The migration of professionals within the EU: any barriers left?

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Abstract

Despite the effort at EU level to harmonize the process of recognition of foreign educational qualifications, the European states differ in their propensity to accept high-school and academic certificates obtained in other EU member states. In turn, a country's higher degree of recognition of foreign qualifications might be an attractor of non-native skilled workers. We provide evidence on this issue using new data on the outcome of the recognition process in every EU country. Estimating different panel data gravity models, we find that the migration rate to a given destination country is positively affected by its propensity to recognize foreign educational qualifications.

Keywords: International migration, Professional Labour Markets, Panel Data

JEL codes: F22, J44, C23

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1 Introduction

Although free labour mobility is one of the pillars of the EU (see Art. 3 of the Treaty on European Union), frictions to the movement of workers may still exist. For example, cross-country differences in labour and housing markets, the difficulty to transfer welfare and social benefits or the imperfect portability of pension rights are all factors which may hinder intra-EU mobility. In this paper, we deal with another highly debated topic: the destination country's propensity to recognize educational and professional qualifications acquired in another EU member state. The policy relevance of this issue is undoubted and proved by the EU legislative activity on this subject since its establishment.

Despite the effort at EU level to harmonize the rules for the recognition of foreign qualifications, empirical evidence is so far missing on whether higher recognition of professional qualifications spurs intra-EU mobility. We fill this gap by addressing the following research question: is the propensity of an EU country to recognize foreign educational qualifications positively linked to the attraction of EU high and medium skilled immigrants?

A positive answer to the above question would seem straightforward, since a wider recognition of degrees and certificates acquired in other EU countries makes it easier for EU (labor) immigrants to search for a job within the EU. Thus, the higher the propensity of a destination country to accept foreign qualifications, the higher its probability should be to attract qualified workers. The latter point is nowadays at the core of the political discussion in several European countries, which have to face the problem of fulfilling the demand for high-skilled workers.

The actual application of the European regulations still depends on the single member states and their national legislations. Given the margin of discretion left by the EU rules, there exists a sizeable amount of cross-country heterogeneity in the level of harmonization, thus on the propensity of recognition. Neither the former, nor the latter are directly observable. However, the propensity of recognition is likely mirrored by the outcome of the recognition process in any given country. Indeed, the request for the acknowledgment of a qualification obtained abroad may not necessarily lead to an immediate and positive recognition. Hence, we construct proxies for the country propensity to accept foreign qualifications based on available data on the number of recognitions in EU member states.

We match the information on recognitions with new bilateral data on migration stocks by skill-level to estimate a gravity model of migration. This approach allows us not only to evaluate the role of the propensity of recognition as an attractor of European migrants, but also to explore to which extent "classical" migration push and pull factors are effective at the EU level, and how their impact compares to the one of our main variable of interest. When estimating different versions of a gravity panel data model, all our results reveal, as expected, a positive relationship between the scale of migration rates and the propensity of recognition. Specifically, such a relationship is highly significant when we estimate a model including time, origin and destination country effects, as it is commonly done in the migration gravity literature. Alternative specifications and sensitivity analysis confirm the overall baseline result, i.e. that the easiness of recognition of foreign qualifications has a positive impact on the intra-EU mobility of workers, but the effect becomes modest.

Related Literature. As several works on the economic assimilation of immigrants have found, immigrants experience a worsening in their wage and occupational status once they first access the host country labour market (Friedberg, 2000; Chiswick et al., 2005). The magnitude of this drop depends, among other things, on the easiness of the skill-transferability from one country to the other, and it can in some cases lead to a serious problem of over-education among the immigrant population. High-skilled individuals are typically the ones who suffer the most from such a skill-depreciation (see, for example, Chiswick and Miller, 2008, 2009; Nielsen, 2011).

Inspired by the above results and considerations, our paper treats the imperfect recognition of educational qualifications and the uncertainty surrounding it as equivalent to a migration cost. Forward-looking agents should take that cost into account before taking the migration decision and when assessing their economic opportunities in a given destination. Hence, the removal of this kind of barrier has a high potential to ease intra-EU mobility, especially for high-skilled individuals, and to become a policy instrument to promote the in-migration of talents. As noted by Dustmann and Glitz (2011), the attraction and successful labour market assimilation of qualified workers benefit first of all the host country because the more immigrants earn, the more they will contribute to the tax and benefit system of the host country as well as to per-capita GDP.

From the methodological point of view, our paper falls into the vast body of literature estimating gravity models of migration. Originally born and still widely used to analyse the determinants of bilateral trade flows, the gravity approach has been successfully applied later on in migration research to identify the migration effects of several factors, most notably migration networks (Pedersen et al., 2008), income opportunities in the destination country (see, for instance, Ortega and Peri, 2013), migration policies and labour mobility restrictions (Ortega and Peri, 2013; Palmer and Pytlikova, 2015) and cultural barriers (Belot and Ederveen, 2012). As already mentioned, our aim is the identification of the effect of the "propensity to recognize foreign degrees" on bilateral migration rates and consequently on the possibility for EU professionals to practice in any of the EU states, independently of the country where they obtained their degree. In so doing, we contribute to the existing literature by providing the first empirical evidence on the implications of the recognition of foreign qualifications for labour mobility at the macro level.

Similarly to the previous literature, we are concerned with potential endogeneity issues in our model. As we will explain in further detail in what follows, both our main variable of interest and the geographical distance may suffer from endogeneity bias due to unobserved bilateral heterogeneity. Indeed, the propensity to recognize qualifications acquired in a given origin may be influenced by unobserved country-pair similarities. Moreover, the geographical distance might be biased if reflecting unobserved preferences of individuals from a given origin to move to a particular destination for historical or cultural reasons. Furthermore, there might be a problem of reverse causality, since destinations with higher migration rates from a given origin might be more prone to integrate those migrants in their labour markets. Reverse causality can also be linked with signal effects in the labour market: indeed, the higher the stock of migrants that obtained the qualification in a given origin, the higher the propensity of employers of a given destination to have more experience and information when hiring those immigrants.

We tackle the unobserved heterogeneity at the country pair level estimating a fixed effects model. We also depart from the standard approaches by using a Hausman-Taylor approach, following a strand of trade literature that deals with the endogeneity of several bilateral variables, and especially of the geographical distance (see for instance, Egger and Pfaffermayr, 2004; Egger, 2004). Similarly to those empirical works, we find that the deterrent effect of the distance on migration patterns is much higher than estimated without taking endogeneity into account.

The remainder of the paper is organized as follows: Section 2 describes the EU institutional background around the harmonization of the rules governing the recognition of foreign qualifications. Section 3 presents the data. Section 4 shows the first empirical specification and the estimation results. We discuss and estimate alternative specifications in Section 5. Section 6 concludes.

2 Institutional background

This section provides an overview on the intense legislative activity of the European Union promoting the mutual recognition of professional qualifications. Besides confirming the already highlighted policy relevance of this issue, this section also clarifies some concepts and and features of the data we use in our empirical analysis.

The harmonization of the education and qualification systems across member states has been one of the pillars to ease the achievement of a common European labour market. The start of the Bologna process in the nineties and the establishment of a European Higher Education Area (EHEA) were among the first initiatives in this direction. Through the Bologna process, the EU countries have adopted similar standards for the quality and structure of their higher education systems. The acknowledgment of educational and professional qualifications is another necessary step to reach the goal of harmonization. To this aim, the Treaty on the functioning of the European Union (Art. 53) already allows the Council and the Parliament to issue directives on this subject. The principle underlying the mutual recognition is the following: any profession or form of work requiring a particular qualification in an EU member state can be practiced also by EU nationals who acquired a similar qualification in a different EU country. This is equivalent to introducing substitutability of academic and professional qualifications throughout the EU. Hence, the application of the above principle should ensure free mobility within the EU, avoiding any workers' discrimination and reducing the barriers to the movement of labour. The EU legislation for the free movement of professionals is quite articulated: the EU directives dating back to the nineties cover the recognition of the qualifications for which a high school diploma and an university degree are needed. They also establish specific rules applying to different professional categories.

In 2005 the EU issued a directive on the harmonization of the regulated professions (Directive 2005/36 EC), which consolidates the existing norms and was implemented in 2007. It applies to all the EEA countries and Switzerland, and it concerns a wide range of professions.[1] In particular, it applies to the sectoral professions,[2] to the trade-industry-business professions and to other professions that might be either regulated or not in a given EU country.

The Directive distinguishes among four broad schemes of recognition. The first one is the "general system," which applies to individuals wishing to settle in the host country. The professional qualifications of the immigrant are recognized if they are at least equivalent to the level immediately prior to that which is required in the host state. Under the general system, the recognition is granted also if the immigrant has practiced a given profession for two years, even if the profession is not regulated in the home country. In some cases, the destination country may check the qualifications by requiring some compensation measures, e.g. adaptation periods, tests or exams.

The second case is the "automatic recognition," which applies to the above-

[1] The Directive does not apply to "sailors, statutory auditors, insurance intermediaries and air controllers, or to some other professions in the field of transport or linked to activities involving toxic products" (see http://ec.europa.eu/internal_market/qualifications/other_directives/index_en.htm). These categories are regulated by different directives.

[2] The sectoral professions comprise architects, dentists, doctors, midwives, nurses, pharmacists and veterinary surgeons.

mentioned sectoral professions. The third case deals with the "recognition of professional experience": individuals working in the craft, commerce or industry sector may be required to take some traineeship or test whenever their qualifications significantly differ from the ones required in the host country for practicing a given profession. Otherwise, they are granted the recognition under one of the two previous systems. Finally, the "temporary mobility" system applies to professionals wishing to practice temporarily in another EU country: in this case, a permit or a registration lasting at most one year is required.[3] Despite the effort to harmonize the existing rules and regulations, no single solution exists among the EU countries; in fact, the rules and compensation measures are left to the discretion of every member state. Hence, from an individual perspective, the process of having one's qualifications accepted and recognized may be complex and long, and it may involve non-negligible monetary and non-monetary costs. Table 1 provides some figures on the outcome of the application process for selected European destinations.[4] For each host country, we report the total number of applications received in the 1997-2014 period, and the number of positive, negative and pending decisions. A given degree of heterogeneity is already apparent from this table, but the cross-country differences might be even more pronounced once we disaggregate by country of origin. For example, as shown in Table 1, the overall rate of recognition in Germany is 60 percent. However, if we only consider the applications coming from Austria, the Netherlands, and Poland (i.e. the three countries from which most applications come in the considered period), Poland has the lowest acceptance rate (41 percent), while Austria and and the Netherlands are at around 71 and 77 percent, respectively. Considering that Germany is one of the

[3] The data on the recognition that we use for the empirical analysis refer to the first three systems, excluding the "temporary mobility" case.

[4] The host countries are the ones included in our estimation sample. See note to Table 1 for details.

preferred European destinations for Polish migrants, this hints that frictions in the application of the norms might really be detrimental for the labour market integration of immigrants.

Table 1: Positive, negative and pending recognitions for any destination country. Period: 1997-2014, row frequencies in italics.

	Positive	Negative	Pending	Total
Austria	19016	1801	857	21674
	0.88	*0.08*	*0.04*	
Denmark	7963	554	1163	9680
	0.82	*0.06*	*0.12*	
Finland	3862	8	281	4151
	0.93	*0.00*	*0.07*	
France	7924	255	2174	10353
	0.77	*0.02*	*0.21*	
Germany	24061	2205	13910	40176
	0.60	*0.05*	*0.35*	
Ireland	18850	421	1458	20729
	0.91	*0.02*	*0.07*	
Luxembourg	6568	86	1	6655
	0.99	*0.01*	*0.00*	
Netherlands	9029	921	1198	11148
	0.81	*0.08*	*0.11*	
Norway	40132	4554	358	45044
	0.89	*0.10*	*0.01*	
Portugal	1713	102	570	2385
	0.72	*0.04*	*0.24*	
Spain	6502	778	490	7770
	0.84	*0.10*	*0.06*	
Sweden	9548	709	1678	11935
	0.80	*0.06*	*0.14*	
Switzerland	23818	28	2845	26691
	0.89	*0.00*	*0.11*	
United Kingdom	82313	5743	7656	95712
	0.86	*0.06*	*0.08*	

Source: Regulated Profession Database (European Commission), authors' elaboration. "Total" is the number of applications received in the host countries. It consists of all qualifications obtained in any EEA country, Switzerland included. The reported countries are only the ones in our estimation sample. Data refer to the cases of "general system," "automatic recognition" and "recognition of professional experience". Data for the "temporary mobility" case are not available.

3 Data and variables

In this section we describe the main data sources we use for our estimation and we provide details on the construction of the main variables of interest.

The IAB Brain Drain Dataset. The source of data for immigrants is the "Brain-drain" dataset (source: Institute for Employment Research, IAB), a new database containing information on bilateral stocks of immigrants by country of birth and level of education, with five year frequency, from 1980 to 2010. We use this information to construct our dependent variable, i.e. the migration rate for any origin-destination country pair. Following the definition used in the IAB Brain-drain dataset, we consider as high-skill those individuals with tertiary education, i.e. with higher than high-school leaving certificate or equivalent (see Brücker et al., 2013). Instead, the medium-skill comprise individuals with secondary education, i.e. with high-school leaving certificate or equivalent. We define the bilateral migration rate as the ratio between the total stocks of high and medium skill immigrants from a given origin country in a given destination over the sum of the population of the origin country plus the stock of high and medium skill from the given origin to all the EU destinations considered in the sample.[5] Hence, the bilateral migration rate from a given origin o to a given destination d at time t is defined as:

$$\text{Rate}_{odt} = \frac{(\text{Stock High} + \text{Stock Med.})_{odt}}{\text{Pop}_{ot} + \sum_d (\text{Stock High}+\text{Stock Med.})_{odt}} \tag{1}$$

Observe that the stocks of migrants and population contain people aged 25 and older. Hence, data are unlikely to include students who migrated for

[5] In our main empirical analysis we aggregate high and medium skill immigrants when computing the migration rate. This is done for consistency with the "Regulated Professions Database," which does not allow to distinguish between professions requiring the high-school diploma and those requiring tertiary education. Regression results for high and medium skilled migration rates separately are presented in the Appendix.

educational reasons (Brücker et al., 2013). This feature of the data is desirable in our case since we are interested in the mobility of professionals, excluding students.

One potential shortcoming of the bilateral migration stocks we use is that they do not contain information on the country of education. This means that they might include individuals who have studied in the destination country, and hence are not relevant for our research question (Beine et el., 2007). Ideally, then, we should select those individuals out of the estimation sample and compute the migration rates only on those who migrated after completing tertiary education in their origin country (i.e. country of birth). One way of doing this could be, as in Beine et al. (2007), controlling for the age of entry in the destination and considering the immigrants who entered after a given age (e.g. after age 22 according to Beine et al.'s definition (2007)) as educated in the country of origin (birth). However, immigrants' age of entry is only obtainable from answers to Census questions that are not always asked, or are hardly comparable across Censuses. The only existing dataset displaying the stocks of immigrants by age of entry is the one developed by the above cited authors, which contains figures on the number of high-skill immigrants aged 22 years and older, by age of entry and for the census-years 1991 and 2001. Using this data would allow us to perform only a cross-section estimation, hence losing the advantage of a longer time-frame.

Moreover, as Beine et al. (2007) show, the migration rates corrected for age at entry are highly correlated with the ones computed using the Doquier and Marfouk dataset (2006), which applies a totally similar methodology as the IAB-Brain-Drain dataset.[6] So, even if our migration rates might be too high (since they might also contain individuals who acquired education in the destination

[6] The IAB-Brain-Drain dataset can actually be considered an extension of Doquier and Marfouk (2006) along the time and gender dimensions.

country), they are likely to closely covary with the ones by age of entry. At least qualitatively, then, our results should still provide a useful piece of evidence on the problem under examination. Finally, in the subsample of individuals who studied in the destination country, according to our line of reasoning, the correlation between incidence of recognition and migration should be zero. Indeed, immigrants who acquired education in the destination country do not need to apply for the recognition of their education at destination. But, as we have previously anticipated, we provide evidence of a positive relationship between the destination country's propensity to recognize foreign qualifications and the migration rate to that destination. Such a relation can only reflect the behaviour of those individuals who studied in the country of origin.[7]

The Regulated Professions Database. To compute the probability of recognition of qualification in the destination country, we use the "Regulated Professions Database", provided by the European Commission, which has information on each EU member state's number of applications for recognition of academic and professional qualifications acquired in any other EU country. The data refer to the "general system, "automatic recognition" and "recognition of professional experience" cases (see the Institutional Background section for details). Data are available for all the EU28 and EEA countries, from 1997 to 2014. While the frequency is biannual from 1997 to 2006, it is annual for the remaining time period. The country's propensity and attitude toward the recognition process may be influenced by different observed and unobserved factors. For instance, it may depend on the general level of bureaucracy and on

[7] Another minor concern would regard those migrants who studied in a third country (i.e. neither the origin nor the destination). The little existing evidence on this topic suggests that this is likely to be a very small group. For example, for Germany, own computations based on the IAB-SOEP New Migration sample show that in 2013 the total number of interviewed immigrants who had at least one episode of migration in a third country (where they could have acquired some education), is just 76 out of 3,710 individuals.

the burden of administrative procedures that are country specific. The difficulty to measure the country's attitude toward the recognition process requires the use of proxies: hence, using the data of the Regulated Professions Database, we build the following indicator:

$$\text{Propensity of Recognition}_{odt} = \frac{\text{Positive Applications}_{odt-1}}{\sum_o \text{Total Applications}_{odt-1}} \qquad (2)$$

The above measure is defined as the ratio between the number of certificates obtained in a given origin country and recognized by a given destination (i.e. with positive outcome) and the total number of applications submitted to the destination country. The latter is the sum of applications recognized (i.e. with a positive outcome), of the applications rejected (negative outcome) and of the applications with a neutral outcome (i.e. the applications for which the decision is pending).[8] To build the indicator for t=2000, we use the number of applications from 1997 to 1999 due to data availability. Similarly, the indicator for t=2005 contains the applications received from 2000 to 2004, while the indicator for t=2010 uses data from 2005 to 2009. We pool the data for different years since the data from 1997 to 2006 are with biannual frequency, so we cannot disaggregate them. The propensity of recognition is lagged by one period, i.e. the indicator for the first year contains the number of applications up to 1999. We do so since expect that the reaction of the migration rates to the propensity of a given destination country to recognize educational qualifications may not be instantaneous. Observe that the indicator could capture the size of migrants from a particular origin to a given destination or the capacity of the latter to attract immigrants from a given origin.[9] Descriptive statistics of both the

[8]Observe that the same individuals may apply more than once; for instance, if an individual receives a negative application in a given year, he might re-apply later.

[9]Suppose that the propensity of recognition of a given destination d from the origin country A is higher than the propensity of the same destination from a different origin country B. This could be due to the fact that destination d attracts a higher number of

migration rates and the propensity indicator are reported in the Appendix.[10]

Other variables and sources. We also control for regressors commonly found in the gravity literature: the distance between capitals, the difference between GDP in the origin and the destination countries (source: World Bank, WDI indicators) and the population in the destination country (source: UN "World Population Prospect" database).

Sample selection. Due to data availability, we restrict the sample to the years 2000, 2005 and 2010. This time-period is characterized by the attempt to harmonize the regulation on the recognition of professional and academic qualifications at the EU level. moreover, the completion of the Single European Labour Market has started from the 2000s, with the 2004 and 2007 EU enlargments and with the gradual removal of the transitional arrangements to the free labor mobility. As destinations, we have data for 14 EU member states before the enlargements, i.e. the destinations taken from the EU15 and the EEA countries including also Switzerland. As origin, we use 29 countries taken from the EU27 and EEA countries, Switzerland included.[11] We thus have a balanced panel dataset, with three years (i.e. 2000, 2005 and 2010), 1095 observations and 365 country-pairs.

immigrants from A than from B.

[10]As a robustness check, we also use an alternative indicator of the propensity of recognition, constructed by using the total applications with positive outcome in a given destination at the denominator. See the Appendix for details on the construction of this alternative indicator and the respective estimation results.

[11]The destination countries are Austria, Denmark, Finland, France, Germany, Iceland, Ireland, Luxembourg, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland and UK. Unfortunately, data on migration stocks for the other EU15 destination countries, i.e. Belgium, Greece and Italy, are not available. As origin countries we have Austria, Belgium, Bulgaria, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Iceland, Ireland, Italy, Latvia, Lithuania, Netherlands, Norway, Poland, Portugal, Romania, Slovak Republic, Slovenia, Spain, Sweden, Switzerland, and UK. Croatia is not included since it entered the EU after 2010.

4 Empirical analysis and results

We investigate the relationship between our main variables of interest by first estimating the following model:

$$\begin{aligned} Rate_{odt} = \delta_0 + \delta_1 \text{Propensity of Recognition}_{od(t-1)} + \delta_2 \text{DIST}_{od} \\ + \delta_3 \text{GDP-diff}_{odt} + \delta_4 \text{POP}_{dt} + \epsilon_{odt} \end{aligned} \tag{3}$$

Where $Rate_{odt}$ is the migration rate and Propensity of Recognition$_{od(t-1)}$ is the previously described indicator lagged one period. We expect to find a positive estimated coefficient of the indicator: the higher the propensity of a destination to recognize foreign educational qualifications, the higher the migration rate to that country. The remaining control variables are the bilateral distance between origin and destination (DIST$_{od}$), the difference between origin and destination GDP (GDP-diff$_{odt}$) and the population in the destination country (POP$_{dt}$). As mentioned in the introduction, we first estimate a model including time, origin and destination country effects, as commonly found in the gravity literature in migration.

$$\epsilon_{odt} = \alpha_d + \alpha_o + \alpha_t + \alpha_{ot} + \eta_{odt}. \tag{4}$$

Based on assumptions (4), we estimate Least Squares Dummy Variables (LSDV) specifications. Tables 2 presents the results of this first estimation. The first, second, third, and fourth columns of of the tables differ with respect to the inclusion of the country and time dummies and of their product.

From these first regression results, we can see that the propensity of recognition of foreign certificates in the destination seems to be a pull-factor of European migrants of any skill-level. Indeed, based on the models including all the time and country effects (LSDV-3 in Table 2), the coefficient of the propensity of acceptance is positive and statistically significant at 1 percent level. Moreover, the bilateral distance has the expected negative sign and is highly significant. In line with the gravity literature of migration, this result seems to indicate that moving costs represent a deterrent to migration, even when relatively close countries are considered, such as in the European context. Incidentally, we also notice that when comparing the model specifications in Table 2, the specification including all time and country dummies (LSDV-3, Table 2) is preferred using the AIC criterion, while specification LSDV-2 (Table 2) is preferred when using the BIC criterion.

The results shown remain stable even after disaggregating the sample into high or medium skill migrants and they confirm an overall importance of the recognition of qualifications to attract European migrants (see Appendix Table A-3). The estimated coefficient suggest that recognition is almost equally relevant for high and medium-skill immigrants. One obvious reason for that could be the cross-country heterogeneity in the education systems, resulting in the same profession requiring different levels of qualification in different countries.

Table 2: Migration rates and propensity of recognition. Baseline estimation results.

Dependent variable:
Migration rate

	LSDV-1	LSDV-2	LSDV-3	LSDV-4
Propensity of Recognition 1	0.403***	0.395***	0.377***	0.385***
	(0.085)	(0.084)	(0.083)	(0.086)
GDP difference	0.011**	0.010**	0.003	0.001
	(0.005)	(0.004)	(0.004)	(0.004)
Population destination	0.004**	0.016***	0.013**	0.015*
	(0.002)	(0.006)	(0.006)	(0.008)
Distance	−0.021***	−0.020***	−0.037***	−0.037***
	(0.005)	(0.005)	(0.009)	(0.009)
R^2	0.533	0.496	0.564	657
Obs.	1043	1043	1043	1043
Aic	-3533.50	-3479.35	-3577.67	-3485.26
Bic	-3370.15	-3380.35	-3349.97	-3000.17
Year-dummies	Yes	Yes	Yes	Yes
Origin dummies	Yes	No	Yes	Yes
Destination dummies	No	Yes	Yes	Yes
Origin*Year dummies	No	No	No	Yes

Notes: All regressions include a constant. Standard errors clustered at the country-pair level in parenthesis. *significant at 10%, ** significant at 5%, *** significant at 1%. "Propensity of Recognition" is the number of certificates obtained in a given origin country and accepted by a given destination at time t, over the total number of applications submitted to the destination country at time t.

5 Alternative specifications

The previously estimated specifications might be plagued by endogeneity problems due to unobserved heterogeneity at the country-pair level. We are particularly concerned with the possible bias of two of our bilateral explanatory variables: the incidence of recognition indicator and the distance. The former might be endogenous if, for example, countries with a higher concentration of migrants are also more prone to efficiently implement the rules on the recognition of certificates. In the same vein, the propensity of recognition may be demand-driven: the need for a particular profession in the destination country may imply a higher tendency to "import" it, thus making the recognition process easier. The geographical distance may also be correlated with the bilateral unobserved propensity to experience migratory flows, e.g. for given cultural or historical reasons.[12]

Therefore, differently from the model specified above, we now introduce time and bilateral effects, making the following assumption on the error term:

$$\epsilon_{odt} = \alpha_{od} + \alpha_t + \eta_{odt} \tag{5}$$

A random effect model (RE), a fixed effect model (FE) and a correlated random effect model (CRE) are estimated. While the FE allows for correlation among the explanatory variables and the unobserved bilateral component, the RE assumes absence of correlation. In the CRE specification, we model the relationship between the country-pair effects and the regressors (as in the approach of Mundlak, 1978[13]). In case of correlation of the explanatory variables with the unobserved heterogeneity at the country-pair level, the RE gives biased estimates. With the FE model, we get rid of all the bilateral unobserved heterogeneity. However, the main drawback of the FE approach in our case is that, with 365 fixed effects over a total estimation sample of 1095 observations, it causes a non-negligible loss of degrees of freedom. This unavoidably undermines the significance of the estimated coefficients. Moreover, due to data constraints, only a limited time variation across the country-pairs can be exploited (indeed, we have a short panel where t=3). To tackle the correlation of the explanatory variables with the unobserved bilateral heterogeneity, we

[12] Also the reverse causality can be an issue: even if we cannot exclude it, we mitigate this type of endogeneity looking at the destination country's propensity of recognition lagged in time with respect to the migration movements.

[13] See the Appendix for the details on the CRE model.

also use a Hausman-Taylor estimation approach (Hausman and Taylor, 1981). This method has already been applied in the gravity trade literature (see, for instance, Egger, 2004 and Egger and Pfaffermayr, 2004) to address the possible endogeneity of the distance. Similarly to our case, the underlying hypothesis is that the distance might be correlated with the unobserved bilateral propensity to trade. Moreover, the approach can be used as a sensitivity analysis since it allows us to identify the regressors that are the sources of correlation with the bilateral component (as in Egger,2004). The Hausman-Taylor method exploits the uncorrelatedness of some of the covariates with α_{od} to consistently and efficiently estimate the coefficients of both the time invariant and time-variant endogenous regressors.[14] Intuitively, the procedure uses the deviation from the individual means of the exogenous time-variant variables to instrument the time-variant endogenous regressors, while their individual means are used as instruments for the time-invariant covariates. Furthermore, the Hausman-Taylor approach offers the possibility to test the correlation of our variables of interest with α_{od} using a standard Hausman-type test.

Table 3 shows the estimated coefficients from the RE, the FE and the CRE models. In the first panel of Table 3, the coefficient of the Propensity of Recognition is highly significant and equal to 0.104 in the RE model, while it decreases to 0.033 in the FE model, where it is significant at the 10 per cent level (this may be due to the above-mentioned loss of degrees of freedom). The same coefficients as in the FE are obtained in the CRE model. The variable addition test does not accept the null hypothesis that the coefficients of the mean groups of the regressors in the CRE model (not reported in Table 3 for notational simplicity) are jointly equal to 0. Hence, the test suggests that the FE specification is preferred to the RE model (see the Appendix for details on the test). The last two columns of Table 3 report the Hausman-Taylor

[14] Appendix A contains a technical and more detailed explanation of the method.

estimation results. Specifically, in HT-1 only the time invariant regressor (i.e. the distance) is considered correlated with α_{od} and hence instrumented. In HT-2 both the distance and the indicator are instrumented. We observe that the coefficients of the indicators of the "Propensity of Recognition" obtained in both HT-1 and HT-2 are equal to the ones in the FE (see Table 3). This might indicate that the indicator is not the source of correlation, especially because the Hausman test does not reject the null of no-correlation even after the instrumentation of the distance only (see column HT-1).[15] The coefficient of the distance is still highly significant in HT-1, and it increases in absolute value with respect to the RE model.

The lower coefficient and significance in the FE and HT models than in the baseline specifications indicate that the positive effect of the propensity of a destination to recognize foreign qualifications on migration rates is less strong when we account for the possible correlation with the bilateral unobserved heterogeneity. Moreover, when we use the disaggregated migration rates and the second indicator, the coefficients of the indicators lose significance. This set of results also indicates that the effect of distance in our previous results was upward biased and suggests that unobserved bilateral factors like individual preferences or cultural similarity could attenuate the role of distance within the European context. Most importantly, this finding proves that there still exist considerable geographical moving costs, even within the EU and even for high-skill individuals. This is in contrast with the common assumption and perception that distance should play a negligible role in high-skill migration.

[15] The Appendix contains a detailed explanation of the test.

Table 3: Migration rates and propensity of recognition. Alternative specifications results.

Dependent variable:
Migration rate

	RE	FE	CRE	HT-1	HT-2
Propensity of Recognition	0.104***	0.033*	0.033*	0.033*	0.033*
	(0.030)	(0.020)	(0.020)	(0.019)	(0.019)
Distance	−0.027***	–	−0.013***	−0.188***	−0.245
	(0.005)		(0.003)	(0.039)	(0.129)
R^2	0.329	0.977	0.525		
Obs.	1043	1043	1043	1043	1043
Variable addition test					
χ^2_3	–	–	44.50***		
Over-identification test					
χ^2				5.24	0.58

Notes: All regressions include a constant. Standard errors (in parenthesis) are clustered at the country-pair level for RE, FE and CRE models, and bootstrap-clustered (200 replications) at the country-pair level for HT-1 and HT-2. *significant at 10%, ** significant at 5%, *** significant at 1%. Additional controls: difference between GDP of origin and destination country, population in the destination country, year dummies. The coefficients of mean groups of the regressors in the CRE are not reported. Chi squared statistic of the variable addition test. The null hypothesis is that the coefficients of the mean group variables in the CRE are jointly equal to 0. See Table 2 for the definition of Propensity of Recognition indicator.

6 Conclusions

Motivated by the possible existence of frictions to the free labour mobility within the EU, we provide the first empirical evidence on the effect of the mutual recognition of educational and professional qualifications on the migration of workers. Specifically, we analyse whether the propensity of a country to recognize foreign qualifications affects the migration rate to that destination country. Using new bilateral data on the recognition of foreign qualifications in the EU, we build two indicators to proxy the propensity of recognition and we estimate different versions of a gravity panel data model. The first model, which includes time and country effects, confirms that the propensity to recognize foreign qualifications positively affects the migration rate. Moreover, as commonly found in gravity models of migration, the bilateral geographical distance negatively affects the migration between two countries.

To tackle the possible correlation among the bilateral explanatory variables and the country-pair unobserved heterogeneity, we specify a different version of the model including the time and the country-bilateral effects, estimated with random, fixed effects, correlated random effects and with a Hausman-Taylor approach. The positive coefficient of the indicators decreases and becomes significant at a lower level in all the FE, CRE and Hausman-Taylor specifications than in the RE.

The findings suggest the following interpretation: the propensity of a country to recognize foreign qualifications might benefit the destination country in terms of increased migration rates of both high and medium skill professional workers. However, the positive effect of migration rates diminishes when we account for the possible correlation between the explanatory variables and the bilateral unobserved components: the harmonization of the recognition process has only a moderate impact on the migration rates. From a policy perspective, the results seem to suggest that the harmonization of the recognition process may still be incomplete. A more efficient implementation of the EU may improve the destination country's propensity to accept foreign qualifications. In turn, this could translate into higher migration rates, attracting more qualified workers and easing their mobility.

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Appendix

A-1 Addtional descriptive statistics

Table A-1: Mean and Standard Deviation for the migration rate and for the "Propensity of Recognition" indicator

Country	Migr. Rate_o	Migr. Rate_d	Prop. of Recognition_o	Prop. of Recognition_d
Austria	0.021	0.035	0.018	0.033
	(0.031)	(0.063)	(0.026)	(0.017)
Belgium	0.039	–	0.104	–
	(0.058)	–	0.183	–
Bulgaria	0.011	–	0.004	–
	(0.013)	–	(0.008)	–
Czech Republic	0.025	–	0.004	–
	(0.040)	–	(0.007)	–
Denmark	0.026	0.030	0.026	0.030
	(0.045)	(0.037)	(0.038)	(0.075)
Estonia	0.028	–	0.012	–
	(0.090)	–	(0.059)	–
Finland	0.039	0.033	0.017	0.031
	(0.961)	(0.084)	(0.044)	(0.079)
France	0.075	0.036	0.050	0.032
	(0.086)	(0.043)	(0.082)	(0.111)
Germany	0.128	0.038	0.0181	0.026
	(0.090)	(0.044)	(0.181)	(0.069)
Greece	0.015	–	0.011	–
	(0.021)	–	(0.013)	–

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Table A-1 – *Continued*

Country	Migr. Rate$_o$	Migr. Rate$_d$	Prop. of Recognition$_o$	Prop. of Recognition$_d$
Hungary	0.016	–	0.008	–
	(0.018)	–	(0.014)	-
Iceland	0.006	–	0.004	–
	(0.011)	–	(0.011)	–
Ireland	0.028	0.032	0.016	0.034
	(0.075)	(0.112)	(0.042)	(0.144)
Italy	0.049		0.027	
	(0.050)	–	(0.033)	–
Latvia	0.004	–	0.002	–
	(0.005)	–	(0.006)	–
Lithuania	0.006	–	0.003	–
	(0.010)	–	(0.006)	–
Luxembourg	–	0.022	–	0.036
	–	(0.041)	–	–
Netherlands	0.029	0.032	0.048	0.029
	(0.015)	(0.051)	(0.095)	(0.076)
Norway	0.018	0.034	0.015	0.036
	(0.033)	(0.055)	(0.032)	(0.080)
Poland	0.062	–	0.028	–
	(0.053)	–	(0.043)	–
Portugal	0.025	0.025	0.008	0.021
	(0.031)	(0.063)	(0.011)	(0.078)
Romania	0.034	–	0.009	–
	(0.053)	–	(0.017)	–

Continued on next page

Table A-1 – *Continued*

Country	Migr. Rate$_o$	Migr. Rate$_d$	Prop. of Recognition$_o$	Prop. of Recognition$_d$
Slov Rep	0.008	–	0.007	–
	(0.010)	–	(0.026)	–
Slovenia	0.006	–	0.001	–
	(0.010)	–	(0.001)	–
Spain	0.031	0.037	0.057	0.032
	(0.027)	0.058	(0.113)	(0.057)
Sweden	0.057	0.037	0.075	0.036
	(0.089)	(0.071)	(0.133)	(0.071)
Switz.	0.017	0.036	0.003	0.037
	(0.013)	(0.062)	(0.005)	(0.113)
UK	0.101	0.037	0.127	0.031
	(0.147)	(0.061)	(0.211)	(0.046)

Notes: Migr. Rate$_o$ is the migration rate from the origin country o to all the destinations d. Migr. Rate$_d$ is the migration rate in country d from all the origins o. Prop. of Recognition$_o$ is the propensity of recognition of qualifications acquired in origin o. Prop. of Recognition$_d$ is the propensities of recognition of qualifications recognized in destination d. See Table 2 in the main text for the definition of the "Propensity of Recognition" Indicator. Observe that only Austria, Denmark, Finland, France and Germany are either origin or destination countries. The other countries are included in the estimation sample only as origins.

A-2 Details on the CRE model

Consider the model:

$$\mathbf{Y}_{dot} = \mathbf{X}_{dot}\beta + \alpha_{do} + \eta_{dot} \tag{A-1}$$

In the random effect case (RE), it is assumed that the unobserved heterogeneity is uncorrelated with the regressors, i.e. $E\left(\alpha_{do}|\mathbf{X_{do}}\right) = 0$ (mean independence assumption). In the correlated random model (CRE), the mean independence assumption is relaxed. Specifically, we follow the approach of Mundlak (1978), who suggests the following specification for the unobserved heterogeneity

$$E\left(\alpha_{do}|\mathbf{X_{do}}\right) = \mathbf{\bar{x}_{do.}}\gamma \tag{A-2}$$

where $\mathbf{\bar{x}_{do.}}$ are the group means of the regressors[16]. Inserting (A-2) into the model in (A-1), we get

$$\begin{aligned} \mathbf{Y}_{dot} &= \mathbf{X}_{dot}\beta + \alpha_{do} + \eta_{dot} \\ \mathbf{Y}_{dot} &= \mathbf{X}_{dot}\beta + \mathbf{\bar{X}_{do.}}\gamma + \eta_{dot} + \left(\alpha_{do} - E\left(\alpha_{do}|\mathbf{X_{do}}\right)\right) \\ \mathbf{Y}_{dot} &= \mathbf{X}_{dot}\beta + \mathbf{\bar{X}_{do.}}\gamma + \eta_{dot} + u_{do} \end{aligned} \tag{A-3}$$

Observe that the CRE model is an intermediate approach between the RE and the FE model. In particular, when γ is equal to 0, we get the RE model. Hence, in the regression Tables, we perform the "variable addition test" for the null hypothesis that $\gamma = 0$. In case we do not accept the null hypothesis, we prefer the FE to the RE specification.

A-3 Details on the Hausman-Taylor model

Consider the model:

$$\mathbf{Y}_{dot} = \mathbf{X}_{dot}\beta + \mathbf{Z}_{do}\gamma + \alpha_{do} + \eta_{dot} \tag{A-4}$$

[16] Note that $\mathbf{\bar{x}_{do.}}$ contains only the time-varying variables.

Let X_1 be the set of regressors in X which are strictly exogenous (i.e. uncorrelated with both α_{do} and η_{dot}), and X_2 be those regressors which are correlated with α_{do}. Similarly, the elements of Z can be either uncorrelated with both error components, or correlated only with α_{do}.[17] Following Hausman and Taylor (1981), the model in (A-4) can be pre-multiplied by $\mathbf{\Omega}^{-1/2}$, to obtain:

$$\mathbf{\Omega}^{-1/2} Y_{dot} = \mathbf{\Omega}^{-1/2}\mathbf{X}_{dot}\beta + \mathbf{\Omega}^{-1/2}\mathbf{Z}_{do}\gamma + \mathbf{\Omega}^{-1/2}\alpha_{do} + \mathbf{\Omega}^{-1/2}\eta_{dot} \tag{A-5}$$

where $\mathbf{\Omega}^{-1/2}$ is made up of $y_{dot} - \theta_{do} y_{do.}$ and

$$\theta_{do} = \left[\frac{\sigma_\eta^2}{\sigma_\eta^2 + T\sigma_{\alpha_{do}}^2}\right]^{1/2}$$

Hausman and Taylor (1981) show that (A-5) can be rewritten as:

$$\begin{aligned} \mathbf{Y}_{dot} - (1-\theta)\mathbf{Y}_{do.} = [\mathbf{X}_{dot} - (1-\theta)\mathbf{X}_{do.}]\beta + \theta\mathbf{Z}_{do}\gamma \\ + \theta\alpha_{do} + [\eta_{dot} - (1-\theta)\eta_{do.}] \end{aligned} \tag{A-6}$$

Where $Y_{do.}$, $X_{do.}$ and $\eta_{do.}$ are the means of Y_{dot}, X_{dot} and η_{dot} in the bilateral dimension.[18] Estimates for the elements of θ are obtained by running two separate regressions. The sum of square residuals from

$$\tilde{\mathbf{Y}}_{dot} = \tilde{\mathbf{X}}_{dot}\beta + \tilde{\eta}_{dot} \tag{A-7}$$

provides estimates for σ_η^2. In order to obtain estimates for σ_α^2, we regress the residuals from (A-7) on the time-invariant endogenous variable (i.e. the distance) instrumented with the exogenous regressors of the model. The sum of squared residuals from this last regression gives a consistent estimate of σ_α^2.

[17] In our case Z has dimension 1 because there is only one time-invariant regressor in our model.

[18] Here we follow the terminology of Egger and Pfaffermayr (2004).

The Hausman-Taylor estimator is equivalent to a Two-Stage-Least-Squares estimator on model (A-5) using as instruments $[\tilde{\mathbf{X}}_{dot}, \mathbf{X}_{1,do.}, \mathbf{Z}_{do}]$, where $\tilde{\mathbf{X}}_{dot}$ is the deviation from the bilateral mean of all elements of $\mathbf{X}$, and $\mathbf{X}_{1,do.}$ are the means in the bilateral dimension as previously defined.

As usual in the instrumental variables setting, the necessary conditions for identification require that the number of endogenous regressors (in the sense defined above) is lower or equal to the set of instruments. In the Hausman-Taylor case, the number of time-variant exogenous variables should be greater or equal to the number of the time-invariant endogenous covariates (Baltagi, 2008).

When we perform the Hausman-Taylor estimation procedure, we require a priori that some of the regressors of X and Z are uncorrelated with α_{do}. When the parameters are over-identified, we can test these restrictions using a test as in Hausman and Taylor (1981). Under the null hypothesis, the individual means of X_1 and Z_1 are uncorrelated with α_{do}. The restrictions can be tested comparing $\hat{\beta}_{ht}$ and $\hat{\beta}_{with}$, where the former is obtained from the Hausman-Taylor estimation and the latter from the Two-Stage-Least-Squares estimator on model (A-5) using as instruments $[\tilde{\mathbf{X}}_{dot}, \mathbf{X}_{1,do.}, \mathbf{Z}_{do}]$. The test statistics is

$$\hat{t} = \hat{q}'(VC(\hat{q}))^{-1}\hat{q} \tag{A-8}$$

where $\hat{q} = \hat{\beta}_{ht} - \hat{\beta}_{with}$ and $VC(\hat{q}) = VC(\hat{\beta}_{ht}) - VC(\hat{\beta}_{with})$. Under the null hypothesis the test statistics is distributed as a χ^2 with degrees of freedom equal to the difference between the number of exogenous and the number of endogenous regressors.

A-4 Robustness checks

This section reports the result of two robustness checks: the use of an alternative indicator for the propensity of recognition and the results considering high and medium skilled migration rates separately.

A-4.1 Alternative indicator of the propensity of recognition

We define our alternative measure of propensity of recognition as the number of certificates obtained in a given origin country and accepted by a given destination at time t, over the total acceptances in the destination country at time t.

$$\text{Propensity of Recognition } 2_{od(t-1)} = \frac{\text{Positive Applications}_{od(t-1)}}{\sum_o \text{Total Positive}_{od(t-1)}} \tag{A-9}$$

Also for this indicator, we numbers for t=2000, t=2005 and t=2010 are built pooling observations from different years. This alternative bilateral indicator can capture two distinguished phenomena. On the one hand, it can be a proxy of the degree of similarity between the education systems of the origin and of the destination countries; the more similar the education system of the two countries, the higher the probability of the destination of recognizing the certificates from the origin country, the higher the indicator. On the other hand, it may capture the easiness of a given destination country to recognize qualifications from a given origin due to presence of bilateral recognition agreements preceding the EU legislation (e.g. between the Scandinavian countries).

In Table A-2 we report the baseline estimation results obtained by using the "Propensity of Recognition" defined in this alternative way. The regressions qualitatively confirm the ones already discussed in the main text.

Table A-2: Migration rates and propensity of recognition. Robustness checks.

Dependent variable: Migration rate				
	LSDV-1	LSDV-2	LSDV-3	LSDV-4
Propensity of Recognition 2	0.325^{***}	0.323^{***}	0.308^{***}	0.314^{***}
	(0.076)	(0.075)	(0.075)	(0.079)
GDP difference	0.013^{**}	0.011^{***}	0.006^{*}	0.004
	(0.005)	(0.004)	(0.004)	(0.004)
Population destination	0.005^{**}	0.017^{***}	0.016^{**}	0.017^{**}
	(0.002)	(0.006)	(0.007)	(0.008)
Distance	-0.022^{***}	-0.020^{***}	-0.036^{***}	-0.035^{***}
	(0.005)	(0.005)	(0.010)	(0.010)
R^2	0.524	0.482	0.550	0.554
Aic	-3513.58	-3450.38	-3544.44	-3449.55
Bic	-3350.24	-3351.38	-3316.75	-2964.464
Year-dummies	Yes	Yes	Yes	Yes
Origin dummies	Yes	No	Yes	Yes
Destination dummies	No	Yes	Yes	Yes
Origin*Year dummies	No	No	No	Yes

Notes: All regressions include a constant. Standard errors clustered at the country-pair level in parenthesis. *significant at 10%, ** significant at 5%, *** significant at 1%. "Propensity of Recognition 2" is the number of certificates obtained in a given origin country and accepted by a given destination at time t, over the total acceptances in the destination country at time t.

A-4.2 High and medium skilled migration rates

This section reports the estimation results using high and medium skilled migration rates as dependent variables separately. As Table and Table show, the results remain stable also when disaggregating the sample into high and medium skilled immigrants.

Table A-3: High-skill and medium-skill migration rates and propensity of recognition. Baseline estimation results.

Dependent variable: High-skill migration rate				
	LSDV-1	LSDV-2	LSDV-3	LSDV-4
Propensity of Recognition	0.348***	0.342***	0.325***	0.333***
	(0.075)	(0.074)	(0.073)	(0.077)
GDP difference	0.010**	0.007**	0.004	0.002
	(0.004)	(0.004)	(0.003)	(0.004)
Population destination	0.014**	0.014**	0.013**	0.015**
	(0.001)	(0.006)	(0.006)	(0.007)
Distance	−0.019***	−0.019***	−0.033***	−0.032***
	(0.004)	(0.005)	(0.008)	(0.008)
R^2	0.534	0.501	0.565	0.570
Obs.	1043	1043	1043	1043
Aic	-3846.19	-3799.15	-3890.28	-3800.00
Bic	-3682.85	-3700.16	-3662.59	-3314.92
Dependent variable: Medium-skill migration rate				
	LSDV-1	LSDV-2	LSDV-3	LSDV-4
Propensity of Recognition 1	0.348***	0.337***	0.323***	0.330***
	(0.064)	(0.064)	(0.061)	(0.063)
GDP difference	0.012**	0.006	0.004	0.001
	(0.005)	(0.004)	(0.003)	(0.003)
Population destination	0.005***	0.013**	0.012**	0.013*
	(0.001)	(0.006)	(0.006)	(0.007)
Distance	−0.021***	−0.020***	−0.037***	0.037***
	(0.005)	(0.005)	(0.010)	(0.010)
R^2	0.461	0.461	0.500	0.506
Obs.	1043	1043	1043	1043
Aic	-3537.25	-3485.01	-3588.87	-3495.94
Bic	-3373.91	-3386.02	-3361.18	-3010.86
Year dummies	Yes	Yes	Yes	Yes
Origin dummies	Yes	No	Yes	Yes
Destination dummies	No	Yes	Yes	Yes
Origin*Year dummies	No	No	No	Yes

Notes: All regressions include a constant. Standard errors clustered at the country-pair level. *significant at 10%, ** significant at 5%, *** significant at 1%. See Table 2 for the definition of "Propensity of Recognition".