Networks and the location of foreign migrants: evidence for Southern Europe

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Abstract.
This paper investigates the effect of co-national immigrant´s communities (social networks) and historical international trade relationships (business networks) on the decision of migrants to locate in a particular territory within a country. We examine separately three Southern European countries (Italy, Portugal and Spain) and check whether these decisions are locally bounded or spur in neighboring territories. We find that spatial dependence plays a significant, positive role in determining migrants' final destination. Once it is accounted for, social networks enhance immigration of co-nationals into the destination provinces of the three countries, a positive effect that is moderated if contiguous provinces have large co-nationals communities from the same origin country. For the case of business networks, contiguous provinces having commercial linkages with the immigrants' origin country compete as alternative destinations in Spain and Italy but not in Portugal.

Keywords: *International migration, networks, spatial interdependence*

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1. INTRODUCTION

During the last two decades the intensity of migration flows has risen worldwide. This phenomenon has renewed the interest in understanding the factors affecting the location of migrants in the host country. It is a well-known fact that migrants from the same nationality are not randomly located in the host country; they tend to be concentrated in certain areas. Local networks in the destination areas may have a costs-reducing effect on immigration, attracting new immigrants. Additionally, as destination economies within the country are not isolated, such attracting effects may spill over other destinations nearby, affecting the propensity to migrate to those closely related locations. Thus, the spatial distribution of immigrants, and the interdependencies among alternative destinations are additional determinants for immigrants' settlement within a country that should be taken into account in order to deepen into the understanding of immigration flows.

Traditionally, the literature on migration flows consider local networks as factors reducing migration costs. The existence of past connections between the different territories of the host country and her country of origin can help new immigrants to access information about the possible destinations easier and less costly as well as facilitate immigrants' settlement in their destination economy. Such connections may include the presence of communities of previous immigrants form the same origin country living in the destination economy (ethnic networks) as well as past commercial bilateral trade relationships (business networks).

So far the literature on migration location has paid little attention to the spatial dependence structure between territories. Anderson (2011) and Bertoli and Fernandez-Huertas (2013) introduce the concept of "multilateral resistance terms to migration" (MRT) as a measure of the (lack) of attractiveness to migrate to alternative destinations. While the failure to control for such term leads to the problem of omitted variable bias, the consistency of the estimates including the MRT with general RUM models of migrants' location decision is based on the cross-sectional independence among destinations in the random term.[1] Notice that, especially in a sub-national framework, the question remains as to whether the inclusion of such MRT – generally a set of origin and destination or time-origin and time-destination fixed effects- are sufficient to ensure cross-section independence among destinations.

Because of that, spatial interdependence is another relevant factor that has to be carefully considered, but little attempts have been made up to our knowledge. An exception is the paper of Nowotny and Pennerstorfer (2017) that estimates a random probability model (RPL) for a sample of EU regions over the period 1997-2008 and provides evidence of spatial spillovers in the effect

[1] The theoretical foundations of the bilateral migration gravity equation show how these gravity models for migration are based on the unrealistic idea of the individual-specific stochastic component of utility that lead to the IIA assumption, (see Anderson, 2010; Beine et al., 2014, for an introduction). Relaxing these assumptions imply that alternative destinations are not irrelevant since choosing one implies the loosing of the benefits that would be obtained when choosing an alternative.

of migrant network on migrants´ choice of target regions. However they do not use spatial econometric tehcniques as we will do.

The main goal of this paper is investigate the importance of spatial interdependences in the impact of networks on bilateral migration flows. Southern European countries –Spain Italy and Portugal- show huge immigration rates over the 2000-2010 and could be regarded as similar and in-competition destination countries. Nevertheless, the uneven distribution of immigrants across their territories emphasizes the relevance of spatial relationships affecting immigrants' destination decisions. Positive effects of co-nationals location choices can spread to other immigrants from the same origin country. Additionally, compatriots' communities in neighboring regions could reinforce social networks positive effects on one region's immigration –that is, proximity to co-national networks in other provinces should also help to facilitate migration inflows in the province. However, those positive effects could decrease rapidly or even become negative as neighboring provinces become substitutive destinations that compete attracting migrants from a certain origin. Despite its effect is unclear, considering spatial interaction among destination alternatives is a requirement in order to better understand immigrants' location choice within a country (Chun, 2008; LeSage and Pace, 2008; Chun et al 2012). In this context, general immigration policies without considering the relevance of space in its definition could prove even counterproductive.

Our empirical analysis is conducted on a reduced form for bilateral international migration flows to each country's provinces, compatible with a hierarchical RUM model, in which both multilateral resistance terms to migration and spatial autocorrelation are considered, constituting a contribution to the network-migration literature that has not been analyzed in sufficient detail. For that purpose we use of three separate datasets from different countries: 103 Italian provinces, 50 Spanish provinces and 18 Portuguese provinces over the period 2000-2010. The three countries have moved from being source of migration flows to become receiving countries since the mid 1990's until 2010, year that seems to be a turning point in the migration tendencies in the decade. Additionally, the use of such small sub-national geographic units allow for greater precision in identifying local networks of immigrants by nationality and in estimating their impact on bilateral immigration flows, and is in this level, once the national characteristics are considered –for example migration policies are instrumented at a national level– where the effect of these provincial interdependences will be more relevant in the migrant's location decision. Finally, we also contribute to the literature by exploring the role of the presence of historical commercial relationship between origin countries and destination provinces that could also enhance migration flows among trade partners, since its effect on migration in empirical literature is not conclusive.

We explore first the possibility of spatial autocorrelation in our model using spatial econometric techniques. Our results confirm the spatial interdependence of migrants' destination choices within the country. Once this spatial dependence is accounted for, our results provide evidence supporting the positive impact of ethnic networks on bilateral migration. This result can be qualified when the role of adjacent provinces is considered. In Spain and Italy, compatriots living in adjacent provinces' communities or commercial linkages with immigrants' origin countries would reduce one province immigration flows as they will compete as attractive destinations. So, the positive impact of social networks on immigration flows would be lower in provinces with large compatriots' communities in their neighborhood; and the non-significant effect of commercial networks would become negative for those provinces having weaker commercial linkages with immigrants' origin countries than its neighbors. Nevertheless, these results cannot be generalized for all the three countries under study, despite the three of them being Southern-Europe host countries with similar immigration growth rates, since the opposite effect of business networks is obtained for Portuguese provinces. This result emphasizes the necessity of immigration policies adapted to the specificities of each destination area, pointing to the even contrary effects that general policies in –apparently- similar migratory enclaves could produce.

The rest of this paper is structured as follows. Section 2 describes the theoretical framework for RUM models. Section 3 introduces the econometric model and estimation issues. Section 4 describes the data and provides empirical evidence on the phenomenon under analysis. It explains the empirical specification of the model used to analyze the impact of trade on immigration and presents the main estimations and results. Finally, Section 5 concludes.

2. A RUM model of bilateral migration.

Bertoli and Fernandez-Huertas (2013) and Peeters and Chasco (2013) describe the location decision problem that individuals face through a Random Utility Maximization (RUM) model where a migrant from country c chooses the highest utility alternative among the I destination alternatives {1,2,…,i,…I}. The unobserved utility of choosing destination i rather than any other destination $k \neq i$, U_{ci}, will depend on a systematic component V_{ci}, and a random term ε_{ci}:

$$U_{ci} = V_{ci} + \varepsilon_{ci} = x_i^{'}\beta - \delta_{ci} + \varepsilon_{ci} \qquad (1)$$

where V_{ci} is a linear function of x_i, a (Ix1) vector of destination-specific characteristics, shared by all migrants from origin c.[2] V_{ci} also depends on the specific cost to migrate to province i, δ_{ci}, expressed in relative terms, that is, with respect to the cost to migrate to other province $j \neq i$ whose resistance to migrate is normalized to one. Finally, the random term, ε_{ci}, is assumed i.i.d. Extreme Value type I distributed. According to McFadden (1979), if x_i is orthogonal to any

[2] Since vector $\boldsymbol{\beta}$ is not origin-specific, pooling migration data across origins poses no problem.

characteristic of the countries of origin, the expected number of immigrants from origin c choosing destination *i* is:

$$E(m_{ci}) = m_c p_{ci} = m_c \frac{\exp(x_i^{'}\beta - \delta_{ci})}{\sum_{l=1}^{I}\exp(x_l^{'}\beta - \delta_{c,l})} = m_c \frac{z_i}{\Omega_c} d_{ci} \quad (2)$$

where m_c is the total population in the country of origin *c*; $z_i = \exp(x_i^{'}\beta)$ is a vector of origin-specific local characteristics and $d_{c,I} = \exp(-\delta_{c,i})$ is the bilateral migration cost (friction). The "inclusive value", $\Omega_c = \ln \sum_{l=1}^{I}\exp(x_l^{'}\beta - \delta_{c,l})$ represents the expected utility that immigrants obtain from all the destinations in the choice set and controls for the fact that alternative destinations are not irrelevant in the destination choice of migration, the so-called inward and outward migration frictions (Anderson , 2011) or multilateral resistance to migrate (Bertoli and Fernandez-Huertas, 2013)

Notice that the ratio of probabilities of immigrants from c choosing destination *i against an alternative destination j in a set of destinations I* can be written as*:*

$$\frac{E(m_{c,i})}{E(m_{c,j})} = \frac{\exp(x_i^{'}\beta - \delta_{c,i})}{\exp(x_j^{'}\beta - \delta_{c,j})} = \frac{z_i}{z_j}\frac{d_{c,i}}{d_{c,j}} \quad (3)$$

This ratio is independent of the number and characteristics of the rest of destination alternatives. That is, the model imposes the restriction that the choice between any two destinations is a binary choice independently of the rest of alternatives: the independence of irrelevant alternatives (IIA) assumption. Additionally, the assumptions on the random term do not allow **interdependences across destination provinces within the same countries or its substitutability** since they share social and cultural characteristics, and have common economic and social policies. To overcome these assumptions frequently considered very restrictive and unrealistic for individual choice models, Bertoli and Moraga (2013) and Beine et al (2014) adopt more general distributional assumptions, allowing for correlation in the stochastic component of utility in (1) and using a Nested Logit model (NL) framework.

Based on these ideas, we consider I location alternatives (provinces) grouped into D nests (countries), in such a way that the migration decision can be analyzed as a sequential decision. First the potential migrant from country of origin c chooses d among the D groups (countries). Next, once one group d is chosen, $d \in \{1, 2, \ldots, D\}$, the individual chooses one specific destination in such group d, that is, a province among the I_d provinces belonging to the nest d, $i \in \{1, 2, \ldots, I_d\}$. The potential migrant chooses the alternative with the highest utility:

$$U_{c,di} = V_{c,di} + \varepsilon_{c,di} = \eta_{c,d} + \mu_{c,di} + \varepsilon_{c,di} \quad (4)$$

where $\eta_{c,d}$ and $\mu_{c,di}$ are nest-specific and province-specific determinants of the utility but not individual-specific.[3] In a RUM context, the conditional distribution of the random term, $\varepsilon_{c,di}$, given the choice of the destination country d is a Gumbel's multivariate extreme value:

$$F_{I|D}(\varepsilon\,|d) = \exp\left[-\left\{\sum_{l\in I_d}\exp(\varepsilon_{c,dl}/\tau_d)\right\}^{\tau_d}\right] \qquad (5)$$

Where τ_d is the measure of the dissimilarity or substitutability of the provinces –exchangeability of $\varepsilon_{c,di}$ - in country d, with correlation 1-τ_d^2, for τ_d ∈ (0,1). Then, the probability of choosing location i among alternatives belonging to destination country d is:

$$P_{c,i|d} = \frac{\exp(\mu_{c,di}/\tau_d)}{\sum_{l\in I_d}\exp(\mu_{c,dl}/\tau_d)} \qquad (6)$$

Where restricting τ_d=1 would lead to the multinomial logistic model and the IIA assumption. At the upper level of the decision process, the joint distribution of the random terms is:

$$F_{D,I}(\varepsilon) = \exp\left[-\sum_{k\in D}\left\{\sum_{l\in I_k}\exp(\varepsilon_{c,kl}/\tau_k)\right\}^{\tau_k}\right] \qquad (7)$$

From which the probability of choosing country d among the alternatives in the destination set D, d ∈ D, can be derived as

$$P_{c,d} = \frac{\exp(\eta_{c,d} + \tau_d\Omega_{c,d})}{\sum_{k\in D}\exp(\eta_{c,k} + \tau_k\Omega_{c,k})} \qquad (8)$$

Where $\Omega_{c,d} = \ln\{\sum_{l\in I_d}\exp(\mu_{c,dl}/\tau_d)\}$ is the inclusive value or the log sum that summarizes the characteristics of all destinations within the country d (indirect utility of locating in province i), and varies across nests (countries of destination). Thus, the probability of migrate to location i is:

[3] All individuals from each origin country *c* face the same nest-specific and local-specific characteristics.

$$E(m_{c,i}) = m_c p_{c,i} = m_c P_{c,i|d} P_{c,d} = m_c \frac{\exp(\mu_{c,di}/\tau_d)}{\sum_{l \in I_d} \exp(\mu_{c,dl}/\tau_d)} \frac{\exp(\eta_{c,d} + \tau_d \Omega_{c,d})}{\sum_{k \in D} \exp(\eta_{c,k} + \tau_k \Omega_{c,k})} \quad (9)$$

Thus, as opposed to the standard multinomial model, this NL model allows relaxing the IIA assumption since the odds ratio among any two destinations belonging to different nests (countries) it is not independent of the characteristics of other provinces. Given that $\partial \ln(m_{c,i}) / \partial \ln \mu_{c,dl} \leq 0$,[4] an increase in the attractiveness of a destination perceived as a close substitute to i will reduce $E(m_{c,i})$, more than the expected migration flow towards a province located in a different country –that is $P_{c,l|d}$ =0- and (or) perceived as less substitutive destination. Thus, all the spatial interdependence across provinces within the nest are considered by the dissimilarity parameter τ.[5]

3. ECONOMETRIC MODEL AND ESTIMATION ISSUES

Our first empirical models are based on the log-linearization of gravity equation models for bilateral migration rates, as a function of origin (X_c) and destination characteristics (X_i), the so called push and pull factors in the migration literature, and some dyadic determinants of bilateral migration and proximity factors approximating the cost of migrate, X_{ci}, for instance Plane (1984), Karemera et al. (2000), Aguiar et al (2007) and Mayda, (2010):

$$m_{ci} = exp[X_c'\beta + X_i'\phi - X_{c,i}'\gamma]\, v_{c,i} \quad (10)$$

In these empirical analyses, the IIA assumption is implied since the attractiveness of alternative destinations or possible sources of unobserved heterogeneity across destinations are not considered in the model. The omission of this multilateral nature of one location's attractiveness -Anderson (2011)'s migration frictions or Bertoli and Fernandez-Huertas (2013)'s *multilateral resistance to migration terms*- and the omission of cross-sectional relationships among alternative destinations would produce biased estimations (Hanson, 2010).

According to Feenstra (2004), the common way to deal with this omitted variable bias is by including origin-time and destination-time fixed effects (or origin and destination fixed effects

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[4] We obtain that $\frac{\partial \ln(m_{c,i})}{\partial \ln \mu_{c,dl}} = -[\tau P_{c,l} + (1-\tau) P_{c,l|d}] \frac{\mu_{c,dl}}{\tau} \leq 0$ and $\frac{\partial \ln(m_{c,i})}{\partial \ln \mu_{c,di}} = [1 - \tau P_{c,i} - (1-\tau) P_{c,i|d}] \frac{\mu_{c,dl}}{\tau} > 0$

[5] Additional levels of nesting can be accommodated -see Neubecker et al (2015) for a three-level nested model where the upper decision is the country to migrate, next the decision is the region, r, within that country and finally the destination province within such region. But, again, they rely on heterogeneous dissimilarity parameters to capture different substitutability among destinations belonging to the same region or to the same country, finding that any change in the attractiveness of one province in the destination set induces non-uniform changes on the bilateral migration rate of province i that are the strongest within regions and the weakest across countries due to the higher similarities across provinces within regions

in a cross-country study) to capture all the origin-specific and destination-specific determinants of migration: Ortega and Peri (2013), Bertoli and Fernandez-Huertas (2013), Mayda (2010). As a result, only dyadic determinants of migration flows, $X_{c,i}$, would enter explicitly in the econometric model, while monodic determinants will be wiped-out by the inclusion of both origin and destination dummy variables[6]:

$$m_{c,i} = exp[\,\alpha_c + \alpha_i + X_{c,i}'\beta]\; v_{c,i} \qquad (11)$$

The estimation of a non-linear model such as (11) implies some issues. Silva and Tenreyro (2006) demonstrate that using the PPML (Pseudo-Poisson maximum likelihood) estimator provides consistent estimates of the nonlinear model in (11) in the presence of heteroscedasticity and performs well even when the data fail to satisfy the equidispersion property that characterizes the Poisson distribution (Silva and Tenreyro, 2010, 2011). Additionally, Schmidheiny and Brülhart (2011) and Bertoli and Fernandez-Huertas (2015) also established the consistency of the PPML estimation of this model with general RUM models of migrants' location decision, based on the cross-sectional independence in the random term. Nevertheless, this assumption becomes highly unrealistic in a location decision among interrelated destinations.

Interdependences among locations can affect the migration decision since changes in one destination characteristics affect the probability to migrate to the other alternative destinations and thus, would make the model incompatible with the theoretical RUM for migration decisions. These spatial patterns may arise from migrants' utility-maximizing location choices when migrants not only choose focusing on one specific destination, but also on its neighboring destinations (spatial spillovers) –which would violate the i.i.d. assumption about the error term. Because of that, spatial interdependence should be carefully considered, mainly when these spatial interdependences may not be sufficiently controlled for by including origin and destination fixed effects.

To address this issue, Peeters and Chasco (2013) propose including *origin-destination fixed effects*, γ_{ic}, to accommodate the correlations that exist among unobservable localized factors across destinations In a similar way, Bertoli and Fernandez-Huertas (2015) include a richer structure of fixed effects (origin dummies interacted with destination nests dummies) assuming a nest-specific cross-sectional correlation among destinations regarded as close substitutes by potential migrants from one origin country (see Guimaraes et al, 2004 for a discussion). Nevertheless, they do not consider any assumption about the spatial patterns for cross-sectional dependence.

[6] It is important to note that the imposition of these fixed effects also controls for credit constraints, migration, housing, or social policies, the omission of which will likely lead to alternative results

Contrary to these attempts, our strategy is addressing the possibility of spatial interdependences affecting provinces' international migration inflows by considering spatial autocorrelation in the model. So, bilateral interdependences can create a diffusion process over space that increase (decrease) the attractiveness of nearby provinces (if they are perceived as complementary/substitutive destinations) or because unobserved factors have a spatial nature that needs to be accounted for in the model (Anselin, 1988; Le Sage and Pace, 2009).This will require the inclusion of spatial autocorrelation in the model, either as an autoregressive spatial factor or a "spatial lag" of the endogenous variable –SAR (Spatial Autorregressive term)- and/or a spatial lag of the random term – SE (Spatial Error term):

$$m_{c,i} = exp[\, \alpha_c + \alpha_i + X_{c,i}'\beta + +W_{.i}\, m_{c,i} \,]\, v_{c,i} \qquad (12)$$

where W is the spatial weighting matrix and $v_{c,i}$ is approximated as: $v_{c,i} = \exp[\rho\ W_{.i}\ v_{c,i}\ ]\ \varepsilon_{c,i}$, and $\varepsilon_{c,i}$ ~$N(0, \sigma^2 I)$.

We first evaluate whether the inclusion of origin and destination fixed effects allow for controlling cross-section spatial interdependences using the Lagrange Multiplier tests (see Anselin and Florax, 1995; Cliff and Ord, 1981). Additionally, following Holmberg et al (2015), we use Holmberg's K test to test for spatial autocorrelation since it is robust against structured heteroskedasticity problems (unlike the common Moran's I or LM tests) and regardless of the underlying distribution.

4. EMPIRICAL ANALYSIS

Our study is focused on migration flows from countries to provinces, covering 93, 112 and 111 countries of origin to 50 Spanish provinces, 18 Portuguese provinces and 103 Italian provinces of residence, respectively. We approximate such immigration flows as the difference of immigrant stocks at province level in the three host countries (Italy, Spain and Portugal) by countries of origin of immigrants over the 2002- 2010 period, a decade of high immigration rates in the three Southern-Europe migration hosts. We will conduct our cross-section analysis in 2010, since around this year a turning point in the migration flows is observed as result of the economic crises that emerged in 2008. Additionally, the use of such small sub-national geographic units allow for greater precision in identifying local networks of immigrants by nationality and in estimating their impact on bilateral immigration flows. (See Table A1 in the Appendix for a list of origin countries in 2010).

Data in Table 1 shows the huge immigration growth rates in the three countries in the South of Europe: Spain, Italy and Portugal. The reason why choosing these destination countries is that after being historically countries emitting emigrants, they have turned into immigration countries in the 1980's but much more prominently in the last decade. Foreign population has been doubled in Portugal; it's three times the foreign population in 2001 in Italy and has been multiplied by four in Spain over the 2001 to 2010 period. In this last year, the share of foreign population reached the 4,3% in Portugal, the 7,0% in Italy and the 12,2% in Spain. Besides, over this decade, the growth of immigration is combined with a geographic concentration of immigrants in some provinces in Spain, Italy and Portugal, as it is pointed to by the reduction of the Florence's geographic association coefficient.

Figure 1 shows the map of provinces (NUTS III) of Spain, Italy and Portugal, filling with color those provinces where there is a high concentration of immigrants from most representative nationalities among the foreign residents in the country: East of Europe, North of Africa and South America. For instance, in Portugal, Brazilian immigrants are mostly located in Lisbon and Setubal; in Spain, immigrants from Rumania are mostly located in provinces nearby Madrid, such as Toledo, Guadalajara and Ciudad Real; in Italy, immigrants from Ecuador are mainly located in Geneva and its neighborhood. Thus, immigrants come from different countries and they are not evenly distributed across provinces in the national territory in Spain, Italy and Portugal. They tend to concentrate on groups of neighbor provinces across the space. This concentration of immigrants should result could be due to spatial autocorrelation in the factors affecting these variables and or potential interaction of socio-economic characteristics of regions since they belong to the same area.

Empirical specification.

We first estimate a gravity-type model for bilateral immigration flows from country *c* to province *i* over the period 2003-2010, $m_{ci,t} = IM_{ci,t} - IM_{ci,t-7}$:

$$m_{ci,t} = exp[c+\beta_1 \ln(PCGDP_{i,\,t-8})+\beta_2 \ln(PCGDP_{c,\,t-8}) + \beta_3 \ln(distance_{ci})+$$
$$+ \beta_4\, border_c+\beta_5\, euefta_c+ \beta_6\, lang\_f_c + \beta_7\, edu\_f_c + \beta_8\, dem\_f_c +$$
$$+ \beta_9 \ln(T_{ci,t-10})+\beta_{10} \ln(IM_{ci,t-8})+\beta]\ v_{ci,t} \qquad (13)$$

The size of the destination economy or its economic activity are pull factors determining migration flows while in the origin economy are factors pushing people to migrate. We approximate economic conditions by GDP per capita in both origin and destination economies. As a deterrent to migration, migration costs are commonly proxied by the distance to origin countries. We consider the geographical distance between origin and destination countries (Head and Mayer, 2000). Additionally, we include other proxies for bilateral distance: *border,* a dummy variable that equals 1 if the origin and destination economies share a land border and *euefta,* a dummy variable that equals 1 if both economies share a trade agreement, 0 otherwise. We also consider bilateral cultural and political distances between economies from Dow and Karunaratna (2006), based on language and education differences, *lang_f* and *edu_f respectively*, and on a proxy for the political system in the origin country based on a political freedom index, *dem_f*,[7].

We aim to analyze the relevance of social and business network effects on bilateral migration flows. Social networks emanating from the communities of fellow people already established in the possible destination attracts new immigrants since they reduce the cost of migrate and facilitate the adaptation of new immigrants by providing them information about the risks associated to immigration and about job opportunities, helping them to find a friendly social environment and facilitating their integration (Balan, 1992; Wilpert, 1992; and Waldorf, 1996). We approximate this social network by the stock of migrants form the same origin country, c, living in the province *i* at the beginning of the decade, referred to the first year we have information available, $IM_{ci,t-8}$, in order to reduce the possible endogeneity problem of this regressor.

We also analyze whether the presence or deepening of the historical commercial relationships between the origin country and the destination province in the past enhance migration flows, since its effect on migration in empirical literature is not conclusive. Several studies point out that the settlement of immigrant population is associated with an increase in trade between the host and origin economies. This is attributed to migrants' superior knowledge of products, legal requirements and market opportunities in both home and host economies, and/or the possibility of establishing trust relationships reinforcing trade contracts (Gould, 1994; Dunlevy et al., 1999; Head and Ries, 199; Girma et al., 2006). On the contrary, a negative migration-trade relationship should be obtained since trade indirectly transfers labor embedded in the traded good, just as migration does directly, the increase in one of these flows implying the decrease of the other. We measure the intensity of historical trade relationships between origin country, c, and destination province, i, by the openness rate computed as the sum of exports and imports between the province and each foreign country divided by country's GDP in 2002. We averaged the volume of trade over the 1995-2000 period, when the analyzed countries exhibit a very low stock of foreign population, to minimize endogeneity problems, T_{ci}. Reverse causality could be an issue, as it has been pointed out in some empirical work on trade-migration link (Peri and Requena-Silvente, 2010), we related current immigration flows to lagged values of (log) GDP per capita of both origin and destination economies, and to a decade-lagged values of trade intensity rates to address such potential endogeneity problem. While it is unrealistic to claim that regional GDPpc and bilateral trade are strictly exogenous, it is plausible to assume that they are

[7] Physic distances can be downloaded from www.mbs.edu/home/dow/research/public/psydist.html.

predetermined, in the sense that immigrant inflows—and third factors in the error term—can only affect contemporaneous and future values of the variables.

Table 2 presents the results of the PPML estimation of the standard gravity equation (13) for migration flows for each host country separately in columns (i), (iii) and (v). Our variables of interest are those measuring past trade relationships and the existence of migrant networks between the country of origin of migrants and the province of destination of the migrants. In general, the results are in line with those in gravity-type migration models. The larger the social network of foreign population from the origin country settled in the province, the larger the migration flow from such country to the province. Past trade links also attract new migrants in Spain but not in Italy and Portugal where a significant negative effect is obtained.

The rest of country-of-origin characteristics exhibit the expected impact in most cases. The larger the economic activity in the origin country, the lower the migration flows from that country. On the contrary, a higher economic activity in the destination province will attract migration, although this effect is only significant in the case of Portuguese provinces.

Next, we analyse the role played by geographic, cultural and political factors. The geographic factors show puzzled results. Increasing the distance between the home and host economies significantly reduces the number of immigrants in Italy and Portugal. On the contrary, a common land border does not appear to affect immigration in Spain, see column (i) in Table 2, while shows negative significant effects on immigration flows in Italy and Portugal. These results differ from those obtained in Mayda (2010) in a multi-country panel data analysis in which positive but not significant effect of this variable on immigration rates in Italy is obtained.

Sharing commercial agreements enhances immigration flows in Spanish and Italian provinces and reduces immigration rates in Portuguese provinces (in this last case the impact is not statistically significant). On the other hand, the larger the distance between home and host countries in terms of language, education and political freedom, have different results in the three countries. The expected negative impact of the first is obtained in the three countries. Distance in education and political freedom among origin and destination countries negatively affect immigration in Italian and Portuguese provinces, and show an unexpected positive impact in Spanish provinces.

As we mentioned earlier, failure to control for the attractiveness of alternative destinations in the migrant's location decision, leads to biased and non-consistent estimates (Hanson, 2010). Thus, our next step is including origin and destination fixed-effect to control for multilateral resistance terms to migration. By doing so, all the monodic variables in our model are dropped from the analysis.

The estimation results for this multilateral resistance terms (MRT) model for immigration flows are shown in Table 2, columns (ii), (iv) and (vi). R-squared increases in all the cases, suggesting that origin and destination fixed effects are controlling for more unobserved factors than those that were previously included in (13) as monodic regressors, mitigating the omitted variables problem. The sign and significance of coefficient estimates for social networks are robust to the new specification, while the magnitudes of coefficient estimates substantially change, pointing to the non–consistency of the previous results. Additionally, business networks effects on immigration change from significant to non-significant in Spain and Portugal and become significant, and negative, for Italy.

Province's immigration spatial dependence. The weighting matrix.

In this section we explore whether spatial dependence matters to understand migration location. In other words, we study whether the pattern in the distribution of immigrants across regions could be the result of spatial interdependencies in migration flows –immigration in nearby provinces could play a role in reinforcing one province's attractiveness as a migrants´ choice of destination.

We investigate the spatial properties of bilateral migration flows from origin countries to provinces. To do that, we compute the standardised Moran's I index (Moran, 1948).[8] Thus, a key issue in order to analyse the presence and magnitude of such interdependence is defining a distance or weight matrix among provinces (Anselin, 1995). Following Neumayer and Plümper (2010), spatial dependence exists whenever the expected utility of one unit of analysis is affected by the decisions or behavior made by other units of analysis. When this analysis comes to a dyadic variable as immigration, where it is possible to distinguish the source, the country of origin c, and the target of interaction, the destination province *i*, we can assume that contagion (the reinforcing effect) does not come from the aggregate policy choices of other sources or other targets, but only on the choices of other sources or targets in relation to the specific dyad under consideration. Specifically, our previous description of the social networks as a factor affecting immigration from country c to the target province *i*, fits with the Neumayer and Plümper's "Specific target contagion" in which other region targets *j* affect i's interaction with *c* only if province *j* have received migrants from the very same source country *c*, being w_{ij} the ij component of the (NxN) weighting matrix, W_N, used to model the connectivity between provinces that form the spatial

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8 $$I = \frac{N}{\sum_i \sum_j w_{ij}} \frac{\sum_{ij} w_{ij}(X_i - \bar{X})(X_j - \bar{X})}{\sum_i (X_i - \bar{X})^2} \quad \text{if} \quad i \neq j$$

where X_i and X_j are the observations for province i and j of the variable of interest, $\bar{X}$ is the regional average, *N* is the number of observations and w_{ij} is the ij element of the row-standardised matrix of weights. As the standardisation factor $\sum_i \sum_j w_{ij}$ equals *N* in the case of a row-standardised matrix of weights, the first quotient is equal to one in our analysis. This statistic is Normal-standard (0,1) distributed (Cliff and Ord, 1981) under the null hypothesis of spatial independence in the variable under analysis. The rejection of the null hypothesis indicates the distribution of one variable in the space according to the patterns defined in the matrix of weights.

dependence. Thus, we assume that immigrants location decision is affected by provinces' interdependences, but is independent across immigrants' nationalities, leading to a weighting matrix, for N provinces in the country and *c* international trade partners is $W= W_N \otimes I_c$ (bloc-diagonal matrix)

Geographical contiguity or bilateral distance (in km) matrices have been widely used in spatial econometrics see, for instance, Jayet et al (2010). However, from a wider perspective, the distance separating two provinces could be more than merely geographical. For example Schumpeter defines the innovative contiguity between productive sectors, as the intensity in their commercial relationships is higher than the average. Following this idea, we can define the proximity between provinces depending on the intensity of their commercial relationships: the higher the volume of trade between them, the higher the closeness of both destination provinces and the better the channel of information about the other province for the immigrant choosing one of the two trading provinces -about its relative advantages or disadvantages or their complementarity or substitutability in terms of being migrant's destination provinces.[9]

Unfortunately, it does not exist bilateral regional trade flows matrices within countries. Thus, to homogenize the interregional weighting matrix measurement for the three countries under analysis, we estimate bilateral trade flows between provinces i and j based on a standard gravity equation (Frankel and Romer, 1999). We compute this inter-provinces GDP-based trade flow estimations according to:

$$w_{ij} = [(GDP_i^{\alpha} GDP_j^{\beta}) / DIST_{ij}^{\gamma} (1- \phi D)] \qquad (14)$$

where α=1 β=1 and γ=-1 according to those values widely accepted in empirical literature. Finally, to also consider contiguity as an additional factor for provinces' interdependences, we include a "border premium" when considering distance, DIST, between i and j in (14). When both i, j regions(provinces) share a common border, D=1, we reduce a 10% the inverse effect of the distance on the trade flow among those provinces, ϕ =0.1, in comparison to those pair of provinces that does not share a common border, D=0. We use the row-standardised version of the asymmetric matrix of weights, W_N, to test the null hypothesis of the absence of provinces autocorrelation in immigration flows to provinces in Spain, Italy and Portugal.

The Spatial model

The previous results and the high spatial concentration of immigrants suggest that previous specifications, that did not include spatial interdependences, may omit an additional

[9] We also checked spatial autocorrelation in immigration flows among provinces with a contiguity matrix and a geodesic distance weighting matrix. In all the cases the results point to the existence of spatial autocorrelation across provinces in the three countries considered

factor of persistence determining migration within the province. When neighboring economies share similar local conditions, transfers and location of immigrants between these regions are likely to be more intense. Spatial interdependences may allow immigrants to access to information about province i's neighbors characteristics: the size of ethnic communities located in such provinces, socio-economic conditions, etc., taking advantage of such information spillovers in their location decision either attracting immigrants to those province i's neighboring provinces in detriment of province *i* immigration, or reinforcing immigration flows into province i given the attractiveness of provinces nearby, reinforcing the positive effect of network effects on migration flows.

We use Lagrange multiplier tests and the heteroscedasticity-robust K test to test the absence of spatial autocorrelation (both as a spatial lag or a spatial error term) in the MRT model for migration flows. [10] The bottom of Table 2 shows the both LM-lag and LM-err provide evidence against the absence of spatial autocorrelation, being the former smaller than the latter, in the three countries. In the same vein, the K test, robust against heteroscedasticity and useful regardless of the underlying distribution, rejects the null in the case of Spain and Italy but provides evidence supporting the absence of spatial autocorrelation among Portuguese provinces. Accordingly, we proceed by estimating a spatial model including a spatial error and testing if a spatial autoregressive scheme is also required in order to control for substantive spatial autocorrelation in models for Spain and Italy.

Table 3 shows the PPML estimation results for the MRT model for Spain and Italy. Columns (i) and (iv) show the base MRT model in Table 2, columns (ii) and (v) show the model's estimation including a spatial error term, and, columns (iii) and (vi) show estimates including both SAR and SE schemes. Evidence provided by the K test points to the absence of spatial autocorrelation in the spatial specifications, while the one with the lowest Akaike's AIC criteria is the one including both SAR and SEM terms.

Table 3 columns (iii) and (vi), are our preferred specifications for migration flows into Spanish and Italian provinces, respectively. In both cases, the estimates for the previous immigrants from the same origin country are positive and significantly different from 0. Thus our results provide evidence supporting the immigration-enhancing effect of ethnic networks in the destination province.

The inclusion of spatial effects in the model mainly affects the business networks impact. Information networks stablished through historical trade relationships will significantly attract immigrants from the trade partners into Spanish provinces by reducing the cost of migrate, in

[10] To test cross-sectional independence in the random term in this non-linear model, H_0: $\rho=0$, we approximate the spatial error term as: exp [ρ $W_{.i}$ $r_{c,i}$], using the zero-mean residuals: $r_{ci} = m_{ci} - \hat{\mu}_{ci}(\overline{m}_{ci} / \overline{\hat{\mu}}_{ci})$, where $\hat{\mu}_{ci}$ is the expected count according to the model and m_{ci} is the actual endogenous variable .

comparison with the non-significant estimates in the MRT model. On the contrary, the inclusion of spatial autocorrelation in the model for Italy implies the direct effect of this variable not being significant. Thus, only for Spanish provinces we find historical trade relationships acting as an attracting factor for immigrants from the trade partner country.

Additionally, spatial interdependences among provinces enhance immigration flows in the province of reference, both in Spain and Italy. The positive and significant estimate for the SAR term implies that the concentration of migrants in adjacent provinces from the same country of origin also affects positively the decision of a new migrant to choose a particular location. It suggests the existence of immigration cost-reducing spillovers across regions emanating from immigration flows from the same origin countries to commercially related provinces within the country, suggesting a certain complementarity of conational immigration across provinces.

Robustness analysis: the neighbors' definition

According to our results, including origin and destination dummies is not enough to control for the influence of the rest of alternative destinations in the destination choice of immigrants –that is, to control for the violation of the IIA assumption in the decision of foreign immigrants on the destination province in the host country. Immigration in provinces nearby affects immigration in the province of reference. We defined closeness between any two provinces within the country depending on the strength of commercial linkages between them. We find immigration spillover positively affecting immigration from an origin country into a destination province, since the arrival of immigrants from one nationality to province's trade partners will increase immigration from such origin country to the province of reference. The next question that arises is whether such spatial autocorrelation might determine both business and ethnic networks effects on immigration. In this case, the immigration-cost reducing effect of networks might affect the attractiveness of alternative destinations in a positive way if there's a complementarity between networks in such alternative destinations or in a negative way if networks decrease the attractiveness of one province compared to another. We consider contiguous provinces as those that can be complementary attractors of immigrants from an origin country o rivals in terms of attracting them. So, we define a 0,1 contiguity matrix, C, for provinces in each country, taking the value 1 when the two provinces considered share a border, 0 otherwise. The inclusion of interacted trade and ethnic networks with this contiguity matrix allow us to determine the relevance of a differential effect on the impact of networks on migration due to spatial relationships. [11]

[11] Since we defined matrix W as an interprovincial trade matrix, not necessarily the closest regions are those sharing borders. Thus, including the differential effect of business and social networks due to contiguity does not generate serious multicollinearity problems in our estimations but for Italy.

Estimation results are provided in Table 4. We base on our preferred specification in Table 3 for Spain and Italy, including both substantive and residual spatial autocorrelation, and the MRT specification in Table 2 for Portugal. These estimations are reported again in Table 4 as the basic models in columns (i), (v) and (vii), for each country. Next, we include a differential effect in the impact of business and social networks on migration inflows due to border effects among destination provinces for Spain, columns (i) and (ii), and Portugal, columns (v) and (vi). In the case of Italy, we only included a differential effect in the impact of business networks due to border effects, columns (iii) and (iv) because overparametrization and multicollinearity problems between the social networks in contiguous provinces and the substantive autocorrelation term leads to misleading results on the estimates of the latter, while the conclusions on the rest of variables remain unaltered.

In both Spain and Italy, contiguity between provinces compensate part of the positive effects of social and business networks on immigration in the province, since neighboring regions are perceived as substitutive locations competing for attracting immigrants from trade-partner countries and/or from origin countries of immigrant communities settled in the province.

On the contrary, rather than competing for immigrants from a determined origin country, only contiguous provinces in Portugal significantly enhance the province's attractiveness as destination for immigrants coming from a trade partner country, while do not show any differential effect concerning the positive impact of social networks on migration inflows in the province

5. CONCLUDING REMARKS.

Migrants are not evenly distributed across space, and regions are not locally bounded, thus, spatial dependence or neighborhood effects among provinces within a destination country may be relevant factors determining the flow of immigrants from the same origin country that locate in a specific province within the destination country. We analyze this issue using spatial econometric techniques in a reduced form of a nested logit model for migrant's location decision. Our assumption is that origin and destination fixed effects, the *so-called multilateral resistance terms to migrate*, are not capturing all the network factors that could reduce the migration and settlement costs. Our PPML estimation results provide evidence supporting this idea since spatial autocorrelation problems persist when multilateral resistance terms are included in our model specification. Addressing the potential spatial autocorrelation problem requires the inclusion of spatial autoregressive and spatial error terms in our model. Our results suggest that spatial interdependences in the migrants' destination decision positively affect migration inflows. Thus, the migrant's destination decision is determined not only by the characteristics of the province under analysis, but also by spatial effects that spill over from immigration into nearby provinces.

Once spatial interdependences are controlled for, ethnic networks proved to be immigration-enhancing factors for the region in which the communities of compatriot immigrants are located. The effects of historical trade relationships between origin country and destination province on migration proved to be non-significant.

The next question that arises is whether such spatial autocorrelation might determine both business and ethnic networks effects on immigration. In this case, the immigration-cost reducing effect of networks might affect the attractiveness of alternative destinations in a positive way if there's a complementarity between networks in such alternative destinations or in a negative way if networks decrease the attractiveness of one province compared to another. In this case, we assume that such alternative destinations are those being close enough to compete for attracting immigrants from one origin country, that is, the adjacent or contiguous provinces.

In the case of Spain and Italy, contiguity between provinces compensate part of the positive effects of social and business networks on immigration in the province, since neighboring regions are perceived as substitutive locations competing for attracting immigrants from trade partner countries and/or from origin countries of immigrant communities settled in the province.

In the case of Portugal, only contiguous provinces significantly enhance the province's attractiveness as destination for immigrants coming from a trade partner country, while do not show any differential effect concerning the positive impact of social networks on migration inflows in the province

The positive impact of ethnic networks on bilateral migration can be qualified when the role of adjacent provinces is considered. In Spain and Italy, compatriots' communities in adjacent provinces or their commercial linkages with immigrants' origin countries would reduce one province immigration flows as they will compete as attractive destinations. While, the positive impact of social networks on immigration flows would be lower in provinces with large compatriots' communities in their neighborhood, the non-significant effect of commercial networks would become negative for those provinces having neighbors with stronger trade linkages with immigrants' origin countries. Nevertheless, the opposite effect of business networks is obtained for Portuguese provinces.

Our results show that the three countries under study are quite different, even though they are Southern-Europe host countries with similar immigration growth rates. Therefore our results emphasize the necessity of immigration policies adapted to the specificities of each destination area in order to be effective, and to the problems that general migratory policies, even in –apparently- similar migratory enclaves, could produce.

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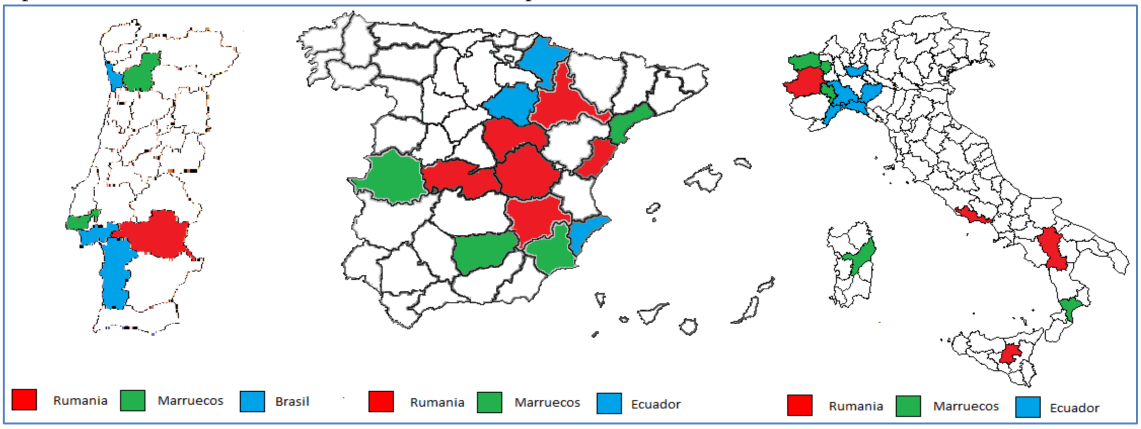
Table 1. Foreign residents in Portugal, Spain and Italy.

	Portugal	Italy	Spain
Foreign residents 2001	208198	1334889	1370657
Foreign residents 2010	454151	4235059	5747730
Growth rate 2001-2010 (%)	118,1	217,3	319,3
Share over total population 2001 (%)	2	2,6	3,3
Share over total population 2010 (%)	4,3	7	12,2
Florence's index 2001	0,8	0,52	0,59
Florence's index 2010	0,64	0,45	0,43
Variation 2001-2010	-0,16	-0,08	-0,16

Source: Own elaboration with data from ISTAT-Italy, Statistics National Institute of Spain, Statistics National Institute of Portugal and SESTAT-Portugal.

Figure 1. Spatial distribution of immigrants by destination province in Portugal, Spain and Italy, 2010. Most representative nationalities from the East of Europa, North of Africa and South America.



Note: The province is filled with color when the Balassa index for immigrants from one country in the province equals the maximum value among the 10 most representative nationalities and is higher than 2. The Balassa index is computed as the ratio of the share of immigrants from one country in the province over the total share of immigrants in the province

Table 2. Determinants of bilateral migration flows. PPML estimates.

Variables	SPAIN		ITALY		PORTUGAL	
	Basic	MRT	Basic	MRT	Basic	MRT
	(i)	(ii)	(iii)	(iv)	(v)	(vi)
$ln(PCGDP_i^{02})$	-0.085		-0.060		1.461***	
	[0.216]		[0.127]		[0.507]	
$ln(PCGDP_C^{02})$	-0.574***		-0.980***		-2.227***	
	[0.066]		[0.041]		[0.224]	
$ln(distance_C)$	0.045		-0.544***		-1.820***	
	[0.086]		[0.057]		[0.345]	
$Border_C$	-0.015		-0.787***		-7.069***	
	[0.157]		[0.087]		[0.999]	
$Euefta_C$	2.523***		0.500***		-0.627	
	[0.212]		[0.120]		[0.476]	
$Lang\_f_C$	-0.122**		-0.724***		-0.926***	
	[0.055]		[0.116]		[0.133]	
Edu_f_C	0.201*		-0.539***		-3.103***	
	[0.110]		[0.066]		[0.421]	
Dem_f_C	0.488***		-0.516***		-0.867*	
	[0.154]		[0.088]		[0.457]	
$\ln(T_{ci}^{95-00})$	0.054**	0.026	-0.024	-0.061	-0.140***	-0.029
	[0.023]	[0.020]	[0.020]	[0.016]	[0.040]	[0.037]
$\ln(IM_{ci,t-8})$	0.744***	0.689***	0.882***	0.798***	0.728***	0.256***
	[0.030]	[0.024]	[0.016]	[0.017]	[0.080]	[0.075]
Moran´s I test	3.07		-3.64		3.13	
p_value	(0.00)		(0.00)		(0.00)	
Country dummies		*yes*		*yes*		*yes*
Province dummies		*yes*		*yes*		*yes*
LM_lag test		2.26		47.66		246.23
LM_err test		62.92		11367.45		187.08
K test		1.91		1.89		0.34
p_value		(0.06)		(0.07)		(0.38)
Num Prov	50		103			18
Num Cou	93		112			110
Observations	4650	4650	11536	11536	1980	1980
R-squared	0.69	0.94	0.86	0.97	0.63	0.95

Table 3. Spatial effects on bilateral migration flows. PPML estimates.

Variables	SPAIN			ITALY			PORTUGAL		
$ln(T_{Ci}^{95\text{-}00})$	0.0255	0.0284	0.0338*	-0.0614***	-0.02	-0.00532	-0.0368	-0.0308	-0.0351
	[0.0199]	[0.0196]	[0.0197]	[0.0165]	[0.0144]	[0.0139]	[0.0323]	[0.0360]	[0.0330]
$\ln(IM_{ci,t-8})$	0.689***	0.687***	0.654***	0.798***	0.811***	0.749***	0.250***	0.255***	0.250***
	[0.0243]	[0.0229]	[0.0236]	[0.0169]	[0.0151]	[0.0161]	[0.0708]	[0.0737]	[0.0711]
$W\ln(m_{ci,t})$			0.433***			0.663***	-0.00235**		-0.00264**
			[0.107]			[0.067]	[0.001]		[0.00106]
ρ		0.00012**	5.90E-05		0.0006***	0.0004***		-6.79E-06	1.01E-05
		[4.98e-05]	[4.87e-05]		[4.02e-05]	[4.40e-05]		[1.11e-05]	[1.16e-05]
Country dummies	yes	yes	yes	yes	yes	yes	yes	yes	yes
Province dummies	yes	yes	yes	yes	yes	yes	yes	yes	yes
K test	1.91	-0.28	-0.22	1.89	0.3	0.22	0.28	0.36	0.24
p_value	(0.064)	(0.384)	(0.389)	(0.067)	(0.381)	(0.389)	(0.383)	(0.374)	(0.388)
Num Prov	50	50	50	103	103	103	18	18	18
Num Cou	93	93	93	112	112	112	110	110	110
Observations	4650	4650	4650	11536	11536	11536	1980	1980	1980
AIC	759750.9	748221.4	730813.1	565882.4	468178.3	439723.8	58036.36	60124.78	57889.93
BIC		749155.9	731754.1		469774	441326.8	58763.17	60851.59	58622.33

Notes. $\ln(T_{Ci}^{95\text{-}00})$ measures the business network effect and $\ln(IM_{Ci,t-8})$ measures the ethnic network effect. Substantive spatial autocorrelation term (SAR): $W_i \cdot IM_{Ci,t}$. Spatially autocorrelated error term (SEM): $v_{ci,t}$ where $v_{Ci,t} = exp[\rho W_{.i} v_{Ci,t}]\, \varepsilon_{Ci,t}$ and $\varepsilon_{Ci} \sim N(0, \sigma^2 I)$.

Table 4. Contiguity and spatial effects on bilateral migration flows. PPML estimates

	SPAIN		ITALY		PORTUGAL	
	(i)	(ii)	(iii)	(iv)	(v)	(vi)
$ln(T_{Ci}^{95\text{-}00})$	0.0338*	0.0440**	-0.00532	0.0112	-0.0293	-0.041
	[0.0197]	[0.0206]	[0.0139]	[0.0143]	[0.0365]	[0.0320]
$C{*}ln(T_{Ci}^{95\text{-}00})$		-0.0894**		-0.0746***		0.00209***
		[0.0432]		[0.0218]		[0.000780]
$\ln(IM_{ci,t-8})$	0.654***	0.678***	0.749***	0.752***	0.256***	0.256***
	[0.0236]	[0.0269]	[0.0161]	[0.0162]	[0.0745]	[0.0698]
$C{*}\ln(IM_{ci,t-8})$		-0.117**				0.00151
		[0.0538]				[0.00288]
$W\ln(m_{ci,t})$	0.433***	0.608***	0.663***	0.663***		
	[0.107]	[0.143]	[0.0674]	[0.0654]		
ρ	5.90E-05	2.91E-05	0.0004***	0.0004***		
	[4.87e-05]	[5.08e-05]	[4.40e-05]	[4.32e-05]		
Num Prov	50	50	103	103	18	
Num Cou	93	93	112	112	110	
Observations	4650	4650	11,536	11,536	1,980	1,980
R-squared	0.937	0.942	0.97	0.971	0.947	0.963
AIC	730813.1	715651.8	439723.8	437202.4	60204.28	57270.35

Appendix.

Table A1. Immigrants' Origin countries by destination country.

ISO3	Origin countries	Destination countries: SPAIN	ITALY	PORTUGAL
AFG	Afghanistan	-------	yes	yes
ALB	Albania	yes	yes	yes
ARE	United Arab Emirates	-------	yes	yes
ARG	Argentina	yes	yes	yes
ARM	Armenia	yes	yes	yes
AUS	Australia	yes	yes	yes
AUT	Austria	yes	yes	yes
BEL	Belgium	yes	yes	yes
BEN	Benin	yes	yes	yes
BGD	Bangladesh	yes	yes	yes
BGR	Bulgaria	yes	yes	yes
BLR	Belarus	yes	yes	yes
BOL	Bolivia, Plurinational State of	yes	yes	yes
BRA	Brazil	yes	yes	yes
CAN	Canada	yes	yes	yes
CHE	Switzerland	yes	yes	yes
CHL	Chile	yes	yes	yes
CHN	China	yes	yes	yes
CIV	Côte d'Ivoire	yes	yes	yes
COL	Colombia	yes	yes	yes
CRI	Costa Rica	yes	yes	yes
CZE	Czech Republic	yes	yes	yes
DEU	Germany	yes	yes	yes
DNK	Denmark	yes	yes	yes
DZA	Algeria	yes	yes	yes
ECU	Ecuador	yes	yes	yes
EGY	Egypt	yes	yes	yes
ESP	Spain	-------	yes	yes
EST	Estonia	yes	yes	yes
ETH	Ethiopia	yes	yes	yes
FIN	Finland	yes	yes	yes
FRA	France	yes	yes	yes
GBR	United Kingdom	yes	yes	yes
GEO	Georgia	yes	yes	yes
GHA	Ghana	yes	yes	yes
GNQ	Equatorial Guinea	yes	yes	yes
GRC	Greece	yes	yes	yes
GTM	Guatemala	yes	yes	yes
HND	Honduras	yes	yes	yes
HRV	Croatia	yes	yes	yes
HUN	Hungary	yes	yes	yes
IDN	Indonesia	yes	yes	yes
IND	India	yes	yes	yes
IRL	Ireland	yes	yes	yes
IRN	Iran, Islamic Republic of	yes	yes	yes
ISL	Iceland	yes	yes	yes
ISR	Israel	yes	yes	yes
ITA	Italy	yes	-------	yes
JAM	Jamaica	-------	yes	yes
JOR	Jordan	yes	yes	yes
JPN	Japan	yes	yes	yes
KAZ	Kazakhstan	yes	yes	yes
KEN	Kenya	yes	yes	yes
KOR	Korea, Republic of	yes	yes	yes
LAO	Lao People's Democratic Republic	-------	yes	-------
LBN	Lebanon	yes	yes	yes
LBY	Libyan Arab Jamahiriya	-------	yes	yes
LKA	Sri Lanka	-------	yes	yes
LTU	Lithuania	yes	yes	yes
LVA	Latvia	yes	yes	yes
MAR	Morocco	yes	yes	yes
MDA	Moldova, Republic of	yes	yes	yes
MDG	Madagascar	-------	yes	yes
MEX	Mexico	yes	yes	yes
	Macedonia, the former Yugoslav Republic of	yes	yes	yes
MKD				
MLI	Mali	yes	yes	yes
MLT	Malta	yes	yes	yes
MOZ	Mozambique	-------	yes	yes
MRT	Mauritania	yes	yes	yes
MYS	Malaysia	-------	yes	yes
NGA	Nigeria	yes	yes	yes
NIC	Nicaragua	yes	yes	yes
NLD	Netherlands	yes	yes	yes
NOR	Norway	yes	yes	yes
NPL	Nepal	yes	yes	yes
NZL	New Zealand	yes	yes	yes
PAK	Pakistan	yes	yes	yes
PAN	Panama	yes	yes	yes
PER	Peru	yes	yes	yes
PHL	Philippines	yes	yes	yes
POL	Poland	yes	yes	yes
PRT	Portugal	yes	yes	-------
PRY	Paraguay	yes	yes	yes
ROU	Romania	yes	yes	yes
RUS	Russian Federation	yes	yes	yes
SAU	Saudi Arabia	yes	yes	yes
SDN	Sudan	-------	yes	yes
SEN	Senegal	yes	yes	yes
SGP	Singapore	-------	yes	yes
SLE	Sierra Leone	yes	yes	yes
SLV	El Salvador	yes	yes	yes
SVK	Slovakia	yes	yes	yes
SVN	Slovenia	yes	yes	yes
SWE	Sweden	yes	yes	yes
SYR	Syrian Arab Republic	yes	yes	yes
TCD	Chad	yes	yes	yes
TGO	Togo	-------	yes	yes
THA	Thailand	yes	yes	yes
TKM	Turkmenistan	yes	yes	yes
TWN	Taiwan, Province of China	-------	yes	yes
TZA	Tanzania, United Republic of	-------	yes	yes
UGA	Uganda	-------	yes	yes
UKR	Ukraine	yes	yes	yes
URY	Uruguay	yes	yes	yes
USA	United States	yes	yes	yes
UZB	Uzbekistan	-------	yes	yes
VEN	Venezuela, Bolivarian Republic of	yes	yes	yes
VNM	Viet Nam	yes	yes	yes
YEM	Yemen	-------	yes	yes
YUG	Yugoslavia	yes	yes	yes
ZAF	South Africa	yes	yes	yes
ZMB	Zambia	-------	yes	yes
ZWE	Zimbabwe	-------	yes	yes

Table A2. Descriptive statistics.

	Spain				Italiy				Portugal			
	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max
$m_{ci,t} = (M_{ci,t} - M_{ci,t-7})$	651.68	3817.67	0.00	163380.00	224.83	1743.78	0.00	122102.00	120.93	1207.00	0.00	42632.00
$ln(PCGDP_i^{02})$	2.78	0.22	2.42	3.20	-3.87	0.27	-4.42	-3.33	-4.47	0.29	-4.98	-3.90
$ln(PCGDP_C^{02})$	14.94	1.49	11.63	17.56	14.78	1.55	11.63	17.56	14.79	1.56	11.63	17.56
$ln(distance_C)$	8.27	0.77	6.52	9.88	8.19	0.93	6.27	9.82	8.44	0.68	6.52	9.88
$Border_C$	0.03	0.18	0.00	1.00	0.04	0.21	0.00	1.00	0.01	0.09	0.00	1.00
$Euefta_C$	0.20	0.40	0.00	1.00	0.17	0.38	0.00	1.00	0.17	0.38	0.00	1.00
$Lang\_f_C$	-0.46	1.54	-3.87	0.53	0.17	0.34	-0.74	0.53	0.13	0.57	-4.35	0.53
Edu_f_C	1.43	0.70	0.10	2.79	1.18	0.75	-0.42	2.53	0.82	0.77	-0.77	2.22
Dem_f_C	0.62	0.63	-0.17	1.97	0.70	0.66	-0.17	1.96	0.77	0.65	-0.07	2.06
$ln(T_{iC}^{95\text{-}00})$	-4.18	2.54	-11.66	3.07	-3.50	2.34	-11.96	4.28	-6.71	3.16	-13.67	2.20
$ln(IM_{iC,t-8})$	3.03	2.28	0.00	11.58	2.18	2.03	0.00	10.22	1.33	1.79	0.00	9.22
Observations	4650				11536				1980			