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Abstract

Migration has become a prominent research theme in geography and regional science and it has been approached from various methodological angles. Nonetheless, a common missing element in most migration studies is the lack of awareness of the overall network topology, which characterizes migration flows. Although gravity models focus on spatial interaction – in this case migration – between pairs of origins and destinations, they do not provide insights into the topology of a migration network. In the present paper, we will employ *network analysis* to address such systemic research questions, in particular: How *centralized* or *dispersed* are migration flows and how does this structure evolve over time? And how is migration activity *clustered* between specific countries, and if so, do such patterns change over time? Going a step further than exploratory network analysis, this paper estimates international migration models for OECD countries based on a dual approach: gravity models estimated using conventional econometric approaches such as panel data regressions as well as network-based regression techniques such as MRQAP. The empirical results reveal not only the determinants of international migration among OECD countries, but also the value of blending network analysis with more conventional analytic methods.

Keywords: immigration, gravity model, complex networks, community detection, MRQAP

1. Introduction

International migration is becoming an important feature of global economy. Declines in transportation and communication costs as well as developments towards less movement restrictions have encouraged the circulation of people across national and international borders. The main objective of this paper is to study international migration from a network stand-point. Although research interest on migration flows has been growing, the focus of most studies is on the level of the country or, in the best case, on the level of country-to-country flows (dyadic level). There are very few exceptions to the above statement, with the work of Maier and Vyborny (2008) being one of them. The starting point of our paper is that international migration flows form a network of connected countries and this could provide the basis of empirical analysis.

To provide a brief introduction, the ideas which underpin this paper derive from the so-called *new science of networks* (Barabási, 2002; Buchanan, 2002; Watts, 2003, 2004), an analytical field of complexity science which has expanded rapidly over the last 10-15 years, the main focus of which is large-scale real-world networks and their universal, structural and statistical properties (Newman, 2003). While the starting point of network science lies in statistical physics and graph theory, strong parallels exist between network analysis and regional science, as traditionally the latter has a strong interest in networks and interregional systems (for a review on spatial complex networks see Barthelemy, 2011; and for a discussion on networks and regional science see Reggiani, 2009).

Two different though complementary streams of network analysis have been developed over time. Most network studies are based on stochastic approaches, which assume an underlying probability model, usually following a power law as the main mechanism for the network creation. The main objective in this strand of research is to identify the underlying mechanisms using constructive modeling and simulation techniques. However, this approach includes the risk that the probability model and the underlying statistical mechanisms do not depict precisely the actual world network (Li et al., 2005).

The second strand of research adopts a 'softer' approach and focuses on ex-post empirical tests for identifying characteristics of theoretical network models in real world networks. Such analysis enables researchers to understand the network attributes of the system and then to model those using network or more conventional modeling techniques. The main drawback of this approach is the rather descriptive nature of the analysis.

In this paper, we attempt to bridge these two different approaches using a panel data set on bilateral international migration flows. The data comes from the online database for the International Migration Statistics (IMS) for OECD countries, which contains information on immigrant flows by country of origin and destination, based on the OECD's continuous reporting system on migration (OECD, 2011). In particular, we use here data on yearly immigration flows between 32 OECD countries for the period 2000-2009[1]. Based on these data, we are able to create 10 migration networks for each individual year. It is important to indicate that OECD online database does not report flows below 1000 observations, therefore our analysis are based on flows above the mentioned figure.

The first two steps of our analysis fit into the second strand of network analysis, as described above. We initially study the different centrality measures and the derived attributes for the countries of our sample. Then, we explore further the topology of this network by identifying the communities formed by the intensity of the migration flows between the country-members of these communities. Finally, based on the knowledge gained from the above investigation, we proceed with the modeling exercise, which is based on a dual approach. Firstly, we use standard econometrics, such as panel data regressions, to estimate the determinants of international migration flows among OECD countries. Then,

[1] Korea and Slovak Republic were excluded from the analysis because of missing data reasons

we validate these results with cross-sectional Multivariate Regression Quadratic Assignment Procedures (MRQAP) models, which utilize the network structure by addressing potential network dependency issues.

The novelty of this paper lies on the adoption of a network perspective. Migration is a network phenomenon and is characterized by network dependencies (see section 5.2). However, the latter are not usually captured by mainstream statistic analysis. This gap in migration analysis is the focal point of this.

The structure of the paper is as follows. The next section presents some insights from the relevant literature on international migration. Next, in Section 3 the different network attributes are explored, and then, Section 4 highlights the different network communities. Section 5 presents the applied modeling exercises, while the paper ends with some concluding remarks and directions for future research.

2. Literature review on international migration

Migration movements can be studied from the perspective of push and pull factors. Push factors such as poverty, unemployment, conflict and natural disasters, and pull factors including employment opportunities, wealth, favorable climate, political stability and low risk from natural hazards, made millions of people to move from their country of origin to other countries even to different continents. In addition, globalization and developments in transport had a great impact on short- and long-range[2] mobility of people (Nijkamp et al., 2011). Long-range mobility can be temporary, or it can lead to permanent settlement. Over the past few decades, cross-border migration has become a mega-trend of the globalizing economy, to the extent that some people even speak of the 'age of migration' (see Goldin et al., 2011; Nijkamp et al., 2012).

[2] For example, short-range mobility refers to commuting between work and home, and social visits, while long-range mobility to international migration, and international tourism.

Nowadays, around 3 per cent (more than 200 million people) of the world population live in a country in which they were not born in (Özden, 2005). Empirical data shows that the majority of OCED countries are final destinations for the largest part of international migration (Gheasi et al., 2011). The foreign-born population in 2006 accounted for about 11.7 per cent of the total population in OECD countries, and this shows a drastic increase in comparison to previous years (OECD, 2011).

Migrants may be considered as a bridge of information between the host and the country of origin. Therefore, there is a growing body of literature on migration and its related economic impacts. Studies have found a close relationship between immigration and international trade (Girma and Yu, 2002; Gould, 1994; Head and Ries, 1998; Lewer and Van den Berg, 2008; Rauch and Trindade, 2002), migration and international tourism (Fischer, 2007; Gheasi et al., 2011; Williams and Hall, 2002), and migration and foreign direct investment (Aroca and Maloney, 2005; Bhattacharya and Groznik, 2008; Gheasi et al., 2011; Javorcik et al., 2011; Kugler and Rapoport, 2007).

As far as it concerns the estimation of migration flows, gravitational models have a long and established tradition. The use of the gravity model has grown considerably since Tinbergen (1962) and Pöyhönen (1963) were the first to use this model to explain international trade patterns. Gravity model has been long recognized for its consistent empirical success in explaining different types of flows, such as migration, commuting, shopping trips, tourism, and trade. Migration, like other type of flows, can also be driven by attraction forces between the country of origin and the country of destination, which decrease by the cost of distance between them (Lewer and Van den Berg, 2008). Such a model suggests that the attraction force between countries depends on labor income and population size differences between two countries.

Studies indicate that demography plays a major role in explaining international migration. The younger the population of a country is the bigger the share of the population that is most likely to emigrate is.

Various studies (Hatton and Williamson, 1998; Hatton and Williamson, 2003; Mayda, 2007) suggest that the share of the origin country's population aged 15-29 has a significant positive impact on outmigration. Moreover, regarding other covariates used in migration gravity models, common language and cultural ties between origin and destination can facilitate migrants' integration into the host society. Adsera and Chiswick (2007) found that there is around 9 per cent earnings premium for immigrant men if they come from a country, where the language spoken belongs to the same language family group as the destination country. A recent study by Belot and Ederveen (2010) shows that cultural barriers may explain patterns of migration flows between developed countries better than traditional economic variables.

The knowledge gained from the above review will support our modeling endeavor later in this paper. But before that, the next sections will shed light into the structure of the international migration network. Such structural characteristics will also influence our modeling strategy.

3. Network attributes of international migration

The first step of the analysis focuses on the different centrality measures based on the international migration flows. Table 1 presents these elements for year 2000. Firstly, the topology of the migration network is analyzed by using only binary links. Such a binary network is represented by an adjacency matrix, the *i,j* element of which is either 1 if there is a migration flow from country *i* to country *j* in 2000, and 0 otherwise. The in-degree centrality denotes the number of different origin countries for every destination. According to Table 1, a quite diverse group of countries is at the top of this hierarchy. On the one hand North American (US and Canada) and European countries (Austria, Finland, Spain and Sweden) can be identified and on the other hand Turkey. At the other end of the spectrum, Chile, Estonia, Greece, Iceland and Mexico do not receive any migration flows. The hierarchy is different, when we focus on the out-degree centrality (column 2), which represents the number of different destination countries for each origin. On the top of the hierarchy, wealthy countries such as UK, US and Canada can be found along with Poland. This measure can be approached as a population mobility indication. For instance, the various locations of the British Diaspora (Bridge and Fedorowich, 2003) become apparent as well as the number of different destinations Americans migrate to. The latter though might indicate a scalar issue related to the emigration volume because of the origin country population size. In total, degree centrality (column 3), which is the sum of the in- and out-degree centrality measures, can be understood as an indication of a country's cosmopolitan and extroversive character.

The picture is somewhat different, when migration flows are introduced. In this case, the *i,j* element of the adjacency matrix represent the number of migrants migrated from country *i* to country *j* during one year. The distribution of migrants across the OECD countries is very unequal: almost 60 per cent of all the migration flows from OECD countries end up in Germany, US and UK, resulting in a Gini coefficient of 0.71. Regarding the weighted out-degree centrality (column 5), 24 per cent of all migration flows originates from Mexico and Poland. Concerning the former, the vast majority of Mexican emigrants targets mostly the US (96 per cent of all Mexican emigrants in 2000), and secondly Spain, Germany and Canada. Poland, on the other hand, has a more balanced profile of emigrant destinations, with the neighboring Germany being the main destination (70 per cent of all Polish immigrants). Furthermore, countries such as US and UK are also on the top of this hierarchy, indicating their extroversive and the mobile character, but also Turkey, which is a well known emigration country (Gibney and Hansen, 2005). 59 per cent of all Turkish emigrants ended up in Germany in 2000. In total, according to the weighted degree centrality (sum of weighted in- and out-degree), an interesting division can be observed in the first six places of the most central countries: Germany, US and UK are the most central ones, mostly due to their attraction as destinations and followed by Mexico, Turkey and Poland, the high weighted degree centrality of which is caused by their intensive emigration.

Table 1: Degree centrality measures, 2000

Country	In-degree (1)		Out-degree (2)		Degree (3)		Weighted in-degree (4)		Weighted out-degree (5)		Weighted degree (6)		Normalized weighted in-degree (7)		Normalized weighted out-degree (8)		Balance (9)	
Germany	30	*8*	23	*3*	53	*3*	318.649	*1*	77.936	*6*	396.585	*1*	0.004	*3*	0.001	*28*	240.713	*1*
United States	31	*1*	26	*1*	57	*1*	256.272	*2*	98.43	*4*	354.702	*2*	0.001	*16*	0	*31*	157.842	*2*
Switzerland	25	*15*	19	*13*	44	*15*	50.822	*6*	10.264	*25*	61.086	*14*	0.007	*2*	0.001	*19*	40.558	*3*
United Kingdom	23	*16*	24	*2*	47	*11*	130.931	*3*	98.693	*3*	229.624	*3*	0.002	*10*	0.002	*16*	32.238	*4*
Spain	31	*1*	20	*9*	51	*5*	53.189	*4*	24.163	*17*	77.352	*10*	0.001	*14*	0.001	*29*	29.026	*5*
Belgium	16	*19*	19	*13*	35	*19*	36.943	*8*	12.556	*22*	49.499	*17*	0.004	*5*	0.001	*24*	24.387	*6*
Australia	30	*8*	15	*25*	45	*14*	53.154	*5*	30.728	*12*	83.882	*9*	0.003	*8*	0.002	*17*	22.426	*7*
Austria	31	*1*	19	*13*	50	*7*	30.76	*13*	18.859	*18*	49.619	*16*	0.004	*4*	0.002	*10*	11.901	*8*
Luxembourg	30	*8*	13	*32*	43	*16*	9.154	*18*	0.92	*32*	10.074	*28*	0.021	*1*	0.002	*12*	8.234	*9*
Netherlands	30	*8*	21	*7*	51	*4*	36.257	*9*	28.24	*15*	64.497	*11*	0.002	*9*	0.002	*15*	8.017	*10*
Ireland	2	*26*	18	*17*	20	*28*	10.9	*17*	8.997	*26*	19.897	*24*	0.003	*6*	0.002	*9*	1.903	*11*
Sweden	31	*1*	18	*17*	49	*8*	18.607	*14*	17.064	*19*	35.671	*19*	0.002	*11*	0.002	*13*	1.543	*12*
Norway	30	*8*	16	*23*	46	*13*	12.465	*16*	11.531	*23*	23.996	*22*	0.003	*7*	0.003	*6*	0.934	*13*
Japan	2	*26*	20	*9*	22	*24*	30.984	*12*	30.44	*13*	61.424	*13*	0	*24*	0	*32*	0.544	*14*
Canada	31	*1*	22	*4*	53	*2*	31.807	*11*	31.58	*11*	63.387	*12*	0.001	*15*	0.001	*27*	0.227	*15*
Estonia	0	*28*	15	*25*	15	*30*	0	*32*	1.626	*31*	1.626	*32*	0	*32*	0.001	*25*	-1.626	*16*
Iceland	0	*28*	14	*29*	14	*32*	0	*31*	2.261	*30*	2.261	*31*	0	*31*	0.008	*2*	-2.261	*17*
Slovenia	14	*21*	14	*29*	28	*22*	0.255	*27*	2.734	*29*	2.989	*30*	0	*25*	0.001	*20*	-2.479	*18*
Denmark	30	*8*	17	*20*	47	*10*	8.914	*19*	13.24	*21*	22.154	*23*	0.002	*13*	0.002	*7*	-4.326	*19*
Israel	18	*18*	17	*20*	35	*20*	3.793	*23*	8.515	*27*	12.308	*27*	0.001	*19*	0.001	*21*	-4.722	*20*
Chile	0	*28*	14	*29*	14	*31*	0	*30*	6.212	*28*	6.212	*29*	0	*30*	0	*30*	-6.212	*21*
Finland	31	*1*	15	*25*	46	*12*	3.383	*24*	11.106	*24*	14.489	*26*	0.001	*17*	0.002	*11*	-7.723	*22*
Czech Republic	3	*25*	17	*20*	20	*26*	0.318	*26*	15.164	*20*	15.482	*25*	0	*27*	0.001	*18*	-14.846	*23*
Hungary	23	*16*	19	*13*	42	*17*	3.058	*25*	24.254	*16*	27.312	*21*	0	*22*	0.002	*8*	-21.196	*24*
Portugal	8	*23*	18	*17*	26	*23*	4.438	*21*	28.528	*14*	32.966	*20*	0	*21*	0.003	*4*	-24.09	*25*
Italy	11	*22*	21	*7*	32	*21*	37.091	*7*	62.554	*8*	99.645	*7*	0.001	*18*	0.001	*26*	-25.463	*26*

Greece	0	*28*	20	*9*	20	*27*	0	*29*	35.939	*10*	35.939	*18*	0	*29*	0.003	*3*	-35.939	*27*
New Zealand	6	*24*	15	*25*	21	*25*	7.254	*20*	46.307	*9*	53.561	*15*	0.002	*12*	0.012	*1*	-39.053	*28*
Turkey	31	*1*	20	*9*	51	*6*	34.983	*10*	84.794	*5*	119.777	*5*	0.001	*20*	0.001	*22*	-49.811	*29*
France	15	*20*	22	*4*	37	*18*	15.166	*15*	73.561	*7*	88.727	*8*	0	*23*	0.001	*23*	-58.395	*30*
Poland	26	*14*	22	*4*	48	*9*	4.423	*22*	106.521	*2*	110.944	*6*	0	*26*	0.003	*5*	-102.098	*31*
Mexico	0	*28*	16	*23*	16	*29*	0	*28*	180.253	*1*	180.253	*4*	0	*28*	0.002	*14*	-180.253	*32*

Note: absolute degree centralities are presented here along with the relevant rankings in italics; normalization occur by dividing centralities by the population of the destination (for in-degree in column 7) and origin (for out-degree in column 8) country; balance (column 9) = weighted in-degree – weighted out-degree

The normalization of the above centralities by the population of the destination (in-degree in column 7) and origin (out-degree in column 8) country reveals new results. As can be seen from Table 1, smaller countries such as Luxemburg and Switzerland are on the top of the hierarchy as they receive significant migration inflows relative to their population. The only country, which is on the highest tier using both the absolute and the relative weighted in-degree centrality, is Germany. Despite its large population, Germany still receives a great inflow of immigrants even in relative terms, while this is not the case for the UK and the US. Similarly, countries such as New Zealand, Iceland, Greece and Portugal are characterized by high migration outflows compared to their resident populations. These countries lose a significant part of their working force with emigration, which is not replaced by in-migration. This can be seen in the last column of Table 1, where the balance (difference) between in- and out-degree centrality is presented. Indeed, countries such as Mexico, Poland, France and Turkey have a negative balance because of migration, as they lost 49 to 180 thousands of people in 2000. At the other end of the spectrum, Germany and the US are by far the net gainers in terms of in/out migration.

Analyzing the same metrics for 2009, some interesting changes can be observed[3]. In total, the 2009 migration network is denser than the 2000 one (from 0.594 to 0.700)[4]. Also, interesting realignments are observed in the rankings, such as the fall in the UK in-degree centrality, as in 2009 immigrants from only 10 countries migrated to the UK contrary to 23 in 2000. This might reflect the migration policy change in the UK during this period, which probably caused lower flows of immigrants[5]. Regarding changes in out-degree centrality, Ireland is the main example as is placed on the 5th position of the standardized out-

[3] The centrality measures for 2009 can be provided upon request.
[4] Network density refers to the number of edges in a network divided by the number of all possible edges. For the case of non-planar networks is defined as $\tilde{a} = E / \frac{1}{2} V(V-1)$ (Taaffe et al., 1996, p. 254) , where E denotes the number of edges present in a network and V the number of nodes.
[5] OECD dataset does not report blow 1000 observations. Lack of data can also cause the disappearance of countries in the UK in-degree centrality.

degree centrality ranking in 2009, four positions higher than in 2000. This increase in the Irish outmigration could be explained by the financial crisis and its impacts on the Irish economy.

4. International migration communities

This section focuses on uncovering the communities that different OECD countries form in the migration network. Before presenting the results of the analysis, the distinction between community detection and cluster analysis needs to be highlighted. The latter refers to multivariate methods aiming to reorganize observations to homogeneous groups known as clusters (Aldenderfer and Blashfield, 1984). Nonetheless, such methods have been developed targeting conventional data sets and not network structures since the emphasis in the latter is not on the behaviour of single observations, but on the information of who is connected to whom (Latora et al., 2003). In such context, the creation of homogeneous clusters takes a different meaning. Instead of creating groups of observations which share the same characteristics, clustering in a network context, which is known as *community detection,* considers the network structure. The main idea is to identify clusters of nodes with dense connections inside the clusters, but not between the clusters (Blondel et al., 2008). While the focus of the community detection lies on the ties between nodes, a conventional cluster analysis method would focus on the nodes attributes neglecting the network topology.

Such an exercise can provide useful insights into the complex structure of the international migration network (Figure 1). Community detection will highlight these clusters of countries, which are characterized by strong bilateral ties. Such knowledge can be used as a first step towards understanding and explaining the push and pull factors behind international migration.

Various methods have been suggested for community detection, including among others the work of Newman and Girvan (2004), Pons and Latapy (2006) and Clauset et al. (2004), with the algorithm developed by Blondel et al. (2008) being the most widely used. This algorithm, which is known as the

Louvain method, aims to maximise *modularity* in a network. This is an indication of the quality of the derived communities, measuring the density of the links inside the community in comparison to these outside the community (Blondel et al., 2008). This algorithm is also able to cope with weighted networks. For the implementation of the Louvain method, the Pajek[6] software was utilized.

Figure 1: International migration network, 2009

The outcome of this analysis reveals familiar structures[7]. The most robust community over time is the US and countries tightly related with the US, including Canada, Mexico, Japan and Israel. From the last four countries, only Japan has more migrant inflows from the US than outflows to the US, something which might be an indication of return migration. The other three countries have substantially more outflows to the US than inflows from the US on a yearly basis. Canada and Mexico are adjacent to the US

[6] For more details for the software see http://pajek.imfm.si/doku.php?id=start
[7] A detailed table of the detected communities can be provided upon request.

countries and, in addition the US hosts the biggest Jewish population reflecting the cultural ties with Israel.

Secondly, the mobility among Scandinavian countries is intensive enough to result in another stable community over time. For most of the years years of the study period, Denmark, Finland, Sweden, Estonia, Norway and Iceland are clustered together denoting the strong cultural ties among Northern European countries. Thirdly, former members of the British Empire form a community, the configuration of which does not remain constant overtime, as other countries such as Spain, Chile and also France join it. Nonetheless, the clustering of the UK, Australia, Ireland and New Zealand highlights the effect of post-colonial and Commonwealth ties in the formation of the migration network. Finally, for some years of the study period, central European countries such as Belgium, France, Luxemburg, The Netherlands and Switzerland are also clustered together with Portugal, Spain and some time France and Italy, highlighting the ease of migration inside European Union. Although modularity for these communities is relatively low and lies between 0.28 (2007) and 0.34 (2001)[8], the stability of these communities over time increases the importance of our findings.

In total, the above analysis reveals interesting clustering patterns in the migration network. Countries form fairly robust communities overtime, revealing the impact of various factors in network migration formation. These factors will be further analyzed and modelled in the next section.

5. Modelling migration flows

Using the knowledge gained from the above analysis, this section aims to build models explaining international migration flows among OECD countries. Our starting point is the generalized gravity model:

$$M_{ij} = A(m_i m_j)/D_{ij}^b \tag{1}$$

[8] A discussion on the quantification of the community variation can be found in Expert et al. (2011)

Following the Newtonian equation, migration flows (M_{ij}) originating from country i to country j are related to the size m of i and j and the distance D between i and j. A is a proportionality constant. Following Zhou's (2011) approach, a two-level research methodology is adopted. Firstly, panel data specifications are adopted for conventional econometric analysis to take advantage of the temporal dimension of the dataset. Then, the focus turns on the network structure of international migration with the use of repeated over time MRQAP regressions.

5.1 Panel data approach

After the relevant log-log transformations, (1) can be transformed to a linear model. More specifically, the empirical model we are estimating is the following:

$$\ln(M_{ijt}) = \beta_0 + \beta_1 ln(GDPpc_{it}) + \beta_2 ln(GDPpc_{jt}) + \beta_3 ln(edu_{it}) + \beta_4 ln(edu_{jt}) + \beta_5 pop1529\_share_{it} + \beta_6 \ln(D_{ij}) + \beta_7 border_{ij} + \beta_8 colony_{ij} + \beta_9 language_{ij} + \beta_{10} region_{ij} + \varepsilon_{ijt} \quad (2)$$

M_{ijt} represents the migration flows from i to j in year t. *GDPpc* denotes GDP per capita in i and j in year t as purchasing power parities (PPPs) at constant prices; edu_{it} and edu_{jt} represents the number of graduates from tertiary institutions; *pop1529_share* denotes the share of population between 15-29 in origin (i) country in year t following Mayda (2007); *border* is a binary variable which takes the value of 1 when i and j share a common border; *colony* is also a binary variable which takes the value of 1 when i and j were part of the same empire; *language* takes the value of 1 when countries i and j have the same official language; and *region* denotes that i and j are part of the same geographic region (The Americas, Asia and Pacific, Scandinavia, and rest of Europe).

The main characteristic of the above is the panel structure. Apart from the cross-sectional dimension, the temporal dimension t, which represents the ten year study period, is also addressed here. Panel data specifications come with advantages. Firstly, panel data improves researchers' ability to control for missing or unobserved variables (Hsiao, 2003). Such an omitted-variable bias as a result of unobserved heterogeneity is a common problem in cross-section models. In addition, potential selection bias in migration flows because of missing data can be addressed more efficiently with panel data. In a nutshell, a panel data specification reduces the risk of obtaining biased estimators (Baltagi, 2001).

While panel data introduces methodological gains, there are also shortcomings that need to be addressed. According to literature (Wooldridge, 2003), the most widely used panel data models are based on either *fixed effects* (FE) or *random effects* (RE). As the main aim of this paper is to estimate the impact of the different variables on migration flows, it is preferred to use an RE model rather than an FE model, as because of the inherent first differentiation process, the latter will result in the elimination of the time invariant explanatory variables which are vital in our analysis (e.g. Brun et al., 2005; Etzo, 2011).

Different specifications are tested here in order to estimate (2) and are presented in Table 2. Firstly, the RE model is estimated without and with country origin and destination effect effects (regressions 1 and 2 respectively). The latter can be useful to address unobserved country specific effects such as the different migration policy among countries. The results in both cases are similar. Distance has a significant negative impact on the intensity of the migration flows and the existence of a common border between origin and destination countries has also a positive impact. The above reflects the inherent cost in migrating in remote countries and on the other hand the easiness in migrating in adjacent countries. In addition, cultural proximity in terms of common language and post-colonial ties has also a positive impact. The ability to speak the same mother language is an asset for potential immigrants and the same applies to the cultural similarity, which come as a consequence of the common colonial past. In regards to the pull and push factors, which represent the masses of the

Newtonian formula, interesting impacts can be identified. The GDP per capita of the origin country does not have significant impact as a push factor. Of course, it needs to be highlighted here that our analysis focuses on the OECD countries, so countries with very low GDP per capita are excluded from the analysis. However, GDP per capita appears to be a significant pull factor as the GDP per capita of the destination country has a significant positive impact on the migration flows. A significant push factor is the share of the young population (15-29 years old) in the origin country. This part of population represents the pool of potential emigrants from the origin countries. In addition, the effect of the education level is also tested here. As expected, when the origin and destination effects are not included in the model, the education level has a positive pull and push effect. However, when the origin and destination effects are included in the analysis, the impact is negative for both cases, indicating a non-stable effect.

Table 2: Panel data regressions on migration flows (ln)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
D_{ij} (ln)	-0.427	-0.649	-0.439	-0.648			
	(0.044)***	(0.059)***	(0.042)***	(0.056)***			
D_{ij}*t (ln)						-0.016	-0.03
						(0.003)***	(0.003)***
$border_{ij}$	1.082	0.445	1.044	0.447			
	(0.190)***	(0.153)***	(0.183)***	(0.145)***			
$border_{ij}$*t						-0.021	-0.005
						(0.010)**	-0.013
$language_{ij}$	0.749	0.631	0.711	0.625			
	(0.172)***	(0.142)***	(0.166)***	(0.135)***			
$language_{ij}$*t						-0.009	0.005
						(0.009)	(0.012)
$colony_{ij}$	1.251	0.947	1.23	0.95			
	(0.273)***	(0.215)***	(0.263)***	(0.203)***			
$colony_{ij}$*t						0.037	0.064
						(0.014)***	(0.019)***
$region_{ij}$	-0.004	-0.012	-0.002	-0.008			
	(0.015)	(0.014)	(0.013)	(0.013)			
$region_{ij}$*t						-0.003	-0.002
						(0.002)	(0.002)
$GDPpc_i$ (origin, ln)	-0.068	0.15	-0.082	-0.164	-0.14		
	(0.105)	(0.170)	(0.108)	(0.205)	(0.204)		
$GDPpc_i$*t (origin, ln)						-0.038	-0.004
						(0.008)***	(0.010)
$GDPpc_j$ (destination, ln)	1.301	0.893	1.436	1.152	1.17		
	(0.093)***	(0.180)***	(0.094)***	(0.221)***	(0.220)***		
$GDPpc_j$*t (destination, ln)						0.029	0.088
						(0.007)***	(0.008)***

pop1529share$_i$ (origin)	1.143	3.428	0.313	0.831	0.461		
	(0.642)*	(1.266)***	(0.657)	(1.642)	(1.638)		
pop1529share$_i$*t (origin)						-0.166	-0.059
						(0.043)***	-0.057
edu$_i$ (origin, ln)	0.471	-0.18	0.511	-0.09	-0.095		
	(0.025)***	(0.053)***	(0.024)***	(0.056)	(0.056)*		
edu$_i$*t (origin, ln)						0.018	0.034
						(0.002)***	(0.002)***
edu$_j$ (destination, ln)	0.396	-0.092	0.431	0.012	0.01		
	(0.025)***	(0.052)*	(0.024)***	(0.052)	(0.051)		
edu$_j$*t (destination, ln)						0.001	0.019
						(0.002)	(0.002)***
yearly effect	-0.016	0.051	-0.023	0.038	0.037	0.088	-1.197
	(0.004)***	(0.006)***	(0.004)***	(0.006)***	(0.006)***	(0.128)	(0.157)***
constant	-20.571	-7.47	-22.327	-12.331	-16.428	-1.471	-1.274
	(1.549)***	(2.321)***	(1.588)***	(2.618)***	(2.437)***	(0.053)***	(0.046)***
origin and destination		yes		Yes			
origin-destination effects					yes		
Wooldridge serial	17.685***	17.685***					
Observations	5046	5046	5046	5046	5046	5046	5046
Number of groups	762	762	762	762	762	762	762

Standard errors in parentheses

* significant at 10%; ** significant at 5%; *** significant at 1%

The above results provide a good overall picture of the international migration. However, going a step further, we should also explore the possibility that the repeated over time observations violate the assumption of independent errors. We know that serial correlation in panel models results in biased standard errors and less efficient results. Using the Wooldridge (2002) test for autocorrelation in panel data, implemented by Drucker (2003), first-order autocorrelation is indeed an issue in our data. In order to address it, we follow (Zhou, 2011) and use the methods derived by Baltagi and Wu (1999). The RE model is estimated with AR(1) correction using the xtregar module in Stata (Stata Corporation, 2007). The results of this model are presented in columns 3 and 4 of Table 2. The difference between the last two specifications is that the latter also includes origin and destination country effects. Both of these regressions validate in large the previous results. The only exemptions are the pull effect of the share of young population, which stops being significant, and the impact of education, which is only positive and significant when the origin and destination effect are excluded from the model.

The next columns in Table 4, provide another robustness test for the impact of the push and pull effects. In this case, instead of using country specific effects, country pair effects are introduced and consequently the variables reflecting bilateral predictors (distance, language, border, colony, and region) are excluded from the analysis as their impact is already included in the country pair effects (Mayda, 2007). This specification highlights the importance of the push effect of the GDP per capita, which is highly significant and positive. Other than this, only the education level of the origin country is marginally significant with a negative sign.

Moreover, in order to examine how the effects change over time, columns 6 and 7 introduce year-by-covariate interaction term for each covariate (Zhou, 2011). Together with the linear year term, these variables are used to estimate migration flows using both RE and the xtregar model. Firstly, we can see that the negative effect of distance becomes more important over time. However, this is not the case for the border effect as its interaction term appears to be negative and significant according to the RE model, but this is not the case when we correct for serial autocorrelation as in this case the interaction term has no significant impact. The same non-significant impact is detected for the common language between origin and destination country. This can be justified by the increasing use of English because of the globalization process. However, the importance of the cultural similarities because of the common colonial past between origin and destination country increases over time. Not surprisingly, no significant coefficients were estimated for the common geographic variable region. The pull effect of the GDP per capita of the destination country increases over time, but this is not the case for the push effect of the share of young population of the origin country, which decreases during our study period. Finally, the positive signs of the education interaction terms are difficult to be interpreted as the impact of the education level was not clear in the previous regressions.

Next, potential endogeneity issues have to be addressed. Endogeneity might arise in our case from reverse causality: although we test the impact of GDP per capita in the destination country as a pull factor, prosperity level might also be affected by the inflows of immigrants. In order to – at least indirectly – address this issue, Table 3 presents the basic models (regressions 3 and 4 from Table 6) using lagged regressors. This 'poor man's exogeneity' approach implies that the past years prosperity level of the destination country or the past year's share of young people in the origin country are not affected by the subsequent year's migration flows. Although it would be interesting to test this at a later stage with an IV approach, the results of this exercise presented in columns 1 and 2 are almost identical with the previous specification without the lagged variables, verifying the previous discussion.

Furthermore, Table 3 introduces a dynamic dimension to our analysis as the stock of immigrants (*stock95$_j$*) in destination country in 1995 is used as an explanatory variable. The underlying assumption is that countries which are well-known destinations will continue attracting migration flows. Migrants mostly migrate to countries where their compatriots have already established a network 'beaten path'. Through the established network, previous migrants transfer their knowledge and experience to the newcomers and make it easier for them to find jobs, accommodation, and even to deal with bureaucratic obstacles. This is verified in columns 3 and 4, which depict the significant and positive impact of the stock of migrants even after the inclusion of the country specific effects.

Table 3: Panel data regressions (lagged) on migration flows (ln)

	(1)	(2)	(3)	(4)
$GDPpc_i$ (origin, ln, t-1)	-0.051	0.28	0.026	1.042
	(0.46)	(1.16)	(0.22)	(3.36)***
$GDPpc_j$ (destination, ln, t-1)	1.054	0.942	0.293	1.937
	(11.76)***	(3.59)***	(2.10)**	(4.64)***
$pop1529share_i$ (origin, t-1)	0.79	1.45	1.552	8.696
	(1.26)	(0.84)	(2.36)**	(3.97)***
edu_i (origin, ln, t-1)	0.029	0.004	0.035	0.004
	(13.86)***	(1.86)*	(14.24)***	(1.66)*
edu_j (destination, ln, t-1)	0.011	-0.01	0.001	-0.004
	(5.34)***	(5.40)***	(0.23)	(1.74)*
$stock95_j$ (destination, ln, t-1)			0.919	1.715
			(25.48)***	(2.30)**
D_{ij} (ln)	-0.252	-0.639	-0.338	-0.586

	(6.60)***	(11.31)***	(8.27)***	(6.44)***
$border_{ij}$	1.217	0.472	0.831	0.766
	(7.28)***	(3.23)***	(5.12)***	(4.50)***
$language_{ij}$	0.926	0.627	0.457	0.214
	(6.10)***	(4.62)***	(2.42)**	-1.12
$colony_{ij}$	1.369	0.899	0.585	0.619
	(5.72)***	(4.40)***	(2.22)**	(2.42)**
$region_{ij}$	-0.006	-0.002	0	0.016
	(0.39)	(0.16)	(0.02)	(0.86)
yearly effect	-0.443	0.096	-0.37	0.011
	(12.74)***	(2.79)***	(9.08)***	(0.26)
constant	-9.422	-4.868	-7.594	-38.455
	(6.01)***	(1.36)	(3.88)***	(4.67)***
origin and destination effects		yes		yes
Observations	4,637	4,637	2,615	2,615
Number of groups	757	757	425	425

Standard errors in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%

All in all, the above analysis signifies the importance of geographical and cultural proximity, but also the importance of push and pull factors in the formation of migration flows among OECD countries.

5.2 Network modeling approach

To further validate the results of the econometric analysis, a second modeling exercise is introduced. This is a cross-sectional analysis, which incorporates the network structure of the international migration. The main modeling tool here is the MRQAP regression, which is primarily used to model social interactions and is widely used in Social Network Analysis (SNA) research. The main advantage of this method is its ability to address potential interdependence across observations, a phenomenon which is quite often in dyadic data known as dyadic autocorrelation (for a discussion see Agaian et al., 1995). Such a problem might arise here as the same country appears in various origin-destination country pairs and this might violate the OLS assumption of observation independence (Zhou, 2011). MRQAP is widely used in order to tackle this issue when the level of analysis is the dyadic ties (Krackhardt, 1987, 1988; Mizruchi, 1993).

Just like with any other methods based on quadratic assignment procedure, both dependent and independent variables are NxN matrices. The algorithm works in two steps. Firstly, a standard multiple regression across the corresponding cells of the matrices representing the dependent and the independent variables takes place. Then, the algorithm randomly permutes rows and columns of the dependent variable matrix and re-estimates the regression. This step is repeated hundreds of times for the estimation of standard errors. The coefficients derived from these iterations are compared with those from the original OLS model and the percentage of these coefficients surpassing the original coefficients indicates the statistical reliability of the original outcome (Zhou, 2011). The Ucinet software is used for this analysis (Borgatti et al., 2002).

After the relevant log-log transformations, (1) can be transformed to a linear model. More specifically, the empirical model we are estimating is the following:

$$\begin{aligned}\ln\left(M_{ij}\right) = \beta_0 &+ \beta_1 ln(GDPpc_i) + \beta_2 ln(GDPpc_j) + \beta_3 ln(edu_i) + \beta_4 ln(edu_j) \\ &+ \beta_5 pop1529\_share_i + \beta_6 \ln\left(D_{ij}\right) + \beta_7 border_{ij} + \beta_8 colony_{ij} + \beta_9 language_{ij} \\ &+ \varepsilon_{ij} \qquad (3)\end{aligned}$$

Apart from the QAP estimation approach, the main difference between (2) and (3) is that the latter is a cross section. In addition, the variable representing geographic regions ($region_{ij}$) has been excluded from the analysis as it failed to provide any insights above.

Table 4 presents the MRQAP results for the ten year study period. The first observation is the consistency of the impact of cultural proximity through the study period, as is reflected in colonial ties and common language between origin and destination. Secondly, geographic proximity is represented here by two different variables: physical distance and adjacency. Distance has a significant negative impact for six years and border effect is positive and significant for eight years. The above indicates the cost that distance imposes in the migration process. Regarding the pull and push effects, the picture is more complicated. Education in both origin and destination countries has a significant positive impact in migration flows. GDP per capita of the destination country has a positive impact for eight years, while the GDP per capita of the origin country does not have a stable impact. Moreover, the magnitude of the coefficient of the latter is much lower than the former. Finally, the share of young population in the origin country also has a positive impact for six cross-sections.

In total, MRQAP validates the previous results on the impact of physical and cultural proximity on international migration, the pull effects of the GDP per capita and the push effect of the young population. The two models disagree is on the impact of education, but MRQAP results are in accordance with the lagged regressions.

Table 4: MRQAP on migration flows (ln)

	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009
D_{ij} (ln)	-0.704	-0.699	-0.925	-0.507	-0.549	-0.383	-0.147	0.016	-0.188	-0.173
	(0.288)***	(0.326)***	(0.385)***	(0.31)**	(0.276)**	(0.267)*	(0.231)	(0.137)	(0.249)	(0.258)
$border_{ij}$	0.928	0.603	0.781	1.406	1.426	1.383	1.245	1.193	1.435	1.133
	(0.575)*	(0.69)	(0.757)	(0.662)**	(0.568)***	(0.567)***	(0.51)***	(0.52)***	(0.512)***	(0.491)**
$colony_{ij}$	1.235	1.494	1.837	1.204	1.251	0.903	0.999	2.097	1.294	1.004
	(0.778)*	(0.899)**	(1.136)*	(0.883)*	(0.868)*	(0.81)	(0.754)*	(0.826)***	(0.713)**	(0.908)
$language_{ij}$	1.355	1.441	0.335	1.274	1.261	1.544	1.186	1.214	1.312	1.138
	(0.624)**	(0.685)**	(0.896)	(0.697)**	(0.573)**	(0.612)***	(0.544)**	(0.557)**	(0.585)***	(0.63)**
$pop1529share_i$ (origin)	3.134	3.386	3.597	4.001	2.524	1.724	1.172	2.144	-0.197	-1.527
	(1.548)**	(1.887)**	(2.355)**	(2.118)**	(1.766)*	(1.63)	(1.632)	(1.585)*	(1.364)	(1.569)
edu_i (origin, ln)	0.566	0.672	0.550	0.402	0.782	0.547	0.777	0.911	0.504	0.850
	(0.272)**	(0.363)**	(0.461)*	(0.366)	(0.36)***	(0.316)**	(0.308)***	(0.167)***	(0.264)**	(0.33)***
edu_j (destination, ln)	0.722	0.710	0.669	0.737	0.728	0.694	0.738	0.677	0.618	0.735
	(0.162)***	(0.183)***	(0.202)***	(0.183)***	(0.173)***	(0.151)***	(0.165)***	(0.131)***	(0.135)***	(0.179)***
$GDPpc_i$ (origin, ln)	2.383	1.864	1.213	1.439	1.971	1.443	2.091	1.346	-0.021	-0.004
	(1.189)**	(1.275)*	(1.546)	(1.342)	(1.204)**	(1.209)	(1.133)**	(0.684)**	(1.09)	(1.063)
$GDPpc_j$ (destination, ln)	0.839	0.757	0.547	0.958	0.521	0.242	0.294	0.293	-0.498	-0.535
	(0.366)***	(0.408)**	(0.506)	(0.435)***	(0.331)**	(0.298)	(0.309)	(0.288)	(0.233)***	(0.26)***
Constant	-45.098	-40.366	-28.401	-37.510	-41.814	-31.947	-43.874	-38.993	-8.728	-13.953
R^2	0.34	0.286	0.245	0.22	0.3	0.254	0.327	0.336	0.246	0.321
Observations	756	600	420	650	756	930	900	540	992	650

Standard errors in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%

6. Concluding remarks

The novelty of this paper is the adoption of a network perspective in studying international migration. Such migration flows create a dense, complex and dynamic network constellation. The topology and the structure of this network change over time, clearly reflecting current economic, social and political conditions. Although the growing attention that research on migration has attracted, and in light of the recent major developments in network science, the interaction between these two fields has been very limited.

Using methods widely used in migration studies and in network analysis, much research effort is spent here to bridge this gap. Exploratory network analysis using centrality measures as well as community detection provides the fundamentals in order to approach international migration as a global network. The outcomes of this exercise support the modeling part of our analysis. In this stage standard econometric techniques are blended with network approaches to gain a better understanding of the determinants of international migration. Both methodological approaches converge on the importance of physical and cultural proximity in the formation of migration flows. Physical distance and border effects are significant predictors of migration flows among OECD countries. Moreover, post-colonial ties and common language between origin and destination countries have a positive impact on migration flows. In addition, both modeling approaches agree on the pull effect of the prosperity level of destination country as well as on the push effect of the existence of a pool of young population in origin country. The value added of this dual approach is the emergence of education as a significant predictor of migration flows. Indeed, according to the MRQAP models, higher level of education can generate both pull and push effects in migration among OECD countries. Nonetheless, traditional regression techniques did not capture the impact of education and it was the network level modeling approach adopted here that highlighted this impact.

In our 'age of migration' countries are increasingly tied together through human capital flows. In a globally ageing world these forces tend to become even stronger. In this new international playing field, education and skills will become increasingly important forces that drive global connectedness. The future of many welfare states will decisively be determined by cross-border migration, not only in terms of volumes, but also in terms of quality. Dew policy attention and advanced quantitative research is needed to achieve a balance in global human capital flows.

To conclude, this paper highlighted the need for borrowing methods and techniques from the network analysis field in order to better understand complex spatial phenomena such as international migration. Although effort was spent to understand international migration as a network phenomenon and to bridge the gap between descriptive and modeling network approaches, there is still much ground to be covered in this respect, with estimation of constructive stochastic migration models being one of the most important elements towards this novel direction.

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