# Knowledge Remittances: Does Emigration Foster Innovation?[a]

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**Abstract**

Does the emigration of high-skilled individuals necessarily reduce innovation in the source country due to the loss of human capital? Combining industry- and inventor-level patenting and migration data from 30 European countries, we show that emigration can positively contribute to patenting in source countries due to the existence of reverse knowledge flows. Both OLS and IV regressions suggest that bilateral knowledge flows (measured by cross-border citations and collaborations) increase in the number of high-skilled migrants. While the high-skilled migrants are not inventing in their home country anymore, they contribute to cross-border knowledge and technology diffusion and thus help poorer countries to catch up to the technology frontier.

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**Keywords:** Migration, Innovation, Knowledge spillovers, Patent citations, EU Enlargement

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# 1 Introduction

Remittances[1] have been established in the literature as an important source of income for developing countries and hence constitute a direct benefit of emigration. Apart from financial contributions, in particular high-skilled migrants can also "send" back the knowledge they have acquired while working in other countries. This remittance of knowledge has the potential to increase innovation and bring the origin countries closer to the technology frontier, thus mitigating the negative effects of the reduction in human capital due to emigration. Given the strong increase in the number of high-skilled migrants over the last decade (see Figures 2 and 3 in the Appendix), it is important to understand the consequences of skilled migration. Should firms and policy-makers think and act in the context of a "global war for talent" or does the international mobility of high-skilled people make everyone better off?

This project analyses the effect of high-skilled migration on cross-border knowledge flows and innovation. Using data on patent citations and migration flows from 30 European countries, we find that migration increases knowledge flows between countries.[2] We also show that emigration of high-skilled people can increase patenting in source countries. An identification strategy based on the changes in EU labour mobility legislation allows a causal interpretation of our results. We further argue that knowledge remittances play a crucial role in the positive effect of emigration on patenting. The international mobility of high-skilled workers enlarges R&D networks and promotes the transfer of tacit knowledge. Countries that experience the emigration of high-skilled workers start to cite patents from the emigrants' destinations more frequently than before and compared with other possible countries. In this way, migration enables a faster diffusion of

[1] Remittances are defined as "the portion of international migrant workers' earnings sent back from the country of employment to the country of origin" by Russell (1986).

[2] Patent citations as a measure for knowledge flows have been criticized for example by Duguet and MacGarvie (2005). Despite the fact that patent citations are a noisy measure, they are the most commonly used measure for knowledge flows in the literature and are available over long periods of time for the countries we study.

knowledge from more to less developed countries and even helps the latter to catch up.

We embed these results within the following theoretical framework. We assume a knowledge production function, where innovation (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 be increased even if labour is reduced. Theoretically, migration has a negative direct and a positive indirect effect on patenting levels in source countries. Our paper provides empirical evidence on the total effect.

The literature this study relates to can be categorized into two broad strands. The first includes several papers on the localization of knowledge. Starting with the seminal contribution by Jaffe et al. (1993), these studies have established that knowledge is localized beyond the effects of agglomeration. Later studies focused on international knowledge spillovers (Jaffe and Trajtenberg (1999), Hu and Jaffe (2003)), showing that knowledge takes time to cross country borders. In fact, Thompson and Fox-Kean (2005) have pointed out that intranational localization effects are not robust to a finer technology classification, whereas international localization remains. Advances in communication technology and lower costs of travelling may be expected to reduce localization over time. Singh and Marx (2013) find that this is true for state border effects. The effect of country borders, however, has even strengthened in their sample. Only recently has the international mobility of skilled labour been analysed as one of the

driving forces of international knowledge flows.[3] Kerr (2008) studies the role of high-skilled immigrants in the U.S. and finds that immigrants form ethnic scientific networks that enhance international patent citations.

The second strand of related literature 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) have used 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) have focused on European countries and established cultural diversity as one of the main channels to generate new ideas and innovation. The effect of migration on source countries has been less researched. Kerr (2008) and Choudhury (2015) have found that source countries benefit from knowledge flows and return migration and consequently increase patenting and innovation. Kaiser et al. (2015) look at worker mobility within Denmark and find that firms that hire knowledge workers increase their patenting activity. Interestingly, their former employers 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 firm benefit from the mobility of knowledge workers. The effects are stronger for interregional mobility.

Our contribution to this literature is three-fold. If countries of origin are to benefit from emigration, the loss of skilled labour has to be compensated. Therefore we first look for evidence of knowledge flows in patent citation data. We find evidence for both, knowledge flows in the direction of migration and reverse knowledge flows of a similar magnitude. 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 robust.

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

Second, we explore the effect of international labour mobility on total patenting. The destination countries gain skilled labour and can, in addition, benefit from the knowledge they bring. Thus we assume positive effects for destination countries. However, the ambiguous theoretical prediction for source countries demands an empirical answer. We find that the benefits of skilled emigration, likely through reverse knowledge flows, outweigh the loss in human capital, such that the total level of innovation (measured by the number of patent applications) rises. Our interpretation of the role of knowledge flows is supported by separate regressions for different skill groups of migrants.

While an increase in total patenting as a result of the emigration of high-skilled emigration helps source countries, which tend to be less developed, it is not clear whether the increase in innovation is large enough for convergence. After all, a positive effect on destination countries might increase the gap, shifting the technology frontier further away. Our results indicate that the relative difference decreases as a result of free labour mobility, such that countries are more likely to catch up.

The paper is organized as follows. The next section describes a theoretical framework to guide our empirical analysis. Section 3 outlines the data, followed by section 4 that presents the empirical specification and describes the instruments. Section 5 discusses the results and section 6 provides robustness checks. Section 7 concludes.

# 2 Theoretical Considerations

This paper is analysing 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 theoretical considerations. The framework is 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 framework models the trade-off between a reduction in knowledge pro-

duction due to a decreasing skilled labour force and an increase due to a better production technology induced by knowledge flows and technological spillovers.

We start with a simplified knowledge production function of the form

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

$K$ is a measure of technical knowledge and determined by research expenditure and past research. $L_s$ stands for skilled labour and $A$ measures total factor productivity. In this case $A$ describes how well labour and capital can be combined to produce the knowledge output $Y$. To measure the output $Y$, one often refers to patents. Following Griliches (1979), we are using a Cobb-Douglas specification for expositional simplicity.

$$Y = AK^{\alpha}L_s^{\beta} \tag{2}$$

If we now think about integrating emigration into the model, the direct effect 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 that works through the total factor productivity $A$. Through emigration, previous employees are now sending back knowledge to their former colleagues and transmit technological information and ideas back to their previous employer. This employer thus becomes better in producing innovation, which is reflected in an increasing $A$. Thus emigration has a positive indirect effect on knowledge production.

Theoretically it is not clear if the negative direct or the positive indirect effect prevails. It depends on several other characteristics such as the industry, technology and innovation process. It is thus important to look at the data and do an empirical analysis of emigration and its effect on innovation.

# 3 Data Description

We created a unique dataset by merging comparable migration data for 30 European countries with European patent data. Migration data is taken from Eurostat Labour Force Surveys. These are yearly harmonized surveys, which take place annually in all EU member countries and cover around 5% of national populations. The survey provides demographic information on individuals, including their destination country and region of origin (EU15, EU8, EU2), education level, occupation, and employing industry. For our instrument we additionally use OECD migration data and EU labour mobility legislation. The OECD DIOC data is sourced from national census data and while it has the disadvantage that it is released only every five years it has the advantage of detailed country of origin information. We use EU labour mobility legislation to construct the Free Movement instrumental variable. Information is taken from the Labour Reforms database (section on labour mobility) of the EU Commission and complemented with information from national legislations of old EU member states.

The data on innovative activity we use is from the EPO's Worldwide Patent Statistical Database (PATSTAT, 2014 Autumn Edition). The main outcomes of interest are the numbers of patent applications in countries and the citations between countries. The International Patent Classification (IPC) of patents allows us to analyse these variables on the more detailed level of country-technology pairs. PATSTAT also contains information about the location of inventors (and applicants, which are usually the organizations employing the inventors) of patents. In general, we use the inventors' locations to assign patents to countries, such that a patent may be assigned to multiple countries if it is the result of an international collaboration. The causes and consequences of such collaborations have been studied by Kerr and Kerr (forthcoming). Collaborations allow us to shed light on this particular channel of international knowledge flows.[4] Through this assignment of patents to the inventors' countries it is possible to link a patent with the location of all the patents which cite it.

[4]The results on collaborations are not yet reported in this draft.

Our control variables are sourced from Eurostat (FDI) and CEPII (trade). The value added of this unique combination of different data sources allows us to draw conclusions about the effects of international mobility for source and destination countries at the same time and analyse patenting behaviour to establish knowledge flows as the main channel. This has not been possible in previous research due to non-comparable innovation data for source and destination countries.

# 4 Econometric Specification

We first analyze industry-level data, exploiting variation across both countries and industries in free movement legislation, to establish the effect of migration on cross-border knowledge flows and patenting activities in destinations and origins. Thereafter we focus on the difference in the level of patenting between origin and destination, providing evidence that the gap decreases as a result of the introduction of free movement.

## 4.1 Baseline Regressions

While "brain drain" is usually thought of as a loss to migrants' origins, reverse knowledge flows could reduce the negative effects or even outweigh them. One speaks of knowledge flows whenever a researcher or an inventor builds on the work done by others to create ideas or 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:

$$Y_{doiy} = \beta_1 M_{doiy-l} + \beta_2 X_{d/o/i/y} + \phi_y + \phi_i + \phi_{do} + \epsilon_{doiy} \tag{3}$$

where the index $d$ indicates the destination country, $o$ the country of origin, and $i$ denotes (2-digit NACE Rev. 2) industry. $Y_{doiy}$ is the outcome

of interest - the log number of cross-border citations. $M_{doiy-l}$ is the log number of migrants from an origin country, working in a given industry in a destination country. $l$ stands for the lag between migration flows and patenting. $X_{d/o/i/y}$ contains time-varying controls. $\phi_y, \phi_i, \phi_{do}$ denote time, industry, and country-pair fixed effects.

We allow for the different direction of knowledge flows and estimate regressions for two dependent variables: $Cite_{doiy}$ - the number of citations to the prior works from the origin country by patents in the destination and $Cite_{odiy}$ - the number of citations to the prior works from the destination country by patents at origin.[5] For example, $M_{DE/PLiy}$ is the number of Polish migrants residing in Germany and working in some industry $i$. $Cite_{DE/PLiy}$ counts how many times German patents cited the prior Polish patents and publications and thus represents the knowledge flows from Poland to Germany. $\beta_1$ captures the elasticity of these flows to the number of Polish immigrants in Germany. $Cite_{PL/DEiy}$ counts citations by Polish patents to previous German patents. In this case, it proxies the knowledge flows from Germany to Poland and $\beta_1$ shows how these flows vary with the number of emigrants from Poland to Germany. To merge industry-level migration data with patent data, we match four-digit IPC patent technology subclasses to NACE Rev. 2 industries and aggregate citation counts on a two-digit industry level.[6]

We further analyse the level effects of labour mobility on patenting. First, we estimate the effect of emigration only in the origin countries:

$$Y_{oiy} = \beta_1 M_{oiy-l} + \beta_2 X_{o/i/y} + \phi_y + \phi_{oi} + \epsilon_{oiy} \tag{4}$$

where $o$ denotes the country of origin and $i$ the 2-digit industry. $Y_{oiy}$ is the log number of patent applications in a given country and industry. $M_{oiy-l}$ is the log number of emigrants from an origin country, working in a given industry in other EU countries. $l$ stands for the lag between migration flows and patenting. $X_{o/i/y}$ contains time-varying controls. $\phi_y, \phi_{oi}$ denote

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

[6]To match patent classes to industries, we use the PATSTAT correspondence table.

time and origin-industry fixed effects. The identifying variation thus comes from the within country-industry changes in the number of emigrants and patent applications. $\epsilon_{oiy}$ is the error term.

We further analyse the effect of migration on patenting asymmetries between destination and origin industries. Agglomeration effects and the resources available for research could lead to richer destinations specializing even more on their comparative advantage. Thus, if we assume that high-skilled migrants move from less innovative to more innovative places, international labour mobility should increase patenting asymmetries. To estimate the effect of migration on asymmetry in the patenting country within industries, we use the specification identical to equation 3, but as the dependent variable we take $log(\frac{P_{diy}}{P_{oiy}})$, which is the log difference in patent applications between the destination and origin industries.

The threat to the identification of $\beta_1$ in the specification 3 and 4 is the endogeneity of the migration flows. To address the possible omitted variable bias, we control for time-varying factors ($X_{d/o/i/y}$), which may influence both migration and cross-border citations: Bilateral trade flows, bilateral direct investments, EU membership (within-EU dummy equals one if both destination and origin countries are EU members), log difference of the countries' GDP per capita, and, in the knowledge flows regressions, for the total number of patent applications in the industries of destination and origin countries. The level of observation allows to control for country-pair, year, and industry fixed effects. In more restricted specifications, we use destination-, origin-, and industry-specific time dummies.

## 4.2 Instrument for Migration Flows

We use changes in EU labour mobility laws as a source of exogenous variation in migration flows. Citizens of all EU member-states have the right to free labour mobility within the EU. In contrast to the free movement of goods and capital, labour mobility is not granted instantaneously and uniformly upon the accession to the EU. The most prominent example is the application of transitional provisions following the EU enlargements

in 2004, 2007, and 2013.[7] For up to seven years, old EU member countries[8] could restrict the access to their labour markets for the citizens of the 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. The labour mobility laws created variation in the migration flows between EU member states on the country, industry, and year level. Table 6 in the annex provides an overview of the precise opening dates and industry details for each of EU15 countries.

The first-stage regression can take the following form:

$$M_{doiy} = \gamma_1 FM_{doiy} + \gamma_2 X_{d/o/i/y} + \nu_y + \nu_i + \nu_{do} + u_{doiy} \tag{5}$$

With the instrument based on the EU labour mobility laws, $FM_{doiy}$ represents a dummy, which is equal to one if a specific industry $i$ in a destination country $d$ is open for labour migrants from a country $o$. $\omega_{do2000}$. $X_{d/o/i/y}, \nu_y, \nu_i, \nu_{do}$ are the same controls and fixed effects used in the baseline OLS specification.

People from closer countries tend to react more strongly to the legislation changes. We can strengthen the free movement variable by interacting it with a measure of bilateral proximity, for example, the inverse log distances between the largest cities of two countries.

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 new member states, 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

[7] The 2004 entry countries (EU8): Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Slovakia, Slovenia; the 2007 entry countries (EU2): Bulgaria, Romania; the 2013 entry: Croatia.

[8] Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, Netherlands, Portugal, Spain, Sweden, United Kingdom - in the text we also refer to these countries as EU15. Other EEA members: Iceland, Liechtenstein, Norway, and Switzerland also applied transitional provisions; however, due to missing data, we exclude them for the moment from our analysis.

multiplied 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 labour factor. These data are available from the EU 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 2-digit industry (aggregate over all EU countries) or alternatively include industry-specific time dummies.

# 5 Results

We document the effect of the international labour mobility on cross-border knowledge flows and then show the level effects of migration on patenting in origins and destinations.

## 5.1 Migration and Knowledge Flows

We first test if international migration intensifies knowledge flows between countries. We start with the sample that includes all EU country-pairs and estimate the baseline specification 3. Table 1 presents the estimation results. The upper panel reports the estimations, where the dependent variable is $Cite_{doiy}$: the count of citations by patents in the destination country to the origin country. This dependent variable proxies the knowledge flows generated by immigrants. The lower panel shows the effect of migration on the knowledge flows from the destination to the origin country, i.e. likely reverse knowledge flows due to emigration. The dependent variable is $Cite_{odiy}$: the count of citations by patents in the origin country to the destination country. 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. In the first column, we take the overall number of migrants as $M_{doiy}$; in the column 2

we use only the number of high-skilled migrants; in the column 3 we use only the number of unskilled migrants.[9]

All specifications include (directional) country-pair fixed effects, which also control for the effect of proximity on migration. We also add country-specific time dummies for a patenting country to net out the effect of country-specific changes, for instance, due to changes in patent laws. In addition, we add the industry and year fixed effects and control for the total number of patents in the origin and destination industries, trade and FDI flows, and EU entry. The withinEU dummy takes a value of 1 if both destination and origin countries are members of EU.

The coefficient of the migration effect is identified from the within country-pair variation in the migration flows 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. A 1% increase in the number of immigrants leads to a 0.17% increase in the number of citations to the origin country of migrants (within a specific industry). This result suggests that migrants help to diffuse the knowledge from their origin country in the destination. However, the knowledge flows are not unidirectional. A 1% increase in the number of emigrants leads to a 0.10% increase in the number of citations to the destination country of migrants. The results become significantly stronger when we consider only high-skilled migrants and (as one would expect) lose their magnitude and statistical significance when we use only low-skilled migrants to measure migration.[10]

We next restrict the sample to the country-pairs, where the origins are the new EU member states and the destinations are more developed EU15

[9]We determine the skill level of migrants according to their occupations in the destination countries.
Due to data limitations, we cannot see the migrants' exact country of origin. Eurostat provides this information only on the aggregated level: EU15 (EU members before 2004), EU8 (countries that entered EU in 2004), and EU3 (countries that joined EU in 2007 and 2013). Therefore, as destinations we use individual countries, but aggregate all origin variables to EU15, EU8, and EU3.

[10]The significant result in column (3) in the upper panel is due to positive correlation between unskilled and overall migration.

Table 1: Migration flows and Cross-border Citations

| | $(Cite_{doiy})$ Migrants | $(Cite_{doiy})$ Migrants_university | $(Cite_{doiy})$ Migrants_unskilled |
|---|---|---|---|
| L2.Migrants | 0.169*** | 0.256*** | 0.107*** |
| | (0.0299) | (0.0780) | (0.0370) |
| patents at origin | 0.385*** | 0.384*** | 0.379*** |
| | (0.0390) | (0.0387) | (0.0391) |
| patents at dest | 0.298*** | 0.298*** | 0.302*** |
| | (0.0244) | (0.0245) | (0.0249) |
| withinEU | 0.282*** | 0.293*** | 0.286*** |
| | (0.0618) | (0.0617) | (0.0617) |
| log_trade_flow | 0.507*** | 0.557*** | 0.545*** |
| | (0.0989) | (0.0987) | (0.0986) |
| log_fdi | 0.800*** | 0.802*** | 0.804*** |
| | (0.0428) | (0.0429) | (0.0432) |
| Observations | 8,560 | 8,560 | 8,560 |
| $R^2$ | 0.901 | 0.901 | 0.900 |
| FE | y i do yd | y i do yd | y i do yd |
| Clusters | 1317 | 1317 | 1317 |

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

**Note:** Citation counts, number of migrants, FDI and trade flows are taken in natural logarithms. The sample includes all EU country pairs. All specifications include year, industry, country-pair, and country-year fixed effects. Robust standard errors are clustered at the country-pair-industry level. Other controls include total count of patent applications in a given industry at the destination and origin.
Sources: Patstat, Eurostat, CEPII

| | $(Cite_{odiy})$ Migrants | $(Cite_{odiy})$ Migrants_university | $(Cite_{odiy})$ Migrants_unskilled |
|---|---|---|---|
| L2.Migrants | 0.105*** | 0.184** | -0.0197 |
| | (0.0300) | (0.0789) | (0.0427) |
| patents at origin | 0.319*** | 0.319*** | 0.320*** |
| | (0.0235) | (0.0235) | (0.0237) |
| patents at dest | 0.264*** | 0.265*** | 0.259*** |
| | (0.0328) | (0.0327) | (0.0331) |
| withinEU | 0.312*** | 0.323*** | 0.324*** |
| | (0.0823) | (0.0826) | (0.0825) |
| log_trade_flow | 0.152** | 0.156** | 0.160** |
| | (0.0743) | (0.0744) | (0.0744) |
| log_fdi | -0.0997*** | -0.0995*** | -0.101*** |
| | (0.0250) | (0.0251) | (0.0250) |
| Observations | 8,560 | 8,560 | 8,560 |
| $R^2$ | 0.906 | 0.906 | 0.906 |
| FE | y i do yo | y i do yo | y i do yo |
| Clusters | 1317 | 1317 | 1317 |

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

**Note:** Citation counts, number of migrants, FDI and trade flows are taken in natural logarithms. The sample includes all EU country pairs. All specifications include year, industry, country-pair, and country-year fixed effects. Robust standard errors are clustered at the country-pair-industry level. Other controls include total count of patent applications in a given industry at the destination and origin.
Sources: Patstat, Eurostat, CEPII

countries. In this way we can apply the identification strategy based on the legislation changes. Table 2 shows the reduced-form results, where as the independent variables we use the free movement dummies $FM$ or the free movement dummies weighted by inverse log distance between the countries $FM/dist$. The first two columns show the effect of free labour mobility on the knowledge flows from the origin to the destination. With the restricted sample, the effect is insignificant, suggesting that the knowledge from new member states is less important for EU15, which are likely to be closer to the technology frontier. Conversely, the reverse knowledge flows from EU15 are positive and strongly significant. The regressions with the Eurostat migration as the independent variable (Table 7 in the Appendix) also speaks for the existence of knowledge remittances by the emigrants from new member states. 1% increase in the number of high-skilled migrants increases patent citations to destinations by 0.31%.[11]

## 5.2 Migration and Convergence

With the positive effect of international labour mobility on reverse knowledge flows, the previous section has uncovered a channel through which emigration can be beneficial for source countries. This section first shows that emigration of high-skilled labour in fact increases overall innovation, measured by the number of patent applications per year in a country. This suggests that knowledge remittances, just as financial remittances, can be more valuable to source countries than keeping the migrant in the domestic labour force. To have a clear direction of migration flows from less to more advanced countries, we restrict the sample to the country-pairs with new EU members as origins and EU15 as destinations.

The results of a regression of patent applications in source countries on the ability of workers to freely migrate to old EU members and work in a certain industry are presented in table 3. In addition to the free movement laws, columns 2 and 4 of the table interact free movement with a weighted

[11]Aggregation of the migration data to EU8 and EU3 lowers the significance of the estimates.

Table 2: Free Movement and Cross-border Citations

| | $(Cite_{doiy})$ FM | $(Cite_{doiy})$ FM/dist | $(Cite_{odiy})$ FM | $(Cite_{odiy})$ FM/dist |
|---|---|---|---|---|
| L2.FM | -0.00637 | -0.00565 | 0.0338*** | 0.0320*** |
| | (0.00412) | (0.00419) | (0.0106) | (0.0100) |
| patents at origin | 0.0442*** | 0.0442*** | 0.0868*** | 0.0868*** |
| | (0.00410) | (0.00410) | (0.00585) | (0.00585) |
| patents at dest | 0.0552*** | 0.0551*** | 0.0689*** | 0.0689*** |
| | (0.00420) | (0.00420) | (0.00498) | (0.00498) |
| withinEU | 0.0243*** | 0.0242*** | 0.0356*** | 0.0355*** |
| | (0.00700) | (0.00700) | (0.00951) | (0.00951) |
| log_trade_flow | -0.00841** | -0.00825* | -0.0197*** | -0.0195*** |
| | (0.00425) | (0.00426) | (0.00623) | (0.00624) |
| Observations | 24,376 | 24,376 | 23,761 | 23,761 |
| $R^2$ | 0.379 | 0.379 | 0.423 | 0.423 |
| FE | y i do yd | y i do yd | y i do yo | y i do yo |
| Clusters | 4905 | 4905 | 4905 | 4905 |

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

**Note:** Citation counts, number of migrants, FDI and trade flows are taken in natural logarithms. The sample includes all EU country pairs. All specifications include year, industry, country-pair, and country-year fixed effects. Robust standard errors are clustered at the country-pair-industry level. Other controls include total count of patent applications in a given industry at the destination and origin.
Sources: Patstat, Eurostat, CEPII

distance measure to account for the fact that the right to free movement is more likely to induce a worker to move if the newly accessible labour market is geographically close to home. As we only have variation at the origin level, we aggregate the free movement dummies across 15 possible destinations. For comparability of the results, we standardise the $FM$ and $FM/dist$ variables to have a mean of 0 and a standard deviation of 1.

The first two columns show that workers' ability to emigrate to old EU member states has a significant and positive effect on patenting in the countries of origin.[12]A one standard deviation increase in the free movement measure, corresponding roughly to the opening of five EU15 labour markets, leads to an increase in the number of patent applications of about 0.122 log points or 13%.[13] The third and fourth columns use citation-weighted patents, i.e. a patent counts as $1+$ the number of forward citations it receives. The number of later patents building on and therefore citing a patent is often used as a measure of quality. The more recent cohorts in our sample are subject to truncation, which is controlled for through year fixed effects. While the coefficients are larger than for the number of patents, they are less significant.

These results suggest that emigration leads to a net increase in source countries' innovativeness. The effects on the difference between source and destination countries are yet to be shown, as migration might lead to a larger increase in patenting in destination than in source countries, such that the gap widens. Convergence in the level of patenting requires that the source countries' knowledge production grows more than that of the destination countries.

Tables 4 and 5 present the estimated effect of labour mobility on patenting asymmetries. We conduct the analysis on the industry level. The dependent variable is within-industry log difference of patent applications

[12]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 earlier than the other way round.

[13]1 st. deviation of the actual $FM$ equals 0.363; since $FM$ represents a mean across 15 destinations, $0.363 * 15 \approxeq 5.4$ open destinations for people working in a given industry of a new member state.

Table 3: Free Labour Mobility and Patenting in New EU Member States

| *Dependent var* | Patent Count | | Cit-weighted Count | |
|---|---|---|---|---|
| *Free movement var* | FM | FM/dist | FM | FM/dist |
| L2.FM | 0.122** | 0.142** | 0.167 | 0.206* |
| | (0.0591) | (0.0584) | (0.107) | (0.112) |
| withinEU | -0.314*** | -0.318*** | -0.221* | -0.229* |
| | (0.105) | (0.105) | (0.128) | (0.128) |
| log_tot_patents_nace | 0.614*** | 0.613*** | 0.348** | 0.346** |
| | (0.127) | (0.126) | (0.136) | (0.136) |
| log_gdp_orig | 0.428 | 0.409 | 3.253*** | 3.235*** |
| | (0.418) | (0.418) | (0.535) | (0.527) |
| log_import | 1.659*** | 1.669*** | -0.230 | -0.227 |
| | (0.484) | (0.481) | (0.732) | (0.726) |
| Observations | 2,242 | 2,242 | 2,242 | 2,242 |
| $R^2$ | 0.892 | 0.892 | 0.874 | 0.874 |
| FE | y oi yo | y oi yo | y oi yo | y oi yo |
| Clusters | 260 | 260 | 260 | 260 |

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

**Note:** Citation counts, number of migrants, FDI and trade flows are taken in natural logarithms. The sample includes all EU country pairs. All specifications include year, industry, country-pair, and country-year fixed effects. Robust standard errors are clustered at the country-pair-industry level. Other controls include total count of patent applications in a given industry at the destination and origin.
Sources: Patstat, Eurostat, CEPII

Table 4: Asymmetry in Patenting Levels and Migration Flows, EU15-NMS

| | patent potential | skilled (uni) | skilled (voc) | unskilled |
|---|---|---|---|---|
| L2.Migrants | -0.300** | -0.250* | 0.00665 | -0.0274 |
| | (0.142) | (0.129) | (0.0357) | (0.0624) |
| withinEU | 0.621*** | 0.620*** | 0.622*** | 0.621*** |
| | (0.147) | (0.147) | (0.148) | (0.148) |
| log_tot_patents_nace | 0.0573 | 0.0559 | 0.0516 | 0.0525 |
| | (0.139) | (0.139) | (0.139) | (0.139) |
| log_GDP_ratio | 0.916* | 0.913* | 0.923* | 0.918* |
| | (0.519) | (0.518) | (0.519) | (0.519) |
| log_tot_flow | -0.736*** | -0.737*** | -0.733*** | -0.732*** |
| | (0.147) | (0.147) | (0.147) | (0.147) |
| Observations | 2,715 | 2,715 | 2,715 | 2,715 |
| $R^2$ | 0.841 | 0.841 | 0.841 | 0.841 |
| FE | y oi od yo | y oi od yo | y oi od yo | y oi od yo |
| Clusters | 515 | 515 | 515 | 515 |

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

**Note:** Citation counts, number of migrants, FDI and trade flows are taken in natural logarithms. The sample includes all EU country pairs. All specifications include year, industry, country-pair, and country-year fixed effects. Robust standard errors are clustered at the country-pair-industry level. Other controls include total count of patent applications in a given industry at the destination and origin.
Sources: Patstat, Eurostat, CEPII

between the destination and origin. In table 4, we use actual migration flows as the independent variable $M_{doiy}$. Table 5 presents the reduced-form results where as the independent variable we use the free movement dummies described in section 4.2. Both specifications allow for two-year lag between migration (or legislation change) and patent application. We control for the bilateral GDP-per-capita ratio, industry-level trade and FDI flows, EU entry, year, industry, country-pair and origin-specific year fixed effects.

Table 4 includes 4 columns corresponding to different migration flows (all measured at the country-pair-industry level): 1) only migrants with patenting potential (engineers or researchers); 2) migrants with university degree; 3) migrants with vocational degree; 4) unskilled migrants. Asymmetry in patenting reduces in the number of high-skilled migrants and is not significant for medium- or low-skilled migrants. Since both the dependent and the independent variables are measured in logs, the reported

Table 5: Asymmetry in Patenting Levels and Free Movement, EU15-NMS

| *Dependent var* | Patent Count | | Cit-weighted Count | |
|---|---|---|---|---|
| *Free movement var* | FM | FM/dist | FM | FM/dist |
| L2.FM | -0.0280*** | -0.0314*** | -0.0198** | -0.0322*** |
| | (0.00876) | (0.00821) | (0.00919) | (0.00845) |
| withinEU | 0.0501* | 0.0504* | 0.164*** | 0.167*** |
| | (0.0265) | (0.0264) | (0.0290) | (0.0290) |
| log_tot_patents_nace | 0.258*** | 0.258*** | -0.0814** | -0.0819** |
| | (0.0453) | (0.0453) | (0.0376) | (0.0376) |
| log_GDP_ratio | 1.215*** | 1.219*** | 2.713*** | 2.723*** |
| | (0.0862) | (0.0861) | (0.102) | (0.102) |
| log_tot_flow | -0.164*** | -0.163*** | -0.350*** | -0.347*** |
| | (0.0291) | (0.0291) | (0.0381) | (0.0381) |
| Observations | 35,944 | 35,944 | 40,922 | 40,922 |
| $R^2$ | 0.881 | 0.881 | 0.851 | 0.851 |
| FE | y oi od yo | y oi od yo | y oi od yo | y oi od yo |
| Clusters | 4180 | 4180 | 4409 | 4409 |

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

**Note:** Citation counts, number of migrants, FDI and trade flows are taken in natural logarithms. The sample includes all EU country pairs. All specifications include year, industry, country-pair, and country-year fixed effects. Robust standard errors are clustered at the country-pair-industry level. Other controls include total count of patent applications in a given industry at the destination and origin.
Sources: Patstat, Eurostat, CEPII

coefficients can be interpreted as elasticities: 1% increase in the number of highly-skilled migrants reduces the within-industry patenting asymmetries between the destination and origin by 0.3%.

Table 5 reports the results with the free movement dummies. The first two columns use patent count as dependent variable, columns 3 and 4 use citation-weighted counts. The coefficient of interest is negative and significant for all specifications. This can be interpreted as causal evidence for a decrease in bilateral patenting asymmetries following the introduction of free labour mobility.

While interpreting the regression coefficients, we implicitly assumed that migrants stay within the same industry. One can expect that, in particular for high-skilled migrants, the losses associated with changing the industry are substantial. Hence, they are more likely to seek employment

in the familiar sector in the destination countries. If still the assumption did not hold for some industries, how would this affect our estimations? Suppose there are two industries: $A$ and $B$ in Poland and Germany. The Polish migrants from industry $A$ move to Germany to work in industry $B$. Empirically, we observe $M_{DE-PL-By}$ increase. The inflow of the high-skilled Polish workers in the German industry $B$ raises its innovation activities (or in the worst case, does not affect them). The performance of the Polish industry $B$ is likely to stay unchanged. The asymmetry measure $log(\frac{P_{DE-B-y}}{P_{PL-B-y}})$ either increases or at most stays the same, which goes in the opposite direction of the reported effect.

# 6 Robustness

One way to check the robustness of our results is to regress the main explanatory variable on the the outcome variable to see if there is any evidence of reverse causality. In table 8 in the Appendix, we regress our instrument on patenting. For all three variations of the instrument (weighted by migration stocks or by distance), we do not see any significant effects of patenting on free movement. Thus past patenting behaviour does not explain future labour market opening. We have checked for a zero, one and two year lag and found no significant coefficients. This validates our results and also hints at the fact that it were not the most or least innovative industries that have opened up to labour migration first.

Another way to check the validity of the results is to examine pretrends. If our results are valid, the coefficient of interest should be zero if we regress citation patterns on future labour market openings. Figure 4 in the appendix 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 is 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.[14] This is reassuring and increases the credibility of our results. It becomes very clear that the effect starts to take effect at the time of the introduction of free movement and develops over the following years.

# 7 Conclusion and Policy Implications

This paper analyses the effects of international migration on innovation in source countries. It answers the question how patenting activities are influenced by losing skilled workers as a result of migration. Mitigating factors, in particular knowledge flows are brought forward as one explanation for positive effects on total patenting.

We find that the international mobility of high-skilled people has increased total patenting activities. Patenting has increased in source countries due to technology and knowledge spillovers.

One policy recommendation that directly follows from these findings is that the EU could benefit from further facilitating high-skilled 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 high-skilled migrants both for destination and source countries.

Another policy implication is to ease high-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,

[14]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.

its scope could be increased to obtain a higher impact and administrative barriers should be reduced. For those high-skilled migrants that are already in Europe, for instance high-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 European innovation system would greatly benefit.

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 can not 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? It is essential to answer these questions in order to provide information about how to increase knowledge flows and maximise its benefits.

Another interesting question is the role of return migration for innovation. On the one hand return migration might accelerate the knowledge flows as the migrant brings his newly gained knowledge back to his country. Many times return migrants create their own start-ups. On the other hand it might also reduce knowledge flows as the migrant has left the place where he innovated and had access to the newest technologies. We leave these questions for further research.

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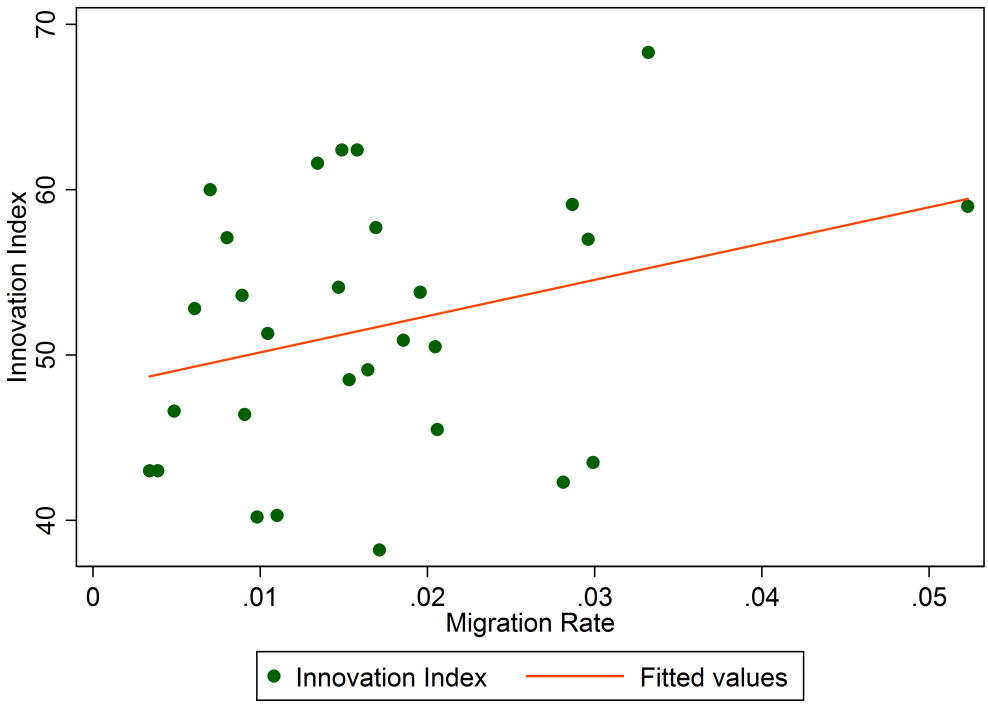
# 8 Appendix

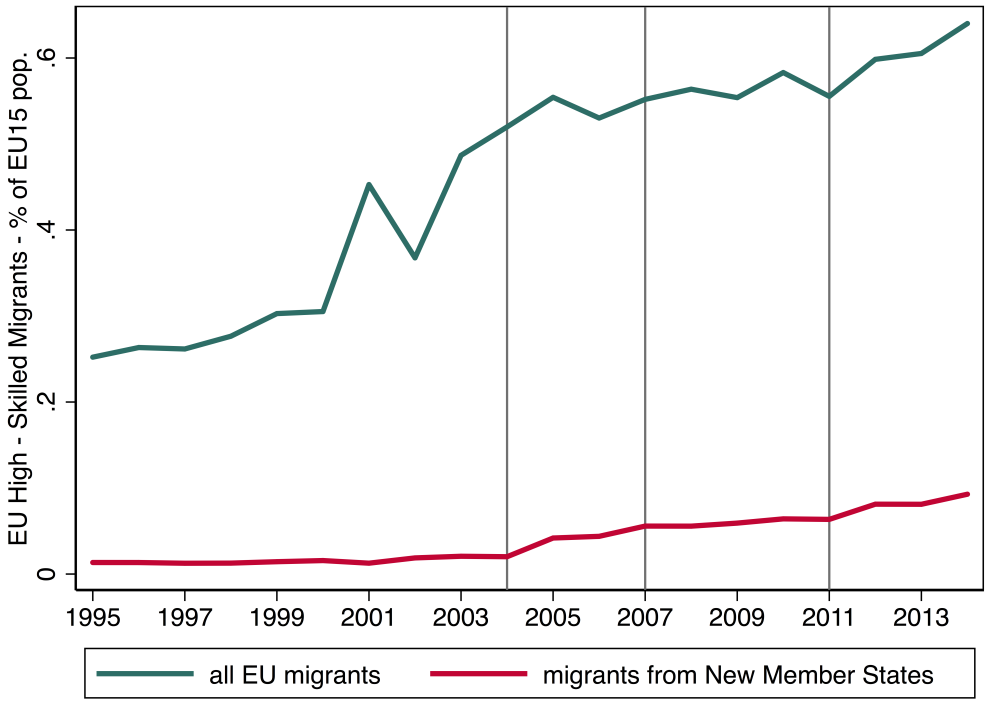
## 8.1 Additional Tables and Graphs

Figure 1: The correlation of migration and innovation



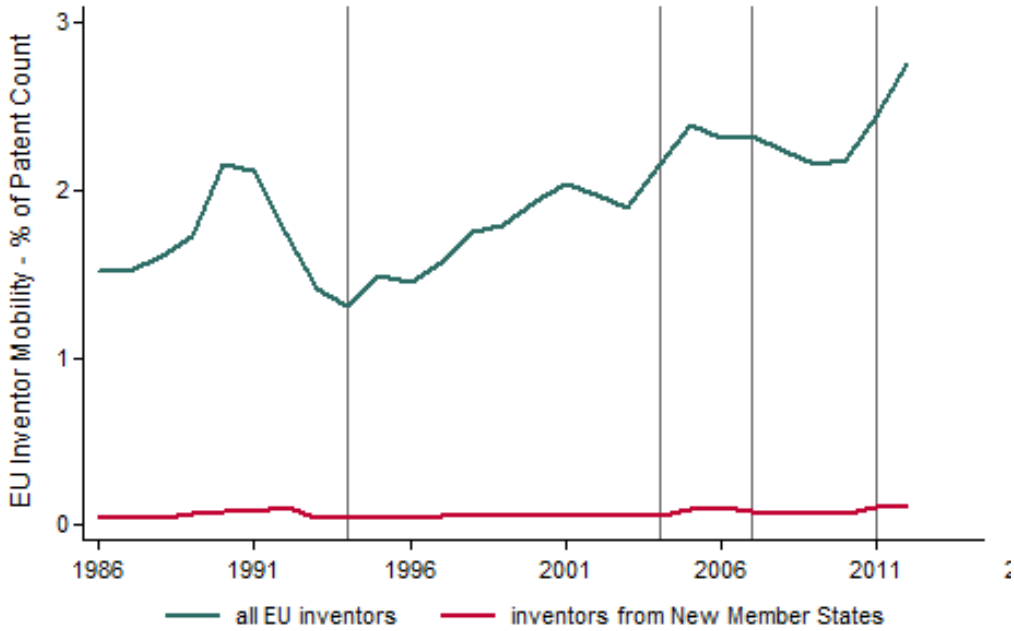

*Note:* The migration rate is calculated as yearly emigration plus immigration as a percentage of total population.
Source: Eurostat and WEF.

Figure 2: High-skilled Migration in Europe



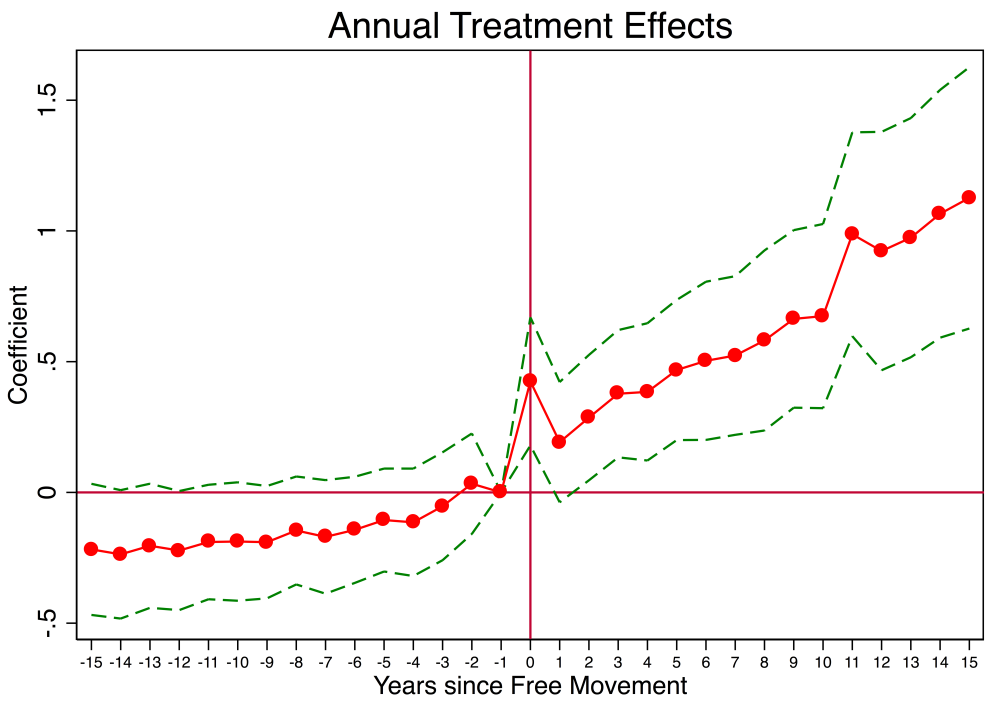

*Note:* Source: Eurostat. The graph shows the share of high-skill migrants (born in other European countries) in the EU15 population. EU15 - EU member states before 2004: Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, Netherlands, Portugal, Spain, Sweden, United Kingdom

Figure 3: Inventor Mobility in Europe




*Note:* Source: PATSTAT. The graph shows the number of mobile inventors normalized to the total number of patent applications. Mobile inventor is defined as an inventor, who changes his country of residence compared to the previous patent application - can be identified only for inventors that have at least two patents in the PATSTAT database

Figure 4: Annual Treatment Effects




Source: PATSTAT, European Commission, own calculations.
Note: 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.

Table 6: Overview of the gradual opening of the EU15 labour markets

| Country | EU8 | EU2 | Sectoral Exceptions |
|---|---|---|---|
| Austria | 2011 | 2014 | EU8 (2007-2010), EU2 (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 | EU8 (2005-2007), EU2 (2007-2013): Agriculture, Construction, Accommodation and food services (tourism and catering), other sectors with labour shortages |
| Germany | 2011 | 2014 | EU8 (2004-2010), EU2 (2007-2013): sectors with labour shortages |
| Greece | 2006 | 2009 | - |
| Iceland | 2006 | 2012 | - |
| Ireland | 2004 | 2012 | - |
| Italy | 2006 | 2012 | EU8 (2004-2005): sectors with labour shortages; EU2 (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 | EU2 (2007 - 2013): Agriculture, Viticulture, Accommodation and food services (tourism and catering) |
| Netherlands | 2007 | 2014 | EU8 (2004-2006), EU2 (2007-2013): International transport, Inland shipping, Health, Slaugther-house/meet-packaging, other sectors with labour shortages |
| Norway | 2009 | 2012 | EU8 (2004-2008), EU2 (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 | EU2 (2007-2013): Agriculture, Food manufacturing |

**Note:** Column 2 shows the year of the labour market opening of the respective country for the EU8 countries, column 3 shows the year of the labour market opening of the respective country for the EU2 countries. Column 4 shows, which sectors were exempt from restrictions.
Source: European Commission.

Table 7: Migration flows and Cross-border Citations, by New EU Member States to EU15

| | $(Cite_{odiy})$ Migrants | $(Cite_{odiy})$ Migrants_university | $(Cite_{odiy})$ Migrants_unskilled |
|---|---|---|---|
| L2.Migrants | 0.0349 | 0.313* | 0.0386 |
| | (0.0325) | (0.177) | (0.0469) |
| patents at origin | 0.191*** | 0.192*** | 0.192*** |
| | (0.0281) | (0.0280) | (0.0281) |
| patents at dest | 0.118** | 0.118** | 0.119** |
| | (0.0530) | (0.0528) | (0.0531) |
| withinEU | 0.104 | 0.0966 | 0.110 |
| | (0.106) | (0.106) | (0.106) |
| log_trade_flow | -0.0862 | -0.0838 | -0.0801 |
| | (0.128) | (0.128) | (0.128) |
| log_fdi | -0.0162 | -0.0203 | -0.0169 |
| | (0.0349) | (0.0348) | (0.0349) |
| Observations | 2,610 | 2,610 | 2,610 |
| $R^2$ | 0.723 | 0.724 | 0.723 |
| FE | y i do yo | y i do yo | y i do yo |
| Clusters | 523 | 523 | 523 |

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

**Note:** Citation counts, number of migrants, FDI and trade flows are taken in natural logarithms. The sample includes country pairs, where EU15 countries are destinations and New EU member states are origins. All specifications include year, industry, country-pair, and country-year fixed effects. Robust standard errors are clustered at the country-pair-industry level. Other controls include total count of patent applications in a given industry at the destination and origin.
Sources: Patstat, Eurostat, CEPII

Table 8: Check for reverse causality

| | FM | FM*migr.stocks | FM/dist |
|---|---|---|---|
| L2.log_patents_orig | 0.00400 | -0.00199 | 0.00753 |
| | (0.00306) | (0.00410) | (0.00767) |
| withinEU | 0.246*** | 0.355*** | 0.623*** |
| | (0.00757) | (0.0286) | (0.0193) |
| log_tot_patents_nace | 0.00509 | 0.0131 | 0.0121 |
| | (0.00550) | (0.00893) | (0.0149) |
| log_gdp_orig | -0.180** | -0.219*** | -0.160 |
| | (0.0706) | (0.0493) | (0.115) |
| log_import | 0.231*** | 0.224*** | 0.310** |
| | (0.0746) | (0.0839) | (0.151) |
| Observations | 2,501 | 2,164 | 2,501 |
| $R^2$ | 0.979 | 0.962 | 0.980 |
| FE | y oi yo | y oi yo | y oi yo |
| Clusters | 260 | 260 | 260 |

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

**Note:** This table shows three regressions where the number of patents lagged by two years is regressed first on the free movement instrument, second on the interaction of the free movement dummy with migration stocks and third on the interaction of the free movement dummy with distance. It is reassuring that the coefficients of L2.log_patents_orig are insignificant and close to zero.
Source: Eurostat and PATSTAT.