Notes:* Column 2 shows the year of the labour market opening of the respective country for the NMS10 countries, column 3 shows the year of the labour market opening of the respective country for the NMS2 countries. Column 4 shows, which sectors were exempt from restrictions.
Source: European Commission.

Table 6: Migration and Free Labour Mobility: First Stage

| | (1)<br>EU19 and NMS<br>all migrants | (2)<br>NMS<br>all migrants | (3)<br>NMS 2004 only<br>all migrants | (4)<br>EU19 and NMS<br>patent potential |
|---|---|---|---|---|
| L3.FM | 2.352*** | 5.039** | 19.37* | -0.563 |
| | (0.754) | (2.320) | (10.48) | (0.645) |
| L4.FM | 1.860*** | 3.271* | 4.298 | 1.156** |
| | (0.630) | (1.704) | (4.065) | (0.506) |
| L5.FM | -0.136 | -0.0996 | 9.662 | 0.350 |
| | (0.375) | (0.418) | (19.23) | (0.292) |
| in EU | 0.447** | -4.541* | | 0.261 |
| | (0.204) | (2.526) | | (0.180) |
| L2.Trade flow | -1.077 | | -74.12 | -2.072** |
| | (1.089) | | (76.99) | (0.953) |
| L2.FDI inflow | 1.14e-05 | 0.000161*** | 0.000185*** | 1.45e-05** |
| | (2.40e-05) | (4.31e-05) | (4.76e-05) | (6.90e-06) |
| Observations | 383 | 186 | 163 | 383 |
| R-squared | 0.597 | 0.683 | 0.701 | 0.363 |
| Region industry FE | yes | yes | yes | yes |
| Year FE | yes | yes | yes | yes |
| F | 10.20 | 48.57 | 660.0 | 10.11 |
| Clusters | 53 | 30 | 23 | 53 |

*Notes:* The regressions in this table estimate the first stage corresponding to table 1 in column 1 and 4: The dependent variable is the (second lag of the natural logarithm) of emigration in a region and outflow of migrants with patenting potential, respectively. The instruments are the free movement variables for the three previous years. The regressions include controls for EU membership, trade flows and FDI inflows. The first pair of columns includes all EU and EFTA countries, the third and fourth column limit the sample to new member states and the last two columns include only the 2004 accessions. All specifications include year and region-industry fixed effects. Robust standard errors are clustered at the region-industry level.

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

Sources: Patstat, Eurostat, CEPII

Table 7: Patent Applications and Free Labour Mobility (Reduced Form)

| | (1) EU19 and NMS Patents | (2) EU19 and NMS cit. weighted | (3) NMS Patents | (4) NMS cit. weighted | (5) NMS 2004 only Patents | (6) NMS 2004 only cit. weighted |
|---|---|---|---|---|---|---|
| L3.FM | 1.075* | 1.309* | -0.276 | -0.0181 | 1.758 | 2.047 |
| | (0.576) | (0.717) | (2.315) | (2.193) | (3.247) | (4.016) |
| L4.FM | 1.786*** | 2.206*** | -0.606 | -0.216 | -4.447 | -4.335 |
| | (0.276) | (0.386) | (0.863) | (0.805) | (3.655) | (3.624) |
| L5.FM | -0.177 | 0.0565 | -0.395 | -0.264 | 3.418 | 4.612 |
| | (0.392) | (0.526) | (0.545) | (0.710) | (3.751) | (3.579) |
| in EU | 0.167 | 0.278** | | | | |
| | (0.107) | (0.121) | | | | |
| L2.Trade flow | -1.399** | -1.456* | | | | |
| | (0.662) | (0.863) | | | | |
| L2.FDI inflow | 3.10e-05** | 4.29e-05*** | 1.45e-05 | 4.15e-05 | 2.49e-05 | 5.34e-05 |
| | (1.26e-05) | (1.28e-05) | (2.70e-05) | (2.75e-05) | (3.15e-05) | (3.20e-05) |
| Observations | 496 | 496 | 209 | 209 | 184 | 184 |
| R-squared | 0.442 | 0.742 | 0.267 | 0.177 | 0.257 | 0.162 |
| Region industry FE | yes | yes | yes | yes | yes | yes |
| Year FE | yes | yes | yes | yes | yes | yes |
| Clusters | 56 | 56 | 32 | 32 | 24 | 24 |

*Notes:* The dependent variables in the regressions shown in this table are the number of patent applications (columns 1,3 and 5) and citation-weighted patent applications (columns 2,4 and 6). More precisely, the dependent variable is the natural logarithm of 1 plus these counts. The same transformation is applied to the trade flow regressor and for FDI inflows, the percentage change from the previous year is used as regressor. The first pair of columns includes all EU and EFTA countries, columns 3 and 4 include all countries which joined the EU in 2004 and later and the last two columns only includes those which joined in 2004. All specifications include year and region-industry fixed effects. Standard errors are clustered at the region-industry level.

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

Sources: Patstat, Eurostat, CEPII

Table 8: Patent Applications and Migration in NMS10, OLS and 2SLS

| | (1) OLS Patents | (2) OLS cit. weighted | (3) OLS Patents | (4) 2SLS Patents | (5) 2SLS cit. weighted | (6) 2SLS Patents |
|---|---|---|---|---|---|---|
| L2.Migrants | 0.0924** | 0.0730* | | 0.115 | 0.212 | |
| | (0.0350) | (0.0375) | | (0.156) | (0.249) | |
| L2.Migr.pat.potential | | | 0.203* | | | 0.101 |
| | | | (0.112) | | | (0.0950) |
| L2.Trade flow | | | | 0.482 | -0.650 | 0.758*** |
| | | | | (0.518) | (0.820) | (0.251) |
| L2.FDI inflow | -1.41e-05 | -5.82e-06 | -3.23e-07 | -1.80e-05 | -3.03e-05 | 9.41e-07 |
| | (1.87e-05) | (1.80e-05) | (1.72e-05) | (3.34e-05) | (4.83e-05) | (1.68e-05) |
| Observations | 163 | 163 | 163 | 163 | 163 | 163 |
| Region industry FE | yes | yes | yes | yes | yes | yes |
| Year FE | yes | yes | yes | yes | yes | yes |
| Clusters | 23 | 23 | 23 | 23 | 23 | 23 |
| F | | | | 16.81 | 26.31 | 65.74 |

*Notes:* The regressions in this table estimate the relationship between the migration flow out of a country and innovation in that country. The first three columns are estimated with OLS and the last three column use a 2SLS estimation with our instrument based on free movement legislation. The dependent variables are the number of patent applications in an industry and origin region in a year or, in columns 2 and 5, the citation-weighted patent applications (i.e. patent applications + forward citations to these patents). Patent application numbers and citation-weighted counts, number of migrants and trade flows are taken in natural logarithms. The sample includes only the 10 countries which joined the EU in 2004. All specifications include year and region-industry fixed effects. Robust standard errors are clustered at the region-industry level.

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

Sources: Patstat, Eurostat, CEPII

Table 9: Patent Applications and Migration, USPTO Patents Only, OLS and 2SLS

| | (1) OLS Patents | (2) OLS cit. weighted | (3) OLS Patents | (4) 2SLS Patents | (5) 2SLS cit. weighted | (6) 2SLS Patents |
|---|---|---|---|---|---|---|
| L2.Migrants | 0.0270 | -0.0894 | | 0.346** | 0.503** | |
| | (0.0535) | (0.0694) | | (0.171) | (0.232) | |
| L2.Migr.pat.potential | | | 0.000889 | | | 0.702 |
| | | | (0.0606) | | | (0.429) |
| in EU | 0.0258 | 0.402 | 0.0182 | 0.115 | 0.567 | -0.0508 |
| | (0.204) | (0.305) | (0.206) | (0.238) | (0.374) | (0.222) |
| L2.Trade flow | 1.623** | 2.409** | 1.740** | 0.252 | -0.144 | 2.493*** |
| | (0.687) | (1.002) | (0.654) | (0.901) | (1.246) | (0.842) |
| L2.FDI inflow | 1.24e-05 | 3.06e-05** | 1.28e-05 | 7.25e-06 | 2.11e-05*** | 1.13e-06 |
| | (1.02e-05) | (1.41e-05) | (9.91e-06) | (1.43e-05) | (8.16e-06) | (1.16e-05) |
| Observations | 383 | 383 | 383 | 383 | 383 | 383 |
| Region industry FE | yes | yes | yes | yes | yes | yes |
| Year FE | yes | yes | yes | yes | yes | yes |
| Clusters | 53 | 53 | 53 | 53 | 53 | 53 |
| F | | | | 32.56 | 273.0 | 26.87 |

*Notes:* The regressions in this table estimate the relationship between the migration flow out of a country and innovation in that country, counting only patents that were filed with the USPTO. The first three columns are estimated with OLS and the last three column use a 2SLS estimation with our instrument based on free movement legislation. The dependent variables are the number of patent applications in an industry and origin region in a year or, in columns 2 and 5, the citation-weighted patent applications (i.e. patent applications + forward citations to these patents). Patent application numbers and citation-weighted counts, number of migrants and trade flows are taken in natural logarithms. The sample includes all EU members and countries in the European Free Trade Association. All specifications include year and region-industry fixed effects. Robust standard errors are clustered at the region-industry level.

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

Sources: Patstat, Eurostat, CEPII

Table 10: Convergence in Patenting Levels ($Patents_{dest}/Patents_{origin}$) and Migration, NMS only, OLS and 2SLS

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | OLS | OLS | OLS | 2SLS | 2SLS | 2SLS |
| | $log(\frac{P_{diy}}{P_{oiy}})$ | $log(\frac{P_{diy}}{P_{oiy}})$ | $log(\frac{P_{diy}}{P_{oiy}})$ | $log(\frac{P_{diy}}{P_{oiy}})$ | $log(\frac{P_{diy}}{P_{oiy}})$ | $log(\frac{P_{diy}}{P_{oiy}})$ |
| | Patents | cit. weighted | Patents | Patents | cit. weighted | Patents |
| L2.Migrants | 0.0289 | 0.0349 | | -0.254* | -0.259* | |
| | (0.0229) | (0.0285) | | (0.141) | (0.151) | |
| L2.Migr.pat.potential | | | 0.118 | | | -1.809 |
| | | | (0.0747) | | | (2.810) |
| Patents, origin | -1.080*** | -1.052*** | -1.081*** | -1.083*** | -1.055*** | -1.065*** |
| | (0.109) | (0.120) | (0.109) | (0.110) | (0.122) | (0.119) |
| Patents, dest | 1.078*** | 1.128*** | 1.080*** | 1.071*** | 1.120*** | 1.044*** |
| | (0.0713) | (0.0910) | (0.0717) | (0.0765) | (0.0962) | (0.0890) |
| Within EU | 0.0435 | -0.0278 | 0.0431 | 0.0572 | -0.0136 | 0.0724 |
| | (0.0529) | (0.0584) | (0.0533) | (0.0555) | (0.0612) | (0.0693) |
| $GDP_d/GDP_o$ | -0.444 | -0.0942 | -0.446 | -0.480 | -0.132 | -0.471 |
| | (0.359) | (0.413) | (0.360) | (0.372) | (0.430) | (0.365) |
| L3.Trade flow | -0.0394 | 0.0516 | -0.0355 | 0.00323 | 0.0959 | -0.0277 |
| | (0.0623) | (0.0792) | (0.0616) | (0.0662) | (0.0842) | (0.0633) |
| L3.FDI flow | 0.00139 | 0.00150 | 0.00108 | 0.000924 | 0.00101 | 0.00544 |
| | (0.00662) | (0.00662) | (0.00663) | (0.00750) | (0.00741) | (0.0112) |
| Observations | 2,763 | 2,763 | 2,763 | 2,681 | 2,681 | 2,681 |
| R-squared | 0.499 | 0.565 | 0.499 | 0.458 | 0.535 | 0.406 |
| Origin-dest-industry FE | yes | yes | yes | yes | yes | yes |
| Year FE | yes | yes | yes | yes | yes | yes |
| Clusters | 559 | 559 | 559 | 477 | 477 | 477 |
| F | | | | 90.89 | 137.0 | 81.10 |

*Notes:* The dependent variable is the natural logarithm of $Patents_{dest}/Patents_{origin}$. Number of patents (in origin and destination countries), number of migrants, FDI, and trade flows are in natural logarithms. The sample includes country-industry pairs, where origins are NMS and destinations - EU19 countries. All specifications include year and origin-destination-industry fixed effects. Robust standard errors are clustered at the origin-destination-industry level.
*** p<0.01, ** p<0.05, * p<0.1
Sources: Patstat, Eurostat, CEPII

Table 11: Convergence in Patenting Levels ($Patents_{dest}/Patents_{origin}$) and Free Labour Mobility (Reduced Form)

| | (1)<br>EU19 and NMS<br>Patents | (2)<br>EU19 and NMS<br>cit. weighted | (3)<br>NMS only<br>Patents | (4)<br>NMS only<br>cit. weighted | (5)<br>EU19 and NMS (all)<br>Patents | (6)<br>NMS only (all)<br>Patents |
|---|---|---|---|---|---|---|
| L3.FM | -0.0135 | 0.00186 | -0.0150 | -0.00166 | 0.0179 | -0.0131 |
| | (0.0368) | (0.0434) | (0.0412) | (0.0496) | (0.0122) | (0.0130) |
| L4.FM | -0.0631 | -0.0573 | -0.0534 | -0.0554 | -0.0403*** | -0.0337** |
| | (0.0440) | (0.0469) | (0.0505) | (0.0554) | (0.0133) | (0.0146) |
| L5.FM | -0.0256 | -0.0393 | -0.0267 | -0.0283 | -0.0166 | -0.00647 |
| | (0.0419) | (0.0449) | (0.0495) | (0.0534) | (0.0127) | (0.0137) |
| Patents, origin | -1.242*** | -1.407*** | -1.094*** | -1.067*** | -0.640*** | -0.618*** |
| | (0.0797) | (0.0873) | (0.111) | (0.122) | (0.0113) | (0.0114) |
| Patents, dest | 1.051*** | 1.090*** | 1.062*** | 1.112*** | 0.800*** | 0.813*** |
| | (0.0725) | (0.0921) | (0.0729) | (0.0929) | (0.0216) | (0.0218) |
| Within EU | -0.00662 | -0.100* | 0.0241 | -0.0442 | -0.0781*** | -0.0527*** |
| | (0.0494) | (0.0549) | (0.0553) | (0.0620) | (0.0141) | (0.0149) |
| $GDP_d/GDP_o$ | 0.00771 | 0.555 | -0.251 | 0.0737 | 0.183*** | 0.175*** |
| | (0.331) | (0.391) | (0.384) | (0.451) | (0.0393) | (0.0402) |
| L3.Trade flow | -0.0450 | 0.00903 | -0.0127 | 0.0766 | -0.0499*** | -0.0341*** |
| | (0.0629) | (0.0810) | (0.0629) | (0.0807) | (0.00866) | (0.00878) |
| L3.FDI flow | 0.00170 | 0.000342 | 0.00259 | 0.00241 | -0.0140*** | -0.0112*** |
| | (0.00656) | (0.00665) | (0.00651) | (0.00659) | (0.00416) | (0.00418) |
| Observations | 2,946 | 2,946 | 2,763 | 2,763 | 71,496 | 66,504 |
| R-squared | 0.487 | 0.552 | 0.500 | 0.565 | 0.217 | 0.225 |
| Origin-dest-ind FE | yes | yes | yes | yes | yes | yes |
| Year FE | yes | yes | yes | yes | yes | yes |
| Clusters | 582 | 582 | 559 | 559 | 5688 | 5304 |

*Notes:* The dependent variable is the natural logarithm of $Patents_{dest}/Patents_{origin}$. Number of patents (in origin and destination countries), number of migrants, FDI, and trade flows are in natural logarithms. All specifications include year and origin-destination-industry fixed effects. Robust standard errors are clustered at the origin-destination-industry level. Specifications 1-4 show the reduced form regressions for the sample used in the OLS/2SLS estimations (i.e. the sub-sample for which migration data are available), specifications 5-6 show estimates for the full sample of country-industry pairs in 2000-2012.

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

Sources: Patstat, Eurostat, CEPII

Table 12: Citations to Destination Industries, NMS only, OLS and 2SLS

| | (1) OLS | (2) OLS | (3) OLS | (4) 2SLS | (5) 2SLS | (6) 2SLS |
|---|---|---|---|---|---|---|
| L2.Migrants | 0.00255 | 0.00895 | | 0.427* | 0.436* | |
| | (0.0281) | (0.0282) | | (0.222) | (0.224) | |
| L2.Migr.pat.potential | | | 0.124 | | | 5.695 |
| | | | (0.133) | | | (5.457) |
| Patents, origin | | 0.124*** | 0.124*** | | 0.146*** | 0.158** |
| | | (0.0332) | (0.0331) | | (0.0369) | (0.0622) |
| L3.Patents, dest | | 0.0118 | 0.0121 | | 0.0183 | 0.0317 |
| | | (0.0224) | (0.0224) | | (0.0248) | (0.0332) |
| Within EU | | -0.00869 | -0.00991 | | -0.0280 | -0.0827 |
| | | (0.0608) | (0.0609) | | (0.0637) | (0.0991) |
| L3.Trade flow | | -0.0575 | -0.0566 | | -0.122 | -0.0791 |
| | | (0.0722) | (0.0724) | | (0.0837) | (0.0895) |
| L3.FDI flow | | 0.00342 | 0.00306 | | 0.00393 | -0.0129 |
| | | (0.0122) | (0.0122) | | (0.0127) | (0.0268) |
| Observations | 2,763 | 2,763 | 2,763 | 2,681 | 2,681 | 2,681 |
| R-squared | 0.083 | 0.087 | 0.088 | | | |
| Origin-dest-industry FE | yes | yes | yes | yes | yes | yes |
| Year FE | yes | yes | yes | yes | yes | yes |
| Clusters | 559 | 559 | 559 | 477 | 477 | 477 |
| F | | | | 11.64 | 8.404 | 6.418 |

*Notes:* The dependent variable is the number of citations from a region and industry to another country in a year. Citation counts, number of migrants, total number of patent application in origin and destination industries, FDI and trade flows are taken in natural logarithms. The sample is limited to new EU member states. All specifications include year and origin-destination-industry level. Robust standard errors are clustered at the origin-destination-industry level.
*** p<0.01, ** p<0.05, * p<0.1
Sources: Patstat, Eurostat, CEPII

Table 13: Citations to Destination Industries and Free Labour Mobility (Reduced Form)

| | (1) EU19 and NMS | (2) NMS only | (3) EU19 and NMS (all) | (4) NMS only (all) |
|---|---|---|---|---|
| L3.FM | 0.00662 | 0.0785 | 0.0400** | 0.0670** |
| | (0.0349) | (0.0516) | (0.0163) | (0.0306) |
| L4.FM | 0.0734 | 0.0856 | 0.0431** | 0.0903** |
| | (0.0451) | (0.0603) | (0.0182) | (0.0392) |
| L5.FM | 0.0480 | 0.0753 | 0.0255 | 0.0406 |
| | (0.0470) | (0.0559) | (0.0169) | (0.0337) |
| Patents, origin | 0.138*** | 0.134*** | 0.0591*** | 0.0974*** |
| | (0.0238) | (0.0308) | (0.00785) | (0.0119) |
| L3.Patents, dest | 0.0478*** | 0.000519 | 0.0258*** | -0.0130* |
| | (0.0137) | (0.0192) | (0.00541) | (0.00687) |
| Within EU | 0.0154 | 0.163*** | 0.00274 | 0.180*** |
| | (0.0361) | (0.0553) | (0.0144) | (0.0247) |
| L3.Trade flow | -0.152*** | -0.0732 | -0.0627*** | 0.0372** |
| | (0.0352) | (0.0596) | (0.00955) | (0.0144) |
| L3.FDI flow | -0.000418 | 0.0114 | 0.0257*** | 0.0235*** |
| | (0.00520) | (0.0113) | (0.00357) | (0.00639) |
| Observations | 7,279 | 3,498 | 29,604 | 11,851 |
| R-squared | 0.174 | 0.133 | 0.099 | 0.110 |
| Origin-dest-industry FE | yes | yes | yes | yes |
| Year FE | yes | yes | yes | yes |
| Clusters | 1322 | 592 | 2304 | 912 |

*Notes:* The dependent variable is the number of citations from a region and industry to another country in a year. Citation counts, number of migrants, total number of patent application in origin and destination industries, FDI and trade flows are taken in natural logarithms. All specifications include year and origin-destination-industry level. Robust standard errors are clustered at the origin-destination-industry level. Columns 1 and 2 show the reduced form regressions for the sample used in the OLS/2SLS estimations (i.e. the sub-sample for which migration data are available), columns 3 and 4 show estimates for the full sample of country-industry pairs in 2000-2012.

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

Sources: Patstat, Eurostat, CEPII

Table 14: Citations to Destination Industries, USPTO Patents Only, OLS and 2SLS

| | (1) OLS | (2) OLS | (3) OLS | (4) 2SLS | (5) 2SLS | (6) 2SLS |
|---|---|---|---|---|---|---|
| L2.Migrants | 0.0476** | 0.0313* | | 0.679*** | 0.288 | |
| | (0.0188) | (0.0178) | | (0.197) | (0.184) | |
| L2.Migr.pat.potential | | | 0.0512 | | | 0.745 |
| | | | (0.0485) | | | (1.703) |
| Patents, origin | | 0.193*** | 0.194*** | | 0.186*** | 0.195*** |
| | | (0.0221) | (0.0221) | | (0.0227) | (0.0227) |
| L3.Patents, dest | | 0.0545*** | 0.0542*** | | 0.0542*** | 0.0491** |
| | | (0.0147) | (0.0147) | | (0.0150) | (0.0195) |
| Within EU | | 0.00444 | 0.00724 | | -0.00468 | 0.0300 |
| | | (0.0332) | (0.0332) | | (0.0343) | (0.0667) |
| L3.Trade flow | | 0.0797* | 0.0858** | | 0.0294 | 0.0853** |
| | | (0.0416) | (0.0417) | | (0.0552) | (0.0418) |
| L3.FDI flow | | -0.00960* | -0.0102* | | -0.00738 | -0.0152 |
| | | (0.00526) | (0.00527) | | (0.00568) | (0.0134) |
| Observations | 7,299 | 7,287 | 7,287 | 7,136 | 7,124 | 7,124 |
| R-squared | 0.132 | 0.150 | 0.149 | | | |
| Origin-dest-industry FE | yes | yes | yes | yes | yes | yes |
| Year FE | yes | yes | yes | yes | yes | yes |
| Clusters | 1322 | 1320 | 1320 | 1159 | 1157 | 1157 |
| F | | | | 44.41 | 35.32 | 34.64 |

*Notes:* The dependent variable is the number of citations from a region and industry to another country in a year. Citation counts, number of migrants, total number of patent application in origin and destination industries, FDI and trade flows are taken in natural logarithms. The sample is limited to citations among US patents. All specifications include year and origin-destination-industry level. Robust standard errors are clustered at the origin-destination-industry level.
*** p<0.01, ** p<0.05, * p<0.1
Sources: Patstat, Eurostat, CEPII

Table 15: Only Citations Added by the Applicant

| | (1) OLS | (2) OLS | (3) OLS | (4) 2SLS | (5) 2SLS | (6) 2SLS |
|---|---|---|---|---|---|---|
| L2.Migrants | 0.0234 | 0.0258 | | 0.489*** | 0.336* | |
| | (0.0176) | (0.0172) | | (0.170) | (0.192) | |
| L2.Migr.pat.potential | | | 0.0759** | | | 1.239 |
| | | | (0.0342) | | | (1.915) |
| Patents, origin | | 0.149*** | 0.150*** | | 0.139*** | 0.150*** |
| | | (0.0220) | (0.0220) | | (0.0231) | (0.0233) |
| L3.Patents, dest | | 0.0253 | 0.0247 | | 0.0249 | 0.0162 |
| | | (0.0161) | (0.0161) | | (0.0165) | (0.0221) |
| Within EU | | -0.0992*** | -0.0958*** | | -0.110*** | -0.0574 |
| | | (0.0335) | (0.0334) | | (0.0354) | (0.0712) |
| L3.Trade flow | | -0.0194 | -0.0143 | | -0.0805 | -0.0153 |
| | | (0.0369) | (0.0369) | | (0.0542) | (0.0373) |
| L3.FDI flow | | 0.00811 | 0.00735 | | 0.0108* | -0.000953 |
| | | (0.00506) | (0.00508) | | (0.00554) | (0.0154) |
| Observations | 7,299 | 7,287 | 7,287 | 7,136 | 7,124 | 7,124 |
| R-squared | 0.070 | 0.080 | 0.080 | | | |
| Origin-dest-industry FE | yes | yes | yes | yes | yes | yes |
| Year FE | yes | yes | yes | yes | yes | yes |
| Clusters | 1322 | 1320 | 1320 | 1159 | 1157 | 1157 |
| F | | | | 22.90 | 20.46 | 18.95 |

*Notes:* The dependent variable is the number of citations from a region and industry to another country in a year. Citation counts, number of migrants, total number of patent application in origin and destination industries, FDI and trade flows are taken in natural logarithms. The sample is limited to citations which have been added by the applicant according to PATSTAT. Robust standard errors are clustered at the origin-destination-industry level.
*** p<0.01, ** p<0.05, * p<0.1
Source: Eurostat and PATSTAT.