Modeling the effect of Social-Network on interregional Trade of Services: how sensitive are the results to alternative measures of social linkages

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Abstract

Recent literature has investigated the impact of social and business networks on the intensity of trade in goods between countries and within countries and the role played by these networks in the reduction of the border effect. This literature has found that such flows are positively correlated with migration stocks between pairs of countries/regions as well as firms linked through their stakeholders. In this study we investigate whether any such relation holds for interregional trade in services, focusing on the case of Spanish intra- and interregional monetary flows generated by certain domestic tourism sectors: namely, the hospitality and restaurant industries and travel agencies. With this aim, we develop a gravity model that captures spatial and network dependence attributable to demographic links between regions. In a previous paper we found that interregional network links had an enhancing effect on trade in services, when they were computed with stocks of immigrants born in exporting region and residing in the importing region. In this extension we explore a number of alternative sources for the information and taste effects. To this end, we consider such alternative mechanisms for face-to-face interaction as "mixed marriages", second-home stocks and previous tourist flows, as well as other sources of social interaction (interregional mail and parcel deliveries; professional interactions through the trade in goods, etc.).

KEYWORDS: social networks, gravity models, trade in services, border effect, internal tourism, Bayesian spatial autoregressive regression model, spatial connectivity of origin-destination flows.

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1. Introduction

The recent literature on border effects shows that, despite decreases in transport costs, countries still engage in more internal trade than external trade (McCallum, 1995; Helliwell, 1996; Wolf, 2000; Chen, 2004; Okubo, 2004; Evans, 2006; Ghemawat et al. 2010). To explain this, research has increasingly focused on informal barriers to trade. One such barrier is the lack of information about international trade and investment opportunities (Rauch and Casella, 2003). Social and business networks are seen as possible ways to overcome such barriers and increase the volume of international trade (Portes and Rey, 2005). Evidence supporting such channels has been found for business groups operating across national borders (Belderbos and Sleuwaegen, 1998), immigrants (Gould, 1994) and long-settled ethnic minorities that maintain co-ethnic business societies.

This literature distinguishes two main mechanisms through which bilateral trade could be promoted by immigration. The first relates to the 'idiosyncratic' preferences of immigrants, or 'taste effect', where the positive impact of immigrants on trade intensity reflects their taste for goods from their countries of origin. The second relates to the reduction of transaction costs, or 'information effects', due to migration; migrant familiarity with the preferences, social institutions, language and legal institutions of both countries reduces communication costs and cultural barriers. Communication between migrants and those living in their country of origin is facilitated by social and business networks, which in turn account for higher bilateral trade flows.

Some authors have tried to quantify the relevance of social and business networks on trade in goods between countries[1]. However, few papers have examined the role of migration in determining patterns of trade flows within a single country (i.e. Helliwell, 1997; Combes et al. 2005, Millimet & Osang, 2007; Garmendia et al. 2012). Helliwell (1997) has argued that, because institutions, flavors, culture, etc. might differ more in from country to country than between the regions of a single country, the trade-creation effect of migrants should be more intense on international than on interregional trade. Despite these results, there remain several reasons to expect larger effects on trade in services. First, domestic trade in services far outstrips domestic trade in goods in all OCDE countries[2]; second, immigration flows can be more intense, and at times more persistent, within countries than between countries; third, because services require face-to-face contact for the interchange to take place (also called 'proximity burden'), information is more important for trade in services than for trade in goods, so we can expect social-network–driven reductions in transaction costs to be larger; finally, in focusing on interregional tourism-related trade flows in services, we must consider (apart from information and taste effects operating in goods) the potential reduction of lodging costs for tourists who take advantage of second homes and accommodations owned by relatives and friends, a reduction most likely to occur within single countries, as tourists travel back to the regions of their birth. Note that at least in some Mediterranean countries, like Spain, Italy and France, this phenomenon is far from sporadic, and may be occurring almost every weekend. However, most of the studies focus on trade in goods, without considering interregional trade in services or the role of interregional migration flows.

[1] Among others: Gould (1994), Head and Ries (1998), Dunlevy and Hutchinson (1999, 2001), Wagner et al. (2002), Rauch and Trindade (2002), Girma and Yu (2002), White and Tadesse (2008)

[2] For example, according to the Spanish National Accounts, more than 60% of Spain's GDP is produced by services, and more than 70% of Spain's total output is consumed within the country.

Then, we consider that an analysis of these effects on services and at the regional level is in order, and for several reasons. First, it is well known that services account for the largest share of total economic activity in all developed countries. Second, the lack of information on bilateral trade in services has stymied empirical work that quantifies border effects on services. Third, as mentioned, given the characteristics of services, we can reasonably expect information and tastes to have a greater effect on trade in services than on trade in goods. And, finally, because of data restrictions, most studies have focused on the link between international migration and international trade, ignoring the fact that most flows in both people and trade take place between the regions of single countries. There are, then, intuitively obvious reasons to analyze the relationships between trade flows in services sectors and immigrant stocks at the interregional level, but a lack of information has limited such analysis. To help fill this gap, we have already investigated—in de la Mata and Llano (2013)—whether similar results exist for regional trade in services linked with tourism[3]: Accommodations, Restaurants and Travel Agencies.

An additional novelty in de la Mata and Llano (2013) that is also explored in the present work is the use of spatial-econometrics techniques, which have elsewhere been used to analyze various topics in international economics, such as the determinants of foreign direct investment (Ledyaeva, 2009) and the effects of bilateral agreements (Porojan, 2001; Egger and Larch, 2008). It is important to include the geographical perspective in such analyses in order to control for the spatial dependence caused by spatial aggregation, spatial externalities, spillover effects and spatial heterogeneity (Anselin, 1988). Finally, Behrens et al. (2010) derived a structural gravity-equation system in which both trade flows and error terms were cross-sectionally correlated and estimable by means of techniques from the spatial-econometrics literature. According to their findings, directly controlling for cross-sectional interdependence reduces border-effect measurements by capturing 'multilateral resistance', which origin- and destination-specific fixed effects do not totally control for. As for social networks, we find—in addition to the trade-creation effects that the literature traditionally ascribes to emigrants and immigrants—potential sources of cross-section autocorrelation in the regional concentration of interregional emigration and immigration stocks. These sources, which we have labeled 'network autocorrelation' or 'demography-based autocorrelation', could also affect bilateral flows between two regions, as explained in Section 2.

In de la Mata and Llano (2013) we explored various models that allowed us to incorporate both spatial and demographic cross-sectional dependence. We estimated three versions of the Spatial Durbin Model (SDM), four versions of the General Spatial Model (SAC) and a Spatial Autoregressive Model that simultaneously incorporated two spatial lags (SAR): based on contiguity and based on regional demographic structure. All these models were estimated for different specifications and given robustness checks with a past-migration-flows variable, given by (a) a matrix of migration stocks in 1981 and (b) a second version of the same 1981 matrix that restricted the concept of 'neighbor' to the most intense demographic links. Our main conclusions can be summarized as follows: the distance coefficient turned out to have a negative sign, and therefore a negative effect, but the effect was mitigated when we

[3] There exist a few studies that analyze internal tourism flows, but they use input-output models (Eriksen and Ahmt, 1999) or time-series approaches (Athanasopoulus and Hyndman, 2008). None use a gravity model with cross-sectional data or pay attention to network effects.

controlled for intraregional flows and migration stocks, because the coefficient, while retaining the negative sign, became numerically smaller; the trade creation effect of social networks was confirmed, although the directionality of this effect (whether it was significant for emigrants, immigrants or both) depended on the spatial model used; the best performing model was the SAC model, which used a restricted version of the matrix (defining demographic neighbors by 1981 migrant stocks, so as to account for the spatial autocorrelation of the dependent variable) and a contiguity matrix (to control for the spatial autocorrelation in residuals). This confirmed a certain level of complementarity between the two types of autocorrelation, although the demography-based "network" autoregressive term was non-significant.

On the basis of these recent approaches and the results of our analysis in de la Mata and Llano (2013), in this paper we study the relationship between interregional trade flows in Accommodations and Restaurants as generated by travel. We use a gravity model that relies on conventional distance measures that are thought to inhibit flows and alternative social network-measures. For estimation purposes, we relied on spatial-econometric methods, incorporating cross sectional dependence based on contiguity and social-network dependence. The last one being measured by a spatial weight structure that links regions based on the stock of interregional immigrants living in each region. This type of interregional dependence is contrasted with more conventional weight structures based on the geographical proximity of regions. As in de la Mata and Llano (2013), we exploit recent estimates of intra- and interregional trade flows in tourism-related service sectors between Spanish regions (de la Mata and Llano, 2012b). We have used Maximum Likelihood (ML) estimation to test four alternative spatial-model specifications: namely, a spatial lag model (SAR), a spatial error model (SEM), a spatial Durbin model (SDM) and a spatial general model (SAC)[4]. Some of these specifications have been defined in such a way as to embed two different weight matrices, which attempt to capture (separately or simultaneously) the two previously described autocorrelation effects: spatial and demographic. We also report additional robustness analyses, using alternative measures that are thought to capture the pro-trade effect of variables representing different types of social networks, as described in Section 5.

One of the novelties of this paper is that we include only domestic flows linked with trips. This allows us to measure home-bias—defined as how many more times a region trades within itself than with any other region, once other factors are controlled for—in the domestic trips of Spanish residents at the regional level, as well as the extent to which strong social networks over short distances can explain the observed internal border effect. Interestingly, once social networks are controlled for, the home-bias of domestic trips tends to decrease or, in some cases, even disappear. With this analysis we confirm that social networks do, by various measurements, exert a trade-creation effect and that in most cases, once social networks are controlled for, the negative effect of distance vanishes. We also confirm the spatial autocorrelation of flows and test it with two complementary matrices: contiguity and main relative social networks.

In Section 2 we discuss trade in services and network influences on its flows. Section 3 presents an

[4] These models have been estimated using the spatial econometrics toolbox provided by James P. LeSage (www.spatial-econometrics.com)

empirical gravity model, detailing a series of increasingly complex specifications that control for spatial/geographical as well as network dependencies. In Section 4 we present and discuss our empirical results by applying the model to intra-and interregional trade flows associated with tourism in Spain. Section 5 includes an additional analysis with the model preferred in light of the results in Section 4, but instead of social-network variables we use different variables that try to capture other ways that social networks can be created.

2. Trade and social networks: background and definitions.

An economic network has been defined as a group of agents that pursue repeated, enduring exchange relations with one another (Podolny and Page, 1998). Using this definition, several authors have analyzed the impact on bilateral trade between origin and destination regions of the stock of immigrants in or emigrants from the importing and exporting region. Rauch (2001) pointed out in his review that any positive impact of immigration on trade may simply reflect immigrant preferences for goods from their countries of origin or a correlation of immigration with the trade-promoting characteristics of the country of origin or destination (e.g., geographic proximity). As other authors have shown, however, apart from these 'taste effects', there also exists a 'network effect' induced by social links that immigrants maintain with their countries of origin. Such links may lead to important reductions in transaction cost, which may in turn boost bilateral trade flows.

For our purposes, an immigrant is an individual born in a region ('homeland') different from his current region of residence ('host region'). Note also that, when considering interregional monetary flows in tourism-related sectors, we define the 'exporting region' as the one producing the service: in this case, the region receiving the tourists. Within these sectors are several channels that may lead to a positive relationship between the intensity of trade and the presence of social networks. We classify these channels into two groups, differentiating between relations that affect the trading regions ('emigrant and immigrant effects', as they have been traditionally labeled in the literature) and relations that affect the neighbors of trading regions (cross-section autocorrelation).

The empirical literature on the trade-creation effect of social networks identifies two main channels between our tourism-linked trade flows and interregional migration stocks:

1. Immigrants select their destination for internal (domestic) touristic trips in accord with family ties in their homeland (home region). Since tourists take advantage of vacations to visit their homeland, they may own homes or have access to property there. Thus the larger the stock of emigrants in a region, the greater the flow of exports from the emigrants' birth regions to their host regions. We call this the '*emigrant effect*'.
2. Conversely, non-migrant relatives and friends may tend to visit immigrants in their host regions, since these visits are made easier by access to information and to less-expensive accommodations than in other tourist destinations. Thus the larger the stock of immigrants in a region, the greater the flow of exports from the host region to the migrant homeland. We call this the '*immigrant*

effect'.

Apart from these two effects, which appear to enhance bilateral flows and have traditionally been analyzed in the literature on trade, there are additional channels of influence that could affect bilateral trade flows in tourism-related sectors. These additional channels arise from what we might consider cross-sectional autocorrelation due to 'spatial' or 'demographic' neighboring, and they tend to connect each bilateral trade flow of services with outflows from or inflows to the neighboring exporting or importing regions under consideration.

For origin and destination flows, Lesage and Pace (2008) described an 'origin-based dependence' and a 'destination-based dependence'. The former associates flows from *i* to *j* with flows from *i*'s neighbors to *j*, whereas the latter associates flows from *i* to *j* with flows from *i* to *j*'s neighbors[5].

Moreover, we could define a 'neighboring region' in terms of geographic proximity / spatial contiguity, as in Lesage and Pace (2008), or, more generally, in terms of proximity as measured by population and demography.

There could be **cross-sectional dependence** between a given flow and a flow from the exporting region's spatial neighbor (**contiguous region**) to the importing region (exporting-based dependence) and another flow from the exporting region itself to a neighbor of the importing region (importing-based dependence):

1. Export flows from a region *i* to a region *j* can be correlated with exports from *i*'s neighbors to *j*. This spatial dependence could be caused by:

   (a) The 'taste effect', in which exports of tourism-related services from one region and its contiguous neighbors to some other region are related because people living in the importing region may select any or all of the exporting regions as their destination for their similar characteristics (weather, culture, etc.).

   (b) People are more likely to have information about the tourism options of regions contiguous to the destination region and shared infrastructure often reinforces this channel.

2. Conversely, from the perspective of the importing region, there could also be some correlation between exports from a given region *i* to *j* and between the exports of the same region *i* and the neighbors of *j*. The mechanisms behind this spatial autocorrelation are equivalent to those described for the regions where flows originate (tourist destinations) but with the forces acting in the opposite direction.

For **cross-section autocorrelation** based on regional **demographic structure** (network dependence), we can also delineate two such mechanisms (on the basis of emigration from and immigration to each region):

1. The first relates a region's historical patterns of emigration with current tourist decisions through 'importing-based dependence'. If a given region's emigrants have concentrated in a group of host regions,

[5] LeSage and Pace (2008) described a third 'origin-destination–based dependence', which related flows between the neighbours of *i* and the neighbours of *j*. This paper, like Fischer and Griffith (2008), does not consider this relationship.

then a social network between home and host regions is likely to appear. People in this social network (e.g., members of one family living in different regions) may decide to travel periodically as tourists to the same region. Thus the imports of one region are not independent of the imports of its demographic neighbor. This cross-relation between a region's demographic neighbors may introduce effects that enhance or compete with the positive relation of migrants and trade in our three services sectors. As noted earlier, immigration is influenced by gravity, so 'demographic neighbors' could coincide with 'spatial neighbors'. However, alternative situations might also arise.

2. A second situation could give rise to 'exporting-based dependence'. If one region's emigrants are highly concentrated in another region, exports from the homeland to any other region *j* will be correlated with exports from the host region to region *j*. The mechanisms that explain this dependence on flows are similar to those explained before but act in a different direction, toward the trip destination (the exporting region).

Finally, it is important to highlight that immigrants could also affect the 'tourism decisions' of non-immigrants living in the same region. Since a large number of immigrants start families with their host region's natives, it is easy to imagine an influence arising from tastes and family ties that acts not only on immigrant tourism decisions but on non-immigrant tourism decisions as well. Moreover, an immigrant's relatives and friends still living in the homeland (but remaining in regular contact) could also spread their travel experiences and tastes to fellow inhabitants of the homeland. Although information and preferences would spread mainly within each of the two regions (homeland and host region), it could also gradually spread to neighboring regions. In Combes et al. (2005), this effect is described as the main force driving the relation between the 'information effect' and the 'border effect' for interregional trade in goods. In this paper, the effect is mixed with and strengthened by the effects described above.

In conclusion, we have described how the stock of immigrants and emigrants can influence bilateral flows between two regions through different channels, but also how a given region's trade flow can be related to the flows to and from contiguous regions and demographic neighbors (where a relatively large concentration of emigrants from one region lives in the other, or where a large share of a region's immigrants have been born in the other). We have described, furthermore, how all these influences could affect both immigrant and non-immigrant tourism decisions. These effects are summarized in **Figures 1** and **2**.

Figure 1 about here

Figure 2 about here

3. The empirical model

In this section, we first discuss the cross-section dependence of flows based on spatial and demographic neighboring and how they relate to our spatial econometric model. We set forth a series of alternative, increasingly complex specifications and compare them.

3.1. Spatial and demographic dependence affecting gravity-model estimates

Black (1992) suggested that network and spatial autocorrelation may bias the classical estimation procedures for spatial interaction models. He suggested that "autocorrelation may […] exist among random variables associated with the links of a network". Bolduc et al. (1992) suggested that classical gravity models do not consider the socioeconomic and network variables adjacent to bilateral origin-destination regions *i* and *j*, arguing that these should also be incorporated into the equation that attempts to explain flows (T_{ij}) between these regions. He emphasized that omission of neighboring variable values gives rise to spatial autocorrelation in the regression errors. The sources of spatial autocorrelation errors include model misspecification and omitted explanatory variables to capture effects related to a region's physical and economic characteristics (distances between zones, size of zones, length of frontiers between adjacent zones, etc.).

More recently, LeSage and Pace (2008) challenged the assumption that the origin and destination (OD) flows in the classical gravity model contained in the dependent variable vector T_{ij} exhibit no spatial dependence. They note that the use of distance alone in a gravity model may be inadequate for the modeling of spatial dependence between observations. Most socioeconomic spatial interactions (migration, trade, commuting, etc.) have several explanations. For example, neighboring origins (exporting regions) and destinations (importing regions) may exhibit estimation errors of similar magnitude if underlying latent or unobserved forces or missing covariates exert a similar impact on neighboring observations. Agents located in contiguous regions may meet with similar transport costs and profit opportunities when evaluating alternative nearby destinations. This similar positive/negative influence among neighbors could also be explained in terms of common factor endowments or complementary/competitive sectoral structures. For example, if natural factor endowments are key variables explaining patterns of trade specialization, neighboring regions with similar factor endowments may be affected in similar ways by demand and supply shocks. Since a large number of factor endowments are conditioned by space (similar natural resources and climate, joint transport infrastructures, etc.), it would be easy, on a sufficiently fine spatial scale, to find spatial autocorrelation in the sector specialization of regional production and trade.

As explained in the previous section, bilateral trade flows of tourism-related services could themselves be affected by these sources of spatial dependence. In the next section, we formally test an extended gravity-model specification that accounts for spatial and network (in our case, demographic) autocorrelation effects in interregional trade flows. The extended model subsumes models that exclude spatial and network dependence as special cases of the most elaborate model, and provides a simple empirical test for the presence of significant spatial and network dependence.

Our empirical model will be based on several alternative specifications that allow us to consider the interdependence of flows between two regions and of flows to and from their neighbors. In this respect, we have defined two different types of neighbors: one based on geography and regional borders (the contiguity matrix) and a second based on the relative importance of certain past migration flows, which allow us to take into account the interdependence of flows caused by the existence of social networks.

3.2. Introducing spatial and network effects in the gravity model

A conventional least-squares gravity-model specification is shown in Eq. (1), where bilateral flows (T_{ij}) between exporting region *i* and importing *j* are modeled as a function of a set of explanatory variables reflecting the economic size of the two regions and the distance (d_{ij}) between them. T_{ij} denotes the n × n matrix of exports in monetary units (current euros) of the services produced by Restaurants + Accommodations between each region *i* and imported by each region *j*. The size of the origin of the flow (exporting region) is proxied by the hospitality-industry gross value added in region *i* (gva_i), while the size of importing region *j* is modeled as depending on population (pop_j) and income (inc_j). A dummy variable $ownreg_{ij}$, taking the value one when trade is intraregional and zero otherwise, has been included to control for the different nature of intraregional trade flows (flows generated by trips within the region of residence), T_{ii}. Past studies (McCallum, 1995; Helliwell, 1997; Wolf, 2000; Chen, 2004; Okubo, 2004; Combes et al. 2005; Requena and Llano, 2010) have interpreted the coefficient associated with this dummy variable as an 'internal border effect' or 'home bias'. Once we have controlled for other factors (size, bilateral distance, presence of a social network), we interpret the coefficient linked with this dummy variable, γ , as the number of times one region tends to trade more within itself than with any other region in the country. We measure the trade creation effect of social networks by introducing the variables m_{ij} and m_{ij}. The former captures the effect of emigrants on trade exports from region *i* to *j*; similarly, the latter captures the variation in flows due to the stock of immigrants hailing from region *j* but living in region *i*. In a first specification we imposed the value of zero on both coefficients, while in a second we obtained both effects simultaneously. For simplicity we are not using alternative specifications with just one of the coefficients set to zero and thus estimating the 'emigrant' and 'immigrant' effect separately. We have already carried out this analysis, although with slightly different data, in de la Mata and Llano (2013).

$$T_{ij} = \alpha i_N + gva_i\beta_1 + pop_j\beta_2 + inc_j\beta_3 + d_{ij}\beta_4 + ownreg_{ij}\gamma + m_{ij}\beta_5 + m_{ji}\beta_6 + \varepsilon_{ij} \quad (1)$$

One may wish to consider the presence of potential multicolinearity problems caused by a high correlation between emigrant and immigrant bilateral flows. To cope with this limitation, Eq. (2) uses a single vector for bilateral "net migration" $m_net_{ij} = (m_{ji} + m_{ij})$ with which to capture the aggregate effect of immigrants + emigrants on trade. This third specification will be considered also for the forthcoming augmented models, which will include spatial and network effects.

$$T_{ij} = \alpha i_N + gva_i\beta_1 + pop_j\beta_2 + inc_j\beta_3 + d_{ij}\beta_4 + ownreg_{ij}\gamma + m_net_{ij}\beta_7 + \varepsilon_{ij} \quad (2)$$

3.3. Alternative spatial models for origin and destination flows

To determine whether spatial dependence on the bilateral flows discussed in previous sections is consistent with the data, we follow the approach set forth in LeSage and Pace (2008) and make our next spatial regression models rely on the spatial lags of the dependent variable. These models also include all the explanatory variables from the previous models, allowing them to subsume the non-spatial regression

models as special cases. We include a spatial lag of the dependent variable (WT_{ij}), the independent variables (WX_{ij}), the error term (Wu_{ij}), or some combination thereof, where W represents a spatial weight matrix of the form suggested by LeSage and Pace (2008).

In a typical cross-sectional model with n regions, where each pair of regions represents an observation, spatial regression models rely on an n × n non-negative weight matrix that describes the connectivity structure between the n regions. For example, $W_{ij} > 0$ if region i is contiguous with region j. By convention, $W_{ii} = 0$ to prevent an observation from being defined as a neighbor to itself, and the matrix W is typically row-standardized. In the case of bilateral flows, where we work with $N = n^2$ observations, LeSage and Pace (2008), Chung (2008), Chun and Griffith (2011) and Fischer and Griffith (2008) suggest using $W^{spa} = W_j^{spa} + W_i^{spa}$, where $W_j^{spa} = I_n \otimes W_s$ represents an N × N spatial weight matrix that captures connectivity between the importing region and its neighbor, and $W_i^{spa} = W_s \otimes I_n$ is another N × N spatial weight matrix that captures connectivity between the exporting region and its neighbor[6]. We row-standardize the matrix W^{spa} to form a spatial lag of the dependent variable.

LeSage and Pace (2008) note that the spatial lag variable captures both 'destination-' and 'origin-based' spatial-dependence relations using an average of flows from neighbors to each origin (exporting) and destination (importing) region. Specifically, this means that flows from any origin to a particular destination region may exhibit dependence on flows from the origin's neighbors to the same destination—a situation that LeSage and Pace (2008) call origin-based dependence. The spatial lag matrix, W^{spa}, also captures destination-based dependence, which is a term used by LeSage and Pace (2008) to reflect dependence between flows from a particular origin region to neighboring regions of the destination region.

We take a similar approach to produce a network-dependence weight matrix, W^{net}, which captures network autocorrelation effects. As in the case of W^{spa}, the W^{net} matrix is formed as a sum of two matrices that specify 'demographic neighbors' to the origin and destination regions, specifically $W^{net} = W_i^{net} + W_j^{net}$. The matrix $W_j^{net} = I_n \otimes W_{81-}^{net}$, where W_{81-sy}^{net} is constructed on the basis of regions with the strongest demographic links as shown by past migration-stock patterns, is an N x N weight matrix that captures connectivity between the importing region and its demographic neighbors. Details on the procedure used to build this matrix are provided in the next section. Similarly, $W_i^{net} = W_{81-sy}^{net} \otimes I_n$, and the matrix W^{net} is row-standardized. This allows us to include in this model a network lag of the dependent variable shown in Eq. (1) and (2).

We will now present our econometric models, which allow us to account for the different structures of the flows' spatial dependence.

A Spatial Lag Model

[6] We use the symbol ⊗ to denote a kronecker product.

Eq. (3) is a spatial lag model, including: i) a spatial lag of the dependent variable (WT_{ij}), in which T_{ij} is the N × 1 vector representing the n × n flows matrix transformed into a vector, W is one of the previously described matrices used to capture spatial autocorrelation based on contiguity or demographic structures; i_N is an N × 1 vector of ones; gva, pop and inc are N × 1 vectors containing the explanatory variables; d is the n × n matrix of interregional distances transformed to an N × 1 vector appropriate for each bilateral flow; $ownreg_{ij}$ is an identity matrix of order n controlling for intraregional flows that has been transformed into an N × 1 vector; m_{ij} and m_{ji} are two n × n matrices of interregional migration stocks transformed into a pair of N × 1 vectors and ε is an N × 1 vector of normally distributed constant variance disturbances.

The scalar parameter ρ denotes the strength of spatial dependence in flows. When it takes the value of zero the model in Eq. (3) becomes the independent regression model. This allows us to carry out a simple empirical test for the statistical significance of spatial dependence in the flows.

$$T_{ij} = \alpha i_N + \rho WT_{ij} + gva_i\beta_1 + pop_j\beta_2 + inc_j\beta_3 + d_{ij}\beta_4 + ownreg_{ij}\gamma + m_{ij}\beta_5 + m_{ji}\beta_6 + \varepsilon_{ij} \quad (3)$$

Then, as in Eq. (3), a new Eq. (4) can be defined, where immigrant and emigrant effects are added in a single net migration vector.

$$T_{ij} = \alpha i_N + \rho WT_{ij} + gva_i\beta_1 + pop_j\beta_2 + inc_j\beta_3 + d_{ij}\beta_4 + ownreg_{ij}\gamma + m_net_{ij}\beta_7 + \varepsilon_{ij} \quad (4)$$

A Spatial Error Model

The spatial error model is appropriate when the error terms of particular regions are can be expected to be linked. The parameter λ captures the presence of spatial dependence in the residuals of the bilateral flows.

$$\begin{aligned} T_{ij} &= \alpha i_N + gva_i\beta_1 + pop_j\beta_2 + inc_j\beta_3 + d_{ij}\beta_4 + ownreg_{ij}\gamma + m_{ij}\beta_5 + m_{ji}\beta_6 + u_{ij} \\ u_{ij} &= \lambda Wu_{ij} + \varepsilon_{ij} \\ \varepsilon_{ij} &\square (0, \sigma^2 I_N) \end{aligned} \quad (5)$$

For the sake of simplicity, in this and the following models we do not include a new equation to describe the corresponding models in which the "net migration" vector would be used instead of their emigrant and immigrant counterparts. However, we analyze the corresponding results in the next section.

Now we briefly describe two of the models that allow us to test for more elaborate structures of dependence in the flows: the spatial Durbin model and the spatial general model.

A Spatial Durbin Model

This model, described in LeSage and Fischer (2008) and elsewhere, has been applied in the context of gravity equations by Angulo et al. (2011). In contrast to the previous models, it assumes spatial dependence in the dependent and independent variables, as described in Eq. 6:

$$T_{ij} = \alpha i_N + \rho_1 W T_{ij} + X\beta + WX\gamma + \varepsilon_{ij} \quad (6)$$

Where WX is the spatial lag of all the independent variables included in X. Note that, in contrast to previous specifications included in this paper, only one weight matrix is used at a time, but it generates two sources of spatial dependence. An SDM gravity model with two alternative W matrices has not been reported in the literature. Here, however, we depart from this common specification and estimate three alternative models using the following weight matrices, as in de la Mata and Llano (2013): (i) $W_1 = W^{spat}$, (ii) $W_2 = W^{net}$, (iii) $W_3 = W^{spa} + W^{net}$.

A Spatial General Model

The last model, based on the spatial general model (SAC) described in LeSage and Pace (2009, p. 32), considers spatial dependence in both the dependent variable and the disturbance term, as described in Eq. (7):

$$\begin{aligned} T_{ij} &= \alpha i_N + \rho W_1 T_{ij} + gva_i\beta_1 + pop_j\beta_2 + inc_j\beta_3 + d_{ij}\beta_4 + ownreg_{ij}\gamma + m_{ij}\beta_5 + m_{ji}\beta_6 + u_{ij} \\ u_{ij} &= \lambda W_2 u_{ij} + \varepsilon_{ij} \\ \varepsilon_{ij} &\sim (0, \sigma^2 I_N) \end{aligned} \quad (7)$$

Note that the model described in Eq. (7) considers two different weight matrices, W_1 and W_2, each capturing the effects on the dependent variable and the disturbance term. Following the recommendations of LeSage and Pace (2009, p. 32), we will consider four alternative cases, without imposing a preferred structure to the data in advance: (i) $W_1=W^{spa}$, $W_2=W^{net}$; (ii) $W_1= W^{net}$, $W_2= W^{spa}$; (iii) $W_1= W_2= W^{spa}$; (iv) $W_1= W_2= W^{net}$.

4. An application to Spanish domestic trade in certain service sectors

4.1. The Data

Like most countries, Spain has no official data on monetary interregional trade flows associated with the two tourism-related sectors we are considering here: Restaurants and Accommodations. To group these sectors between the Spanish regions, our application takes advantage of recent estimates of intra- and interregional trade flows. To generate our dataset for 2000–2009 (de la Mata and Llano, 2012b)—a dataset constructed as part of a larger research project (www.c-intereg.es)—we improved on the methodology presented for 2001 in Llano and de la Mata (2009) and analyzed in De la Mata and Llano (2012a). Schematically, the methodology comprises two steps:

1. Estimation of the portion of each region's output that is consumed by Spanish citizens (i.e., that is not exported internationally);

2. Determination of the bilateral distribution of each region's non-internationally-exported output. This second step uses existing information on the daily expenses of domestic travelers in the destination region and origin and destination matrices (Familitur surveys and Occupancy Surveys) that capture the overnight stays and displacements of Spanish residents, depending on the accommodation types available in destination regions. The estimation uses different daily expenses in 'Accommodations' and 'Restaurants and the Like' for hotels, apartments, campsites, rural tourism, the homes of friends and relatives, second residences and excursions, covering all possible trip motives (leisure, work, education, etc.). We have performed separate estimations for Accommodations and Restaurants. By not including expenses for transport, shopping or any other goods or services in our data, we avoid endogeneity problems between interregional trade flows of tourist services and transport costs related to bilateral distance.

3. Proportional adjustment of bilateral flows for Accommodations to total output, and adjustment of the sum of interregional exports for '*Restaurants and the Like*' to output, under the assumption that the difference is the daily consumption in this sector[7].

In summary, the estimates for the interregional monetary flows of the two service sectors analysed (Accommodations and Restaurants) use the most accurate statistical sources available in Spain, obtaining figures that are constrained by the regional and national output of the sector (Instituto Nacional de Estadística, INE), the Balance of Payment (Bank of Spain) and the widest available sample of surveys on people movements within the country (Familitur, Instituto de Estudios Turísticos).

Figure 3. about here

To provide an overview of internal flows for the Spanish sectors considered in this work, **Figure 3** shows the largest average interregional monetary flows in Accommodations and Restaurants, as well as the distribution of the population and the location coefficient for the 'Hotels and Restaurants' sector (LCRegion = Regional Hospitality Industry GVA / National Hospitality Industry GVA). Arrows from eastern coastal regions (Andalucía, C. Valenciana and Cataluña) to the landlocked region of Madrid show that a large share of interregional exports (in current euros) in Accommodation and Restaurants flow from these regions to Madrid. This is a consequence of the large number of travelers from Madrid to Andalucía. It is easy to see from the figure that the major exporting regions are located along the coast, with the largest importers located in the most populous high-income regions. There are also large exports from the islands to populous regions (Canarias to Madrid and Baleares to Madrid and Cataluña). In addition, there are many flows between the largest regions, such as exports from Cataluña to Madrid and Madrid to Cataluña or Andalucía. Note also that some of the largest interregional flows occur between distant regions. Finally, there are strong flows from the landlocked larger regions to contiguous, richer regions (Castilla y León and Castilla–La Mancha to Madrid). These results can be explained first by the

[7] In de la Mata and Llano (2013) we included the consumption for restaurants not linked to trips and travel agencies. These two types of consumption only increase intraregional flows, but since they have a different nature, we have in this case preferred to keep them out of the analysis. Note that we have nevertheless retained intraregional flows generated by trips within the region of residence.

size of the regions (in terms of population and income or gross domestic product) and second by important social networks that have arisen as a result of historical bilateral migration flows.

For the remaining variables, we use the hospitality – industry gross value added (*gva*), regional income (*inc*) from the Spanish Regional Accounts (INE) and population (*pop*) from the Spanish Register (INE). The interregional migration matrices are also obtained from the Spanish Register (INE), which offers information on the stock of region inhabitants born in other regions. The direct effects captured by the m_{ij} and the m_{ji} terms enter as two independent column vectors.

Distances are obtained from the 2001 Movilia survey (Ministerio de Fomento); these are the actual distances travelled by Spanish residents in their displacements, both within and between regions. The inclusion of both inter- and intraregional distance is one of the most interesting features of this measure. In line with Head and Mayer (2010), then, we are able to escape from the a priori quantification of intraregional distances assumed in other papers. Moreover, the distance used is an average of the actual distance travelled in each of the more than 500 million displacements estimated by the 2001 Movilia survey. These displacements cover all motives, so that reported distance is not constrained to the distance between capitals, which, while perhaps predominant for business trips, does not reflect the distances between peripherally located tourist spots (beaches, skiing resorts, the countryside, etc.).

The spatial weight matrices have been built to take into account first-order contiguity relations based on shared borders, with islands treated as having no adjacent regions. The demographic network weight matrix W_{81}^{net} is built to depart from an OD matrix of the stock of immigrants born in one region and living in another, with diagonal elements set to zero. We obtain this weight matrix through the following steps: (i) We create a matrix containing the stock of interregional migrants in 1981 as reported in the Spanish census. (ii) For $W_{81_born}^{net}$ we use every home region's share of interregional immigrants with respect to every host region's total (forming the rows), while for $W_{81_residence}^{net}$ we use the every host region's share of interregional emigrants with respect to each home region's total (forming the columns). (iii) Next, we compute the 90th percentile in the distribution of the shares of interregional migration for each *home* and *host region*. We then consider two regions to be neighbors when the threshold defined by the 90th percentile is lower than the corresponding share. In this case, the corresponding W matrix will either contain this share or have a value of zero. Note that by obtaining our two matrices, $W_{81_residence}^{net}$ and $W_{81_born}^{net}$, in this way, we ensure that every region has a positive number of neighbors and that the neighbor relation depends not on the size of both regions but on the relative weight that each region represents in the overall demographic structure of all the regions[8]. (iv) Adding these two matrices, we

[8] For example, emigrants from the Islas Canarias, with their small population, do not represent more than 2% of interregional immigrants living in any other region. The largest shares are found in Andalucía, Baleares and Murcia. In these regions, immigrants from the Islas Canarias represent a 1.4%, 1.2% and 1.3% of total interregional immigrants. Their relative weight is higher in those regions than in Madrid (although in absolute terms are higher in Madrid), where they represent just the 0.2% of total interregional immigrants. According to our definition, then, Canarias is a demographic neighbor of Andalucía, Baleares and Murcia and not of Madrid, because its relative magnitude is higher for the former group of regions than for the latter.

obtain a general matrix $W_{81}^{net} = W_{81_{born}}^{net} + W_{81_{residence}}^{net}$. (v) Then we add the W_{81}^{net} matrix to its transpose, imposing bidirectional links between regions and obtaining a symmetric version, $W_{81-sy}^{net} = W_{81}^{net} + W_{81}^{net\prime}$. In de la Mata and Llano (2013), $W_{81_{born}}^{net}$ and $W_{81_{residence}}^{net}$ were used independently as two alternative W matrices, with very similar results. This matrix has also the virtue of capturing a stock of interregional relations with a twenty-year lag with respect to the interregional bilateral flows used as endogenous variables in all of our models. This strategy overcomes the main criticism of endogeneity and circular causation.

Figure 4 about here

Figure 4 helps determine whether the patterns described by the two baseline W matrices considered in this work (contiguity and social networks) are similar or very different. Cells with an "O" represent country-pairs that are contiguous but not considered demographic neighbors. Cells with an "X" are country-pairs that are considered demographic neighbors but are non-contiguous. Finally, cells with a "$\otimes$" represent country-pairs that are both contiguous and demographic neighbors. From **Figure 4**, although thirty-six (of a total 289) country-pairs are neighbors in both matrices, twenty are contiguous but not demographic neighbors and twenty-two are demographic neighbors but non-contiguous. Thus a certain level of complementarity between both W matrices exists. Cataluña, for example, is simultaneously (i) contiguous with but not a demographic neighbor to the Comunidad Valenciana, (ii) a demographic neighbor to non-contiguous regions like Andalucía and the Islas Baleares and (iii) a demographic neighbor and contiguous region to Aragón. By working with two W matrices instead of just one, we expand our ability to capture complexities and complete relations.

4.2. Alternative measures for capturing the pro-trade effect of social networks

As a robustness check, we define certain alternative social-network measures, which enter into the model by substituting for the interregional migration stocks captured by m_{ij} and m_{ji}, or $m_net_{ij} = (m_{ji} + m_{ij})$ in the case of net effects.

For the sake of simplicity, since all these alternative variables are dyadic, and connect the trading regions *i* and *j*, we retain the same variable names (m_{ij}; m_{ji}; m_net_{ij}) as in Eq. (7). However, the model is re-estimated eighteen times with these alternative proxies for the social links between each pair of Spanish regions. It is important to remark that we intend this robustness analysis to consider alternative channels through which information and taste effects might be enhancing interregional trips and, thereby, the corresponding interregional flows of services in euros.

<Table 1 about here>

A brief description of each of these variables is shown in **Table 1**. Here, as when the stock of migrants was considered, these variables are likely to have a bidirectional effect. That is, an individual will travel to visit the members of his social network in regions other than his region of residence, but the members

of his social network will also travel to visit him.

The variables **soc-net-2** and **soc-net-10** are equivalent to the interregional stock of migrants from the 1981 Spanish census but draw from the 2001 and 1991 censuses respectively. The use of these two alternative variables will illustrate the stability of interregional links as well as the persistence of the effects in different periods. The **soc-net-8** variable restricts this concept to employed individuals over sixteen years of age. Despite some differences, the pattern of interregional migrations is similar for all migrant stocks[9] and similar to the born-residence links of 1981. This new measure is meant to determine whether information and taste effects are equivalent for employed people and for the general population. The purpose of testing this is twofold: (i) on the one hand, part of our interregional flows of services can be caused by professional trips within Spain; (ii) on the other, we should remember that information and taste effects can be transmitted between co-workers as well as between relatives and friends. Moreover, social connectivity can operate between different generations and social groups. An 'active' person's decision to travel, for example, can affect the travel decisions of other active or non-active people.

Soc-net-3 measures the impact of second-home ownership. This variable is drawn from the 2001 Spanish census and defined as the stock of people living in one region and owning a second home in any other. Although some of the main bilateral relations exist between region-pairs with strong migration relationships, others do not. For example, while immigrants from Andalucía living in Cataluña account for almost 11% of the total stock of interregional migration, residents in Cataluña owning a second home in Andalucía account for just 2% of total second homes in a region other than the region of residence. People living in Madrid and owning a second home in Castilla–La Mancha or Castilla y León represent the 11.7% and 10.3 % respectively of total second homes in a region other than the region of residence, while emigrants from these regions living in Madrid each account for the 6.5% of total interregional migration stocks, according to the 2001 Spanish census. It is also important to note the high share of second homes in the Comunidad Valenciana owned by residents in Madrid (10.4% of the total), while emigrants from the Comunidad Valenciana in Madrid accounted for less than 1% of total interregional migration stocks. An additional example of this unclear relationship between interregional migration stocks and interregional second-home ownership is found in the País Vasco. First, residents in the País Vasco that own a second home in Castilla y León account for 4.6% of total second homes owned by residents of any other region. This can be explained by the share of emigrants from Castilla y León living in the País Vasco, but it is also notable that Basques own a large share of second homes in nearby regions, such as Cantabria, and represent 3.2% of total second homes in Cantabria owned by residents in different regions, whereas first-generation Cantabrian emigrants in the País Vasco account for less than 0.5% of total interregional migration stocks, according to the 2001 Spanish census. Although this variable is affected by certain interregional migration relationships, it also describes other patterns related to frequent trips by one region's residents to other regions, patterns that could promote the advantages of owning a second home in these regions. Because of the bidirectional effect of this variable, we should expect: (i)

[9] The main emigration stocks are found from Andalucía to Cataluña; from Castilla y León, Castilla–La Mancha, Andalucía and Extremadura to Madrid; from Castilla–La Mancha and Andalucía to the Comunidad Valenciana; from Castilla y León to the País Vasco and Cataluña; and from Extremadura to Cataluña.

that the larger the share of second homes owned by non-residents, the larger the interregional export flows of services from the region of residence to the region where the second homes are located, and (ii) that personal relationships created in the region where the second home is located will create incentives to travel to the region of residence of the individuals who own the second homes.

Soc-net-4, soc-net-5, soc-net-13 and **soc-net-14** concern the social networks created between the region of residence and the birthplace of the residents' mothers or fathers as drawn from the 2001 (**soc-net-4, soc-net-5**) and 1991 Spanish censuses (**soc-net-13, soc-net-14**). These variables try to measure the impact of second-generation migration, although they can also capture the effect of families that move to other regions once their children are born; such children are considered first-generation or generation 1.5. In any case, in a country like Spain, part of the social network of individuals whose parents are migrants might pertain to the parents' family in the region of origin, independently of the individuals' region of residence. Despite some differences, the largest interregional stocks correspond to those of **soc-net-2** and **soc-net-10**. A fifth variable from the 1991 census (**soc-net-15**) relates the birth region of the father and mother. It shows the strongest links between contiguous regions or regions linked by migration stocks (birth vs. residence). All these variables are in relation to the previously mentioned 'mixed couples' concept, where the two partners are born in different regions of the country.

In addition, migrations that take into account the link between previous and current places of residence are relevant to determining the existence of social networks. We are drawing our links between current and previous region of residence (**soc-net-6**) from the 2001 census (and disregarding individuals' date of migration), our links between current region of residence and region of residence ten years earlier from the 2001 and 1991 censuses (**soc-net-7**, **soc-net-11**) and our links with any of region of residence over the previous ten years (**soc-net-12**) from the 1991 census. Of course, the previous region of residence sometimes coincides with an individual's birth region, but not always. For instance, an individual might migrate to a region and spend part of his life there before moving back to his home region for retirement. Such a displacement from host to home region is captured as an interregional movement by these variables, whereas in the matrix capturing the birth-vs.-residence relationship it is counted as an intraregional migration (birth and residence in the same region), although the person in question would still probably keep friends and part of his family in the region where he has been living part of his life. Thus the birth-vs.-residence variable is unable to capture this type of relation. On the other hand, we can capture an individual migration dating more than ten years into the past as an intraregional movement by using the matrices describing past vs. actual residence. But in this case we cannot capture the migration as an effect of the social network in the migrant's homeland, whereas the birth-vs.-residence matrix would allow us to do so.

An additional cause of social-network creation is work relationships. To take this into account, we are including links between regions of residence and workplace regions (**soc-net-9**). Commuters may create an additional social network with co-workers, providing them with information about their regions of residence as well as feeding their home-region social networks with information about their workplace regions. The main commuting links exist between close and contiguous regions, like Madrid and Castilla–La Mancha (and vice versa), Castilla y León and Madrid, and the Comunidad Valenciana and Murcia. It

is surprising to find relatively strong links between such distant regions as Extremadura and Madrid. It could be that certain people spend only a short part of the year working in other regions and thus do not change their region of residence. It could also be that at the time the census they were living in a region (region of residence) where they used to work.

Additionally, past interregional trips (**soc-net-16**) and overnight stays, whether in any kind of establishment (**soc-net-17**) or in a regulated establishment (**soc-net-18**), are included. Such trips correspond to the average reported in the official statistics for 2000–2004—that is, the period preceding the one captured by the endogenous variable (in euros). Past bilateral trips can help account for more recent flows in two ways. First, traveling individuals come into contact with residents in their destination regions and can create a network with them, thereby inspiring trips from these destination regions to the individuals' regions of origin. We can capture this kind of effect by including these variables. Moreover, their transpose versions capture the inertia of the series and how the trips of one region's residents to any other region can subsequently inspire fellow residents of the origin region to travel to the same destination. Finally, we include a matrix of parcel posts **soc-net-19** as a proxy for social and business networks. This last variable captures both tight social-network links (as between Andalucía and Madrid) and tight business-network links (as between Madrid and Cataluña). As we explain below, the nature of this variable has implications for the results generated with it. Although with this variable we try to capture all kinds of networks—and not just social networks driven by different types of migration— the truth is that high parcels links can be found between regions with strong social and business links as well as between distant regions, so post and parcel traffic might be a satisfactory alternative to face-to-face relations for the members of a social network to keep in contact.

<Figure 5a, 5b about here>

Figures 5a and **5b** show the pattern of the eighteen alternative social-network measures described in **Table 1**. Although all the variables enter the model as column vectors, they are all obtained as the vectorialization of an equivalent set of origin-destination matrices. For comparison, the first graph in both **Figure 5a** and **Figure 5b** corresponds to the pattern for the migration variable used in the previous section, which represents the stock of people born in one region and residing in any other, as reported in the 1981 Spanish census. The other eighteen graphs correspond to the origin-destination matrices of these alternative measures for social networks, where *i* and *j* are ranked in accord with the 1981 census stock of interregional migrants. To avoid scale problems, intraregional flows are not included in these graphs. However, both intra- and interregional connections are included when they are entered into the regressions. A glance at these graphs should make the differences and similarities between the flows clear.

4.3. Estimation results

Here we compare results from the sequence of models estimated for the bilateral flows between seventeen NUTS 2 Spanish regions (N = 17 × 17 = 289 observations based on the average of the flows in 2005–2009), with Ceuta and Melilla excluded. In this case, since two of the alternative social network variables

(**soc-net-17** and **soc-net-18**) that we want to test is the previous trips, we have decided to select the flows for the last 5 years available in the dataset in order to construct the dependent variable. All the variables (except dummy variables) are averaged and log-transformed, as is customary in the estimation of gravity models. We could have estimated the same specifications for each year, but, for the sake of simplicity, in this section we will comment on the results with averaged data, which reduces the effect of outliers.

Table 2 shows the results for three different specifications estimated by Ordinary Least Squares, all of them accounting for more than 84% of the variation of the 289 bilateral flows. The first excludes both m_{ij} and m_{ji}, the second includes both, and the third substitutes m_net_{ij} for both. The estimated coefficients are significant and have the expected signs -positive for size variables and negative for distance-, but the signed numerical value of the latter increases once the social-network variables are included. Similarly, the border-effect variable halves when social-network variables are introduced, suggesting, in agreement with Garmendia et al. (2012), that social networks reduce the magnitude of the border effect. However, we still have a positive and significant coefficient, which suggests that bilateral flows are more than 150% larger than interregional ones, even when we control for region size, interregional distance and interregional social networks. This result, obtained with trip-generated bilateral flows only, contrasts with the results in de la Mata and Llano (2013), where the inclusion of other types of intraregional flows, such as travel-agency services and non-trip-linked consumption in Restaurants and the Like, generated a more intense 'border effect'.

Finally, we also obtain a positive and significant impact for all social-network variables.

Table 2 about here

Table 3 about here

We now move on from these first estimates to consider several statistical tests, with the aim of motivating the inclusion of spatial lag and/or spatial error terms. This analysis is conducted by computing the I-Moran, and the classic and robust versions of the LM-lag and the LM-error statistics over the residuals obtained for the three models. In all of them we consider the spatial structure based on three different spatial weight matrices (each row-normalized): (i) W_i^{spa}, to capture the "spatial origin-based" autocorrelation; (ii) W_j^{spa}, to capture the "spatial destination-based" autocorrelation; and (iii) $W^{spa} = W_i^{spa} + W_j^{spa}$, to capture the aggregate spatial autocorrelation (as previously stated, we omit the origin-to-destination–based element). The results for the three models, five tests and three spatial autocorrelation matrices are reported in the first three columns of **Table 3**. All cases show spatial autocorrelation in the residuals (Moran I analysis). This result is found for the 'origin-based' and 'destination-based' weight matrices, as well as when both are mixed in a single spatial matrix ($W^{spa} = W_i^{spa} + W_j^{spa}$). As for the LM tests, in all cases except when both 'emigrants' and 'immigrants' are introduced and $W = W_i + W_j$ is used (Model 2, LM error tests for spatial correlation in the dependent variable), the test confirms the suitability of a spatial lag model (SAR) as well as a spatial autoregressive error model (SEM). When the robust version of these two previous tests is used, non-significant results are obtained in the robust LM error tests for spatial autocorrelation in the dependent variable generate non-significant results when $W = W_i + W_j$, but the results are indeed significant when '*origin'*- and '*destination'*-based dependence are tested for separately.

We then conduct a similar exercise using the network (demographic) weight matrices to analyze the results for the same three models. These results are reported in the columns (4)–(6) of **Table 3**, and consider three alternative demography-based weight matrices: namely, the origin-based demographic-neighbor structure (W_i^{net}), the destination-based demographic-neighbor structure (W_j^{net}) and the aggregate origin+destination–based demographic-neighbor structure ($W^{net} = W_i^{net} + W_j^{net}$). Although most of the tests confirm the presence of network (demographic) autocorrelation effects when origin- and destination-based weight matrices are used, some tests are non-significant in some cases[10].

In conclusion, although non-significant cases exist[11], the significant results obtained in most cases, for both spatial and demographic weight matrices, support the wisdom of estimating a number of alternative specifications, which would preferably consider two potential sources of autocorrelation (spatial and demographic) affecting the dependent variable and/or the disturbance term. We therefore now proceed to analyze the results obtained using the Spatial Lag Model (SAR), the Spatial Error Model, the Spatial General Model (SAC) and the Spatial Durbin Model (SDM). These models have been estimated with maximum likelihood methods (cf. LeSage and Pace (2009), Chapter 3).

Next we analyze the results obtained for the augmented gravity models that consider the presence of spatial and/or network (in our case, demographic) effects. But first it is important to keep in mind, as pointed out in LeSage and Pace (2009), Chapter 8, that the coefficient estimates on the explanatory variables in these models are not interpretable in the same fashion as those in non-spatial models. However, the sign of the coefficient estimates reflects the correct direction of impact on flows that would arise from changes in the explanatory variables[12].

Estimation results for the spatial autoregressive model (SAR) are shown in **Table 4**. Unlike non-spatial least-squares estimates, which treat all flows as independent, these models allow for the spatial dependence of flows for neighboring regions and for spatial dependence based on the influence of social networks. The two specifications that include any social-network measure ($m_{ij}, m_{ji}, m_net_{ij}$) have each been estimated with the two different W matrices considered. The first and second columns in **Table 4** consider the spatial dependence of flows as based on the contiguity matrix, while the third and fourth column consider the spatial dependence based on demographic links.

Table 4. about here

In all cases, the coefficients for size variables are significant and have positive signs; the coefficient controlling for intraregional flows is also significant, with a coefficient ranging from 1.051 (column 1) to

[10] Non-significant results are found when: i) the W_i is considered in the model without migration variables and with m_{ij} and m_{ji} included separately (column 4 and 5) according to the Robust LM test in the residuals; and when the net migration variable is included (column 6) according to the Moran I test and to the LM error tests for spatial correlation in residuals; ii) the W_j is considered in the model without migration variables and with m_{ij} and m_{ji} included separately (column 4 and 5) according to the Robust LM lag test.

[11] For these non-significant results it is important to remark that the tests used here cannot combine the two alternative autocorrelation effects at the same time, while some of our models can.

[12] The correct approach to calculating partial derivatives, showing the impact of changes in the explanatory variables on the dependent variable in spatial gravity models, is studied in Lesage and Thomas-Agnan (2012).

1.135 (column 4). For the distance variable, we obtain a low negative coefficient, significant in all the cases except where migration variables are included separately and spatial dependence is based on contiguity. In addition, the trade-creation effect of migration is confirmed in all cases, although the magnitude of the impact depends on the type of autocorrelation considered and on the social-network variable included (emigrants, immigrants or total migration linkage). When immigrants and emigrants are included separately, immigrants have a greater effect than emigrants. In fact, the effect of emigration is not significant when spatial lag based on demographic structure is considered. When the effect of migration is measured as the net effect of emigrants and immigrants, the effect is positive and significant but lower than that of immigrants when the emigrant and immigrant stocks are included separately. Finally, the estimated parameter ρ, which captures the dependence of flows, is positive in all cases although non-significant, unless at 5% when the W matrix considered is the contiguity matrix. It is positive and highly significant when we control for the dependence of flows based on social-network links.

Judged by likelihood-function values, the higher pseudo R^2 and lower noise variance estimate($\widehat{\sigma^2}$13) model in column three, with dependence based on social networks and emigrants and immigrants included separately, has the best fit.

Once we have confirmed the presence of autocorrelation in the flows, it is interesting to test whether a similar autocorrelation exists also in the residuals of the models. **Table 5** shows the results for the spatial error model. As before, we get positive and significant coefficients for the variables that capture the size of the regions. In this case, the distance and the 'intra' variables are non-significant when the spatial autocorrelation based on contiguity is controlled for (columns 1 and 2), while they are significant when the network autocorrelation of the flows is controlled for (columns 3 and 4). The effect of the migration variables is significant and positive in all cases, although the magnitude of their effect depends on the type of autocorrelation considered: when we consider contiguity, the effect of emigrants is greater than that of immigrants, while the opposite is true when we consider social-network autocorrelation. The parameter estimates of the spatial correlation of the residuals are positive and significant in all cases, with greater magnitudes generated by contiguity.

Table 5. about here

After confirming the presence of spatial and demographic autocorrelation in the flows and the residuals, we focus on the results for the general spatial model and the four specifications described above: SAC-I: ($W_1 = W^{spa}$; $W_2 = W^{net}$); SAC-II: ($W_1 = W^{net}$; $W_2 = W^{spa}$), SAC-III: ($W_1 = W_2 = W^{spa}$); SAC-IV: ($W_1 = W_2 = W^{net}$). These results are shown in **Table 6**.

The first thing to note is the strong similarity between the two specifications in each of the four cases. The more remarkable difference across each of the four cases is that in SAC-II and SAC-III (when the spatial autocorrelation in the residuals is based on the contiguity matrix), neither the dummy controlling for intraregional flows nor the distance variable is significant. However, in SAC-I and SAC-IV, both of which use W^{net} on the error term, the negative coefficient of distance runs from –0.16 to –0.19 and the

[13] The pseudo R^2 was calculated using $\hat{T}' \hat{T}/T' T$, where $\hat{T} = (i_N - \rho_1 W^{spa} - \rho_2 W^{net})^{-1} X\hat{\beta}$.

dummy coefficient for intraregional flows runs from 0.5 to 0.6; these are close to the values we obtain in the SEM model when using the W^{net}. In SAC-II and SAC-III, the effect of emigrants is greater than the effect of immigrants, while the opposite is the case in SAC-I and SAC-IV. In addition, with regard to the parameters of spatial and network dependence, it is important to highlight that the parameter measuring the dependence in the residuals is positive and significant in all cases, and is of lesser magnitude when the dependence is based on social networks rather than contiguity. On the other hand, the spatial lag of the flows is non-significant except with SAC-III, but in this case we get a negative sign.

Table 6. about here

Finally, the results reported in **Table 7** for the SDM are complementary to those for the SAR, the SEM and the SAC estimates: the coefficients for the spatial and network (demographic) autocorrelation terms are positive and significant for the dependent variable, with high values for ρ in the six specifications reported. Moreover, the coefficients for the spatial and network (demographic) autocorrelation terms for the explanatory variables are not always significant and the signs vary with the variable. For example, variables such as $W\text{-}gva_i$ and $W\text{-}pop_j$ show negative and significant coefficients for all specifications, suggesting that, on average, flows between the trading regions decrease as their neighbors' population and hospitality-industry gross value added increase—whether we define a 'neighbor' geographically (shared border), by the intensity of demographic links or both. In another example, a negative sign in the lag of both the emigrant and the net migration variables suggests that trade flows between a given country-pair decrease as their neighbors' average emigration (or emigration+immigration) stocks increase. We might attribute these results to some kind of competition between regions. Finally, with regard to the effect of distance on bilateral trade flows when an SDM is estimated, it is remarkable that the coefficient is negative and significant when we include the W^{net} matrix in the pattern of the spatial autocorrelation considered (in **Table 6**, –0.186 and –0.2), but non-significant when we include the contiguity-based W^{spa} matrix.

Table 7. about here

Another thing worthy of note is the difference in the significance of the coefficients of the migration variables depending on the model estimated. When a SAR model is estimated, the level of significance and the magnitude of the coefficient for emigrants is lower than for immigrants (0.21 in column three of **Table 4**), while both variables are significant and positive when an SEM or SAC model is estimated. Finally, when an SDM is estimated, the significant effect is found for the stock of emigrants and not for immigrants except when we consider W^{net} (column three in **Table 7**), where both emigrants and immigrants are significant and immigrants get a higher coefficient. The effect of migration on trade flows, regardless of its direction (emigrants or immigrants), does not disappear when the spatial autocorrelation of the flows is controlled for, although it changes with the type of model.

Figure 6a, 6b about here

Next, **Figure 6a and 6b** reports the Moran scatterplots for the residuals of the main specifications that use row-normalized spatial ($W^{spa} = W_i^{spa} + W_j^{spa}$) and network (demographic) ($W^{net} = W_i^{net} + W_j^{net}$) weight matrices to capture the aggregate spatial autocorrelation of both exporting and importing regions. As in

LeSage and Pace (2009) and de la Mata and Llano (2013), each graph is divided into quadrants: Q-I (red points): *ij* flows where both the residuals and the average of neighboring *ij* flows (origin-based+destination-based) are above the mean; Q-II (green points): *ij* flows where the residuals are below the mean but the average of neighboring *ij* flows is above it; Q-III (blue points): *ij* flows where both the residuals and the average of the neighboring *ij* flows are below the mean; Q-IV (purple points): *ij* flows where the residuals are above the mean and the average of neighboring *ij* flows is below it.

By means of the Moran scatterplot we can verify a positive association between the residuals (horizontal axis) and the spatial lag (vertical axis). The magnitude of this positive association grows as the number of green and purple points decreases and the number of blue and red points increases. Here unlike in other papers using scatterplots, the residuals cannot be plotted in a map, because our dataset is referred to each region-pair. Such a graphical analysis would required specialized GIS systems for transport modeling (Berglund and Karström, 1999a, 1999b; Berglund, 2001), which are beyond the scope of this paper. The results in **Figure 6a,b** suggest a positive association between the residuals of the three main specifications obtained by simple OLS estimation and the two different cross-section autocorrelation structures—one purely spatial, the other purely demographic—under consideration. It is also worth mentioning the differences in the shapes of the dot clouds generated by each weight matrix, which indicate the complementary nature of both structures.

Then, **Figure 6a and 6b** show the Moran scatterplots for the residuals obtained from the SAR, SEM, SDM and SAC-I-IV estimations, and a row-normalized weight matrix obtained as a sum over all the weight matrices described here ($W_3 = W^{spa} + W^{net}$)[14]. This approach is an attempt to show in a single picture whether after the use of these spatial models the residuals still show a significant association with a lag based on spatial and demographic structure. As these graphs show, the SAR, SEM and SDM still have a clear positive relation, while the SAC model—especially SAC-II and SAC-III—seems to do a better job of eliminating the positive association between the residuals and the spatial and demographic lags.

4.4. Results using alternative measures for social networks

In this section we test the preferred model as determined by the residuals in **Figure 6a** and **6b**—that is, the SAC-III model[15] (column five of **Table 6**)—using the alternative social-network measures described in **Table 1**. **Table 8** shows the corresponding results. It is important to remark that the alternative social-network measures enter into the model as substitutes for the 1981 interregional migration stocks through the vector variables (m_{ij}, m_{ji}, m_net_{ij}), while the $W_1 = W_2 = W^{spa}$ is just based on spatial contiguity as in the baseline model (SAC-III).

<Table 8 about here>

[14] The Moran scatterplots for the residuals using each matrix W^{spa} and W^{net} instead of the sum of both and for the rest of the models are available upon request.

[15] The results using the alternative social network variables for the SAC-II model (column three of **Table 6**) are reported in the Appendix. This model was the one that perform better in de la Mata and Llano (2013).

The results obtained with these alternative variables are, in general, robust with those obtained in the previous models, with expected signs and levels of significance. As for the size of the trading regions as measured by gross value added (for the exporting region), population and per-capita income (for the importing region), positive and significant signs are obtained in all cases, much as with the baseline model in **Table 6.** The only remarkable difference occurs when social networks created by previous trips with stays in regulated establishments are included (**soc_net_18**), where the coefficients decrease notably. Also, when the variables **soc_net_16**, **soc_net_17** and **soc_net_18** are included, the coefficient for per-capita income is lower than one –reducing its significance in the latter-, contrary to what happens in all other cases. These results can be attributed to gravity's effect on previous trips, so part of the effect of the gravity variables is captured in the coefficient for previous trips.

It is interesting to note that, while the intraregional dummy gets a positive and significant sign in some cases, certain social-network variables help overcome this home bias (**soc-net-2; soc-net-11; soc-net-15; soc-net-16; soc-net-17; soc-net-18 and soc-net-19**) or reduce its significance **(soc-net-3; soc-net-14**). When the variables **soc-net-7** and **soc-net-12** (which concern individuals' previous residences) are used, the intraregional dummy gets a negative sign, probably because of the disproportionate intraregional linkages (more than 95%) in each of the two variables.

Another interesting result is that, as in column three of **Table 6**, the distance variable is in most cases non-significant when alternative social-network measures are considered—with the following exceptions: **soc-net-6; soc-net-16** and **soc-net-18** (significant at 5%), **soc-net-11 and soc-net-12** (significant at 10%) and **soc-net-19**. The last variable contains 'parcel flows' as a proxy for networks. That this variable gets the most significant coefficient for distance and the highest coefficient for the *intra* variable has to do with its nature, which allows it to capture other kinds of relations (e.g., business networks) as well. Parcel flows, moreover, can substitute for face-to-face contact when travel costs are high, as it over-weights the existence of networks at greater distances.

The effect of social networks is confirmed in both directions in most cases, with coefficients similar to the one in the baseline regression. There are some exceptions. For example, with the variables **soc-net-11** and **soc-net-12** the social-network effect is confirmed in only one direction, and with **soc-net-15** and **soc-net-19** it seems to have almost no impact. As previously stated, the latter can serve as an alternative form of contact, other than trips, with the members of a social network. In **soc-net-16**, **soc-net-17** and **soc-net-18**, the effect is confirmed in both directions, although at different intensities, with stronger effects linked with a certain inertia in the flows.

In all cases, the positive autocorrelation in the residuals is confirmed and the spatial lag of the dependent variable is found to be significant, although with a negative impact. In the SAC-II model, when the spatial lag of the dependent variable is based on demography, it is significant and positive when the variable **soc-net-19** is included.

Table A1 in the appendix shows a similar analysis for all the alternative matrices, but the social-network variable is included only in its unidirectional version ($m_net_{ij} = (m_{ji} + m_{ij})$). This produces similar results.

5. Conclusions

In this article we have analyzed the relation between interregional trade in services and social networks and how these social networks can explain part of the resulting border effect on such services. We have also considered whether interregional trade flows in tourism-related services exhibit spatial and/or social-network dependence. Conventional empirical gravity models assume that the magnitude of bilateral flows between regions are independent of flows to/from geographically proximate regions or to/from regions connected by social/cultural/ethnic networks.

We provide an extended empirical specification that relaxes the assumption of independence between bilateral flows inherent to any least-squares regression. Our argument is that bilateral flows between an exporting region *i* and an importing region *j* can exhibit dependence on: (1) flows to regions that are geographically near exporting and importing regions *i* and *j* (spatial dependence) and (2) flows to regions that are socially/demographically "related" to exporting and importing regions *i* and *j*. We have used a spatial weight matrix elaborated in the way suggested by LeSage and Pace (2008) to quantify the spatial structure of the connectivity between interregional bilateral flows. And we have constructed a social-network matrix with information on the bilateral stock of interregional migrants between seventeen Spanish regions.

Estimates from a set of models have shown evidence of statistically significant spatial and network (demographic) dependence in the bilateral flows of the service trade considered. The analysis has been applied to data averages for the period 2005–2009, with alternative datasets for migration stocks and alternative definitions for network effects. It has produced robust results and shown the high inertia that exists in these social phenomena, where patterns from 1981 affect flows that exist twenty years later. We might interpret the significant network dependence thus brought to light as a general preference for destinations in or near one's home region or for destinations in or near regions where natives of one's birth region have settled heavily. Significant spatial dependence is an indication that bilateral flows between two regions are associated to those to/from neighboring regions.

One finding of interest is that the introduction of explanatory variables to control for emigrant and immigrant stocks and for spatial and network dependence (as well as conventional measures of the economic size of origin and destination regions) results in a low coefficient estimate for bilateral distance between origin and destination regions and a high coefficient for the internal border effect—such that distance and home bias are, in certain cases, no longer significant. This suggests that social networks might exert sufficient influence on the selection of destinations to overcome the traditional obstacle of distance, which typically diminishes the magnitude of bilateral flows. It also suggests that the distribution of social networks over short distances may partly explain the gravity effect on trip decisions, especially within the region of residence.

Further analysis for the interpretation of these parameters, in the spirit of Lesage and Thomas-Agnan (2012), is certainly in order. Although the effect of social networks has been widely tested in this work, it would be an important next step to take into consideration, for instance, the effect of business networks.

6. References

Angulo, A. M., Mtimet N., Dhehibi B., Atwi M., Ben Youssef O.,Gil J. M. & Sai M. B. (2011): 'A Revisited Gravity Equation in Trade Flow Analysis: An Application to the Case of Tunisian Olive Oil Exports', *Investigaciones Regionales*, **21**, 225–239.

Anselin, L. (1988): *Spatial Econometrics: Methods and Models*, Kluwer Academic Publishers.

Athanasopoulos, G. & Hyndman, R. J. (2008): 'Modelling and Forecasting Australian Domestic Tourism', *Tourism Management* **29** (1), 19–31.

Behrens, K., Ertur, C & Koch, W. (2010): '"Dual" Gravity: Using Spatial Econometrics to Control for Multilateral Resistance', *Journal of Applied Econometrics*, vol. 27(5), pages 773-794, 08.

Belderbos, R. & Sleuwaegen, L. (1998): 'Tariff Jumping FDI and Export Substitution: Japanese Electronics Firms in Europe', *International Journal of Industrial Organization* **16**(5), 601–638.

Berglund S. & Karström, A (1999a): 'Identifying Local Spatial Association in Flow Data'. Journal of Geographical Systems, **1** (3), 219–236.

Berglund S. & Karström, A (1999b): 'TECHNICAL REPORT: Computing Gi and Gij". Program Documentation. Mimeo.

Berglund S. (2001): 'GIS in Transport Modelling', Royal Institute of Technology, Department of Infraestructure. Report. ISSN 1104-683X.

Black, W. R. (1992): 'Network Autocorrelation in Transport Network and Flow Systems', *Geographical Analysis* **24**(3), 207–222.

Bolduc, D., Laferriere, R. & Santarossa, G. (1992): 'Spatial Autoregressive Error-Components in Travel Flow Models', *Regional Science and Urban Economics* **22**(3), 371–385.

Chen, N. (2004): 'Intra-National versus International Trade in the European Union: Why Do National Borders Matter?', *Journal of International Economics* **63**(1), 93–118.

Combes, P. P., Lafourcade, M. & Mayer, T. (2005): 'The Trade-Creating Effect of Business and Social Networks: Evidence from France', *Journal of International Economics* **66**(1), 1–29.

Chun, Y. (2008): 'Modeling Network Autocorrelation within Migration Flows by Eigenvector Spatial Filtering', *Journal of Geographical Systems*, **10**(4), 317–344.

Chun, Y., & Griffith, D. A. (2011): 'Modeling Network Autocorrelation in Space-Time Migration Flow Data: An Eigenvector Spatial Filtering Approach', *Annals of the Association of American Geographers*, **101**(3), 523–536.

De la Mata, T & Llano, C. (2012a): "Spatial pattern and domestic tourism: An econometric analysis using inter-regional monetary flows by type of journey, *Papers in Regional Science*, **91** (2), June 2012, 437-470.

De la Mata T. & Llano C. (2012b): 'How Tradable are Non-Tradables? Measuring Interregional Flows of Accommodation, Restaurants and Travel Agencies in Spain', Mimeo.

De la Mata T. & Llano C. (2013): 'Social Networks and Trade of Services: Modelling Interregional Flows with Spatial and Network Autocorrelation Effects', *Journal of Geographical Systems*, 15 (3), pp.319–367, DOI 10.1007/s10109-013-0183-6.

Dunlevy, J. A. & Hutchinson, W. K. (1999): 'The Impact of Immigration on American Import Trade in the Late Nineteenth and Early Twentieth Centuries', *Journal of Economic History* **59**(4), 1043–1062.

Dunlevy, J. A. & Hutchinson, W. K. (2001): 'The Pro-Trade Effect of Immigration on American Exports during the Late Nineteenth and Early Twentieth Centuries', IZA Discussion Papers 375, Institute for the Study of Labor (IZA). http://ideas.repec.org/p/iza/izadps/dp375.html

Egger, P. & Larch, M. (2008): 'Interdependent Preferential Trade Agreement Memberships: An Empirical Analysis', *Journal of International Economics* **76**(2), 384–399.

Eriksen, L. & Ahmt, T. (1999): 'Measuring and Modelling the Regional Impact of Tourism in Denmark', *Int. J. Tourism Res.* **1**(5), 313–327.

Evans, C. L. (2006): 'Border Effects and the Availability of Domestic Products Abroad', *Canadian Journal of Economics-revue Canadienne D Economique* **39**(1), 211–246.

Fischer M.M. & Griffith, D. A. (2008): 'Modeling Spatial Autocorrelation in Spatial Interaction Data: An Application to Patent Citation Data in the European Union', *Journal of Regional Science*, **48**, (5), 969–989.

Garmendia, A., Llano, C., Minondo, A. & Requena, F. (2012): 'Networks and the Disappearance of the Intranational Home Bias', *Economics Letters*, vol. 116(2), 178–182.

Ghemawat, P., Llano, C. & Requena, F. (2010): 'Competitiveness and Interregional as Well as International Trade: The Case of Catalonia', *International Journal of Industrial Organization* **28**(4), 415–422.

Girma, S. & Yu, Z. H. (2002): 'The Link between Immigration and Trade: Evidence from the United Kingdom', *Weltwirtschaftliches Archiv-review of World Economics* **138**(1), 115–130.

Gould, D. M. (1994): 'Immigrant Links to the Home Country—Empirical Implications for United-States Bilateral Trade-Flows', *Review of Economics and Statistics* **76**(2), 302–316.

Head, K. & Mayer, T. (2010): '*Illusory Border Effect: Distance Mismeasurement Inflates Estimates of Home Bias in Trade'*, Vol. The Gravity Model in International Trade: Advances and Applications, Cambridge University Press.

Head, K. & Ries, J. (1998): 'Immigration and Trade Creation: Econometric Evidence from Canada', *Canadian Journal of Economics-revue Canadienne D Economique* **31**(1), 47–62.

Helliwell, J. F. (1996): 'Do National Borders Matter for Quebec's Trade?', *Canadian Journal of Economics-revue Canadienne D Economique* **29**(3), 507–522.

Helliwell, J. F. (1997): 'National Borders, Trade and Migration', *Pacific Economic Review* **2**(3), 165–185.

Ledyaeva, S. (2009): 'Spatial Econometric Analysis of Foreign Direct Investment Determinants in Russian Regions', *The World Economy* **32**(4), 643–666.

Lesage J.P & Fischer M. M. (2008): 'Spatial Growth Regressions: Model Specification, Estimation and Interpretation', *Spatial Economic Analysis*, **3:3**, 275-304

LeSage, J. P. & Pace, R. K. (2008): 'Spatial Econometric Modeling of Origin-Destination Flows', *Journal of Regional Science,* **48**(5), 941–967.

LeSage, J. P. & Pace, R. K. (2009): *Introduction to Spatial Econometrics*, Chapman & Hall/CRC Press.

Lesage, J. P. & Thomas-Agnan, C. (2012): 'Interpreting Spatial Econometric Origin-Destination Flow Models', Working Paper, Mimeo presented in Southern Regional Science Association Conference hold in Charlotte, March, 2012.

Llano, C. & de la Mata, T. (2009): 'El comercio interregional en España: Una estimación de los flujos bilaterales del sector turismo', *Revista ICE* **848**, 67–87.

McCallum, J. (1995): 'National Borders Matter: Canada-U.S. Regional Trade Patterns', *The American Economic Review* **85**, 615–623.

Millimet, D.L & Osang,T. (2007): 'Do State Borders Matter for U.S. Intranational Trade? The Role of History and Internal Migration', *Canadian Journal of Economics,* Canadian Economics Association, vol. **40**(1), 93–126, February.

Okubo, T. (2004): 'The Border Effect in the Japanese Market: A Gravity Model Analysis', *Journal of the Japanese and International Economies,* **18**(1), 1–11.

Podolny, J. M. & Page, K. L. (1998): 'Network Forms of Organization', *Annual Review of Sociology,* **24**, 57–76.

Porojan, A. (2001): 'Trade Flows and Spatial Effects: The Gravity Model Revisited', *Open Economies Review,* **12**(3), 265–280.

Portes, R. & Rey, H. (2005): 'The Determinants of Cross-Border Equity Flows', *Journal of International Economics,* **65**(2), 269–296.

Rauch, J. E. (2001): 'Business and Social Networks in International Trade', *Journal of Economic*

Literature, **39**(4), 1177–1203.

Rauch, J. E. & Casella, A. (2003): 'Overcoming Informational Barriers to International Resource Allocation: Prices and Ties', *Economic Journal,* **113**(484), 21–42.

Rauch, J. E. & Trindade, V. (2002): 'Ethnic Chinese Networks in International Trade', *Review of Economics and Statistics,* **84**(1), 116–130.

Requena, F. & Llano, C. (2010): 'The Border Effects in Spain: An Industry-Level Analysis', *Empirica,* **37**(4), 455–476.

Wagner, D., Head, K. & Ries, J. (2002): 'Immigration and the Trade of Provinces', *Scottish Journal of Political Economy,* **49**(5), 507–525.

White, R. & Tadesse, B. (2008): 'Cultural Distance and the US Immigrant-Trade Link', *World Economy,* **31**(8), 1078–1096.

Wolf, H. C. (2000): 'Intranational Home Bias in Trade', *Review of Economics and Statistics,* **82**(4), 555–563.

Table 1 Alternative social-network matrices

Social-network variable	Definition	Source	Interpretation – Social networks
Soc_net_2	Stock of individuals born in region *i* and residing in region *j* in 2001	Spanish census, 2001, INE	Effect of emigration
Soc_net_3	Stock of individuals owning a second home in region *i* and residing in region *j* in 2001.	Spanish census, 2001, INE	Effect of second homes owned by non-residents
Soc_net_4	Stock of individuals residing in region *j* in 2001and with mothers born in *i*.	Spanish census, 2001, INE	Effect of second-generation emigration on region of mother's birth
Soc_net_5	Stock of individuals residing in region *j* in 2001 and with fathers born in *i*	Spanish census, 2001, INE	Effect of second-generation emigration on region of father's birth
Soc_net_6	Individuals whose previous residence was *i* and who resided in *j* in 2001	Spanish census, 2001, INE	Effect of previous residence
Soc_net_7	Stock of individuals who lived in *i* in 1991 and in *j* in 2001	Spanish census, 2001, INE	Effect of residence 10 years earlier
Soc_net_8	Stock of individuals born in region *i* and living in *j* in 2001 (employed and over 16)	Spanish census, 2001, INE	Effect of emigrations for employed individuals over 16
Soc_net_9	Stock of individuals who work in *i* and lived in *j* in 2001 (employed and over 16)	Spanish census, 2001, INE	Social networks generated by commuting
Soc_net_10	Stock of individuals who were born in region *i* and lived in region *j* in 1991	Spanish census, 1991, INE	Effect of emigration
Soc_net_11	Stock of individuals that lived in *i* in 1981 and live in *j* in 1991	Spanish census, 1991, INE	Effect of residence 10 years earlier
Soc_net_12	Stock of individuals that lived in *i* from 1981 to 1991 and moved to *j* in 1991. (Note: said individuals could have lived in multiple places over 10 years.)	Spanish census, 1991, INE	Effect of previous residences
Soc_net_13	Stock of individuals living in region *j* in 1991 and with fathers born in *i*	Spanish census, 1991, INE	Effect of second-generation emigration on region of father's birth
Soc_net_14	Stock of individuals living in region *j* in 1991 with mothers born in *i*	Spanish census, 1991, INE	Effect of second-generation emigration on region of mother's birth
Soc_net_15	Stock of individuals with fathers born in region *i* and mothers born in region *j*	Spanish census, 1991, INE	Effect of marriages
Soc_net_16	Average number of trips to *j* taken by individuals living in *i* in 2000–2004	Familitur 2000–2004, IET	Social networks generated during previous trips and inertia on destination
Soc_net_17	Average number of overnight stays in *j* in 2000–2004 by individuals living in *i* (all kinds of establishments)	Familitur 2000–2004, IET and Encuesta de Ocupación, INE	Social networks generated during previous trips and inertia on destination
Soc_net_18	Average number of overnight stays in j in 2000–2004 by individuals living in *i* (hotels, apartments, rural tourism, campsites)	Encuesta de Ocupación 2000–2004, INE	Social networks generated during previous trips and inertia on destination
Soc_net_19	Parcels received in *i* and sent by *j* in 1995–2000.	Ministerio de Fomento.	Proxy of interregional information flows or social networks

Table 2. Ordinary Least Squares

	(1)	(2)	(3)
R-squared	0.848	0.881	0.876
Rbar-squared	0.846	0.878	0.874
i_N	-26.365***	-27.701***	-24.51***
	(-12.63)	(-13.187)	(-12.881)
gva_i	0.84***	0.57***	0.647***
	(24.782)	(12.747)	(16.589)
pop_j	0.942***	0.683***	0.674***
	(24.006)	(14.22)	(13.802)
inc_j	1.337***	1.76***	1.395***
	(7.075)	(8.776)	(8.158)
d_{ij}	-0.454***	-0.107*	-0.16***
	(-9.19)	(-1.806)	(-2.764)
$ownreg_{ij}$	1.903***	0.957***	0.981***
	(10.633)	(4.896)	(4.935)
m_{ij}		0.06**	
		(1.994)	
m_{ji}		0.248***	
		(6.817)	
m_net_{ij}			0.142***
			(7.985)

Source: Authors' calculations. T statistics in brackets. Significance:. *** p<0.01, ** p<0.05, * p<0.1. Dependent variable: Interregional monetary flows of Accommodations and Restaurants generated by trips. (Average 2005–2009.)

Table 3. Spatial autocorrelation tests

	(1)	(2)	(3)	(4)	(5)	(6)
Origin-based autocorrelation with row-normalized 'Wo' (neighbors of exporting region *i*)						
Moran I-test for spatial correlation in residuals						
Moran I	0.201	0.147	0.152	0.168	0.112	0.076
Moran I-statistic	5.213	3.969	4.026	3.352	2.340	1.642
Marginal Probability	0.000	0.000	0.000	0.001	0.019	0.101
Mean	-0.011	-0.014	-0.012	-0.012	-0.014	-0.013
Standard deviation	0.041	0.041	0.041	0.054	0.054	0.054
LM error tests for spatial correlation in residuals						
LM value	23.612	12.616	13.432	9.621	4.235	1.939
Marginal Probability	0.000	0.000	0.000	0.002	0.040	0.164
chi(1) .01 value	6.635	6.635	6.635	6.635	6.635	6.635
LM error tests for spatial correlation in dependent variable						
LM value	14.567	66.299	73.063	55.612	40.231	39.542
Marginal Probability	0.000	0.000	0.000	0.000	0.000	0.000
chi(1) .01 value	6.640	6.640	6.640	6.640	6.640	6.640
Robust LM error test						
LM value	29.819	22.948	24.320	2.153	2.510	5.743
Marginal Probability	0.000	0.000	0.000	0.142	0.113	0.017
chi(1) .01 value	6.640	6.640	6.640	6.640	6.640	6.640
Robust LM lag test						
LM value	20.774	76.632	83.951	48.145	38.506	43.346
Marginal Probability	0.000	0.000	0.000	0.000	0.000	0.000
chi(1) .01 value	6.640	6.640	6.640	6.640	6.640	6.640
Destination-based autocorrelation with row-normalized 'Wd' (neighbors of exporting region *j*)						
Moran I-test for spatial autocorrelation in residuals						
Moran I	0.373	0.423	0.446	0.494	0.518	0.561
Moran I-statistic	9.329	10.700	11.196	9.314	9.849	10.601
Marginal Probability	0.000	0.000	0.000	0.000	0.000	0.000
Mean	-0.009	-0.013	-0.011	-0.009	-0.012	-0.011
Standard deviation	0.041	0.041	0.041	0.054	0.054	0.054
LM error tests for spatial correlation in residuals						
LM value	80.817	103.986	115.851	82.788	91.045	106.766
Marginal Probability	0.000	0.000	0.000	0.000	0.000	0.000
chi(1) .01 value	6.635	6.635	6.635	6.635	6.635	6.635
LM error tests for spatial correlation in dependent variable						
LM value	25.471	17.382	25.802	47.193	30.054	26.036
Marginal Probability	0.000	0.000	0.000	0.000	0.000	0.000
chi(1) .01 value	6.640	6.640	6.640	6.640	6.640	6.640
Robust LM error test						
LM value	69.973	94.556	104.028	37.475	61.496	84.276
Marginal Probability	0.000	0.000	0.000	0.000	0.000	0.000
chi(1) .01 value	6.640	6.640	6.640	6.640	6.640	6.640
Robust LM lag test						
LM value	14.626	7.952	13.979	1.879	0.505	3.546
Marginal Probability	0.000	0.005	0.000	0.170	0.477	0.060
chi(1) .01 value	6.640	6.640	6.640	6.640	6.640	6.640
Autocorrelation using row-normalized first contiguity matrix 'W=Wo+Wd' (neighbors of *ij*)						
Moran I	0.312	0.353	0.401	0.326	0.315	0.339
Moran I-statistic	9.766	11.218	12.555	8.257	8.052	8.613
Marginal Probability	0.000	0.000	0.000	0.000	0.000	0.000
Mean	-0.011	-0.015	-0.013	-0.010	-0.013	-0.012
Standard deviation	0.033	0.033	0.033	0.041	0.041	0.041
LM error tests for spatial correlation in residuals						
LM value	84.063	107.736	139.111	62.365	57.960	67.365
Marginal Probability	0.000	0.000	0.000	0.000	0.000	0.000
chi(1) .01 value	6.635	6.635	6.635	6.635	6.635	6.635
LM error tests for spatial correlation in dependent variable						
LM value	8.238	2.324	3.868	63.589	44.886	44.123
Marginal Probability	0.004	0.127	0.049	0.000	0.000	0.000
chi(1) .01 value	6.640	6.640	6.640	6.640	6.640	6.640
Robust LM error test						
LM value	76.030	106.396	136.111	15.986	22.056	29.357
Marginal Probability	0.000	0.000	0.000	0.000	0.000	0.000
chi(1) .01 value	6.640	6.640	6.640	6.640	6.640	6.640
Robust LM lag test						
LM value	0.206	0.984	0.867	17.210	8.982	6.115
Marginal Probability	0.650	0.321	0.352	0.000	0.003	0.013
chi(1) .01 value	6.640	6.640	6.640	6.640	6.640	6.640
W matrix based on…	**Contiguity**	**Contiguity**	**Contiguity**	**Social networks**	**Social networks**	**Social networks**

Source: Authors' calculations. Dependent variable: Interregional monetary flows of Accommodations and Restaurants generated by trips. (Average 2005–2009.)

Table 4. Spatial Autoregressive Model

	(1)	(2)	(3)	(4)
R-squared	0.879	0.874	0.884	0.878
Rbar-squared	0.876	0.871	0.881	0.875
sigma^2	0.267	0.276	0.231	0.240
log-likelihood	-118.840	-123.750	-100.360	-106.229
i_N	-27.611***	-24.641***	-28.638***	-25.633***
	(-13.379)	(-13.182)	(-14.911)	(-14.697)
gva_i	0.568***	0.639***	0.507***	0.578***
	(12.927)	(16.613)	(12.007)	(15.485)
pop_j	0.673***	0.661***	0.644***	0.635***
	(14.146)	(13.7)	(14.472)	(13.979)
inc_j	1.735***	1.391***	1.799***	1.454***
	(8.78)	(8.283)	(9.812)	(9.279)
$ownreg_{ij}$	1.051***	1.101***	1.109***	1.135***
	(5.08)	(5.243)	(6.086)	(6.114)
d_{ij}	-0.095	-0.14**	-0.107**	-0.158***
	(-1.615)	(-2.437)	(-1.987)	(-2.975)
m_{ij}	0.061**		0.032	
	(2.067)		(1.145)	
m_{ji}	0.238***		0.211***	
	(6.532)		(6.241)	
m_net_{ij}		0.137***		0.109***
		(7.688)		(6.318)
rho	0.034	0.044*	0.252***	0.257***
	(1.402)	(1.792)	(6.175)	(6.226)
W matrix	Contiguity	Contiguity	Demography	Demography

Source: Authors' calculations. T statistics in brackets. Significance:. *** p<0.01, ** p<0.05, * p<0.1. Dependent variable: Interregional monetary flows of Accommodations and Restaurants generated by trips. (Average 2005–2009.)

Table 5. Spatial Error Model

	(1)	(2)	(3)	(4)
R-squared	0.935	0.934	0.914	0.913
Rbar-squared	0.933	0.932	0.912	0.911
sigma^2	0.147	0.149	0.194	0.196
log-likelihood	-59.207	-60.239	-87.697	-89.973
i_N	-22.725***	-24.637***	-28.13***	-25.722***
	(-7.86)	(-9.388)	(-12.306)	(-13.079)
gva_i	0.542***	0.514***	0.545***	0.601***
	(11.264)	(11.593)	(10.845)	(14.307)
pop_j	0.54***	0.544***	0.693***	0.696***
	(9.327)	(9.392)	(12.511)	(12.437)
inc_j	1.389***	1.609***	1.867***	1.564***
	(4.577)	(6.013)	(7.764)	(8.241)
$ownreg_{ij}$	0.227	0.218	0.62***	0.649***
	(1.368)	(1.311)	(3.735)	(3.904)
d_{ij}	-0.051	-0.047	-0.165***	-0.185***
	(-0.89)	(-0.818)	(-2.813)	(-3.182)
m_{ij}	0.282***		0.091***	
	(6.744)		(2.811)	
m_{ji}	0.158***		0.215***	
	(3.483)		(5.517)	
m_net_{ij}		0.222***		0.145***
		(11.617)		(7.786)
lambda	0.853***	0.844***	0.599***	0.609***
	(23.602)	(22.342)	(9.784)	(10.069)
W matrix	Contiguity	Contiguity	Demography	Demography

Source: Authors' calculations. T statistics in brackets. Significance:. *** p<0.01, ** p<0.05, * p<0.1. Dependent variable: Interregional monetary flows of Accommodations and Restaurants generated by trips. (Average 2005–2009.)

Table 6. Spatial General Model

	SAC-I		**SAC-II**		**SAC-III**		**SAC-IV**	
	$W_1=W^{spa}$; $W_2=W^{net}$		$W_1=W^{net}$; $W_2=W^{spa}$		$W_1=W_2=W^{spa}$		$W_1=W_2=W^{net}$	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
R-squared	0.914	0.913	0.934	0.934	0.937	0.936	0.917	0.919
Rbar-squared	0.912	0.912	0.932	0.933	0.936	0.935	0.915	0.917
sigma^2	0.193	0.195	0.150	0.149	0.142	0.144	0.186	0.183
log-likelihood	-87.803	-89.666	-60.442	-59.994	-53.564	-55.061	-87.237	-88.672
i_N	-28.153***	-25.722***	-23.058***	-24.884***	-22.781***	-24.352***	-26.995***	-24.097***
	(-12.292)	(-13.064)	(-8.011)	(-9.322)	(-8.038)	(-9.527)	(-10.887)	(-11.137)
gva_i	0.545***	0.602***	0.545***	0.513***	0.526***	0.502***	0.541***	0.589***
	(10.823)	(14.271)	(11.372)	(11.569)	(11.112)	(9.607)	(10.504)	(13.763)
pop_j	0.699***	0.7***	0.544***	0.544***	0.539***	0.544***	0.696***	0.704***
	(12.443)	(12.327)	(9.489)	(9.373)	(9.487)	(9.607)	(12.139)	(11.962)
inc_j	1.874***	1.566***	1.407***	1.621***	1.472***	1.657***	1.836***	1.529***
	(7.756)	(8.232)	(4.741)	(6.025)	(4.93)	(6.359)	(7.281)	(7.721)
$ownreg_{ij}$	0.593***	0.634***	0.267	0.233	0.104	0.091	0.496***	0.468***
	(3.446)	(3.688)	(1.543)	(1.343)	(0.62)	(0.544)	(2.745)	(2.603)
d_{ij}	-0.168***	-0.187***	-0.05	-0.046	-0.067	-0.066	-0.177***	-0.197***
	(-2.873)	(-3.213)	(-0.88)	(-0.809)	(-1.209)	(-1.179)	(-3.034)	(-3.408)
m_{ij}	0.091***		0.272***		0.279***		0.101***	
	(2.802)		(6.484)		(6.8)		(3.058)	
m_{ji}	0.216***		0.16***		0.172***		0.217***	
	(5.524)		(3.531)		(3.838)		(5.457)	
m_net_{ij}		0.145***		0.22***		0.227***		0.154***
		(7.75)		(11.042)		(12.072)		(7.973)
rho	-0.013	-0.007	0.008	0.018	-0.075***	-0.078***	-0.082	-0.123**
	(-0.592)	(-0.305)	(0.186)	(0.428)	(-3.358)	(-3.57)	(-1.379)	(-2.065)
lambda	0.608***	0.617***	0.824***	0.849***	0.853***	0.836***	0.682***	0.74***
	(9.94)	(10.199)	(19.404)	(22.422)	(23.286)	(21.047)	(10.506)	(12.736)

Source: Authors' calculations. T statistics in brackets. Significance:. *** p<0.01, ** p<0.05, * p<0.1. Dependent variable: Interregional monetary flows of Accommodations and Restaurants generated by trips. (Average 2005–2009.)

Table 7. Spatial Durbin Model

	(1)	(2)	(3)	(4)	(5)	(6)
R-squared	0.915	0.898	0.897	0.892	0.906	0.900
Rbar-squared	0.911	0.893	0.8922	0.887	0.901	0.895
sigma^2	0.150	0.160	0.1867	0.190	0.164	0.152
log-likelihood	-46.401	-58.182	-77.223155	-81.683	-58.242	-54.474
i_N	-15.823***	-14.588***	-11.364***	-7.371**	-18.357***	0.173
	(-7.289)	(-7.516)	(-3.111)	(-2.299)	(-8.206)	(0.052)
gva_i	0.56***	0.47***	0.527***	0.597***	0.589***	0.561***
	(10.045)	(8.895)	(8.364)	(12.273)	(9.535)	(10.939)
pop_j	0.592***	0.579***	0.734***	0.791***	0.652***	0.677***
	(8.496)	(8.081)	(9.62)	(10.606)	(8.321)	(9.319)
inc_j	0.626**	0.649***	1.978***	1.531***	0.899***	2.09***
	(2.45)	(2.843)	(6.364)	(6.818)	(3.295)	(7.142)
$ownreg_{ij}$	0.598**	0.433*	0.922***	1.029***	0.928***	0.901***
	(2.401)	(1.701)	(3.961)	(4.523)	(3.607)	(3.719)
d_{ij}	-0.028	-0.045	-0.186***	-0.2***	-0.075	-0.093
	(-0.453)	(-0.707)	(-3.008)	(-3.205)	(-1.164)	(-1.515)
m_{ij}	0.365***		0.073**		0.258***	
	(7.958)		(1.996)		(6.361)	
m_{ji}	0.051		0.203***		0.065	
	(0.986)		(4.257)		(1.335)	
m_net_{ij}		0.224***		0.123***		0.162***
		(9.619)		(5.46)		(7.022)
$W\text{-}gva_i$	-0.306***	-0.143	-0.225**	-0.255***	-0.329***	-0.311***
	(-3.202)	(-1.64)	(-2.289)	(-3.001)	(-3.173)	(-3.517)
$W\text{-}pop_j$	-0.242**	-0.219**	-0.432***	-0.551***	-0.237**	-0.524***
	(-2.242)	(-2.01)	(-3.536)	(-4.744)	(-1.99)	(-4.498)
$W\text{-}inc_j$	0.495***	0.265	-1.32***	-1.212***	0.376*	-2.323***
	(2.616)	(1.454)	(-2.983)	(-3.549)	(1.879)	(-4.979)
$W\text{-}ownreg_{ij}$	1.164***	1.244***	0.483	0.421	1.125***	1.046***
	(3.226)	(3.374)	(1.483)	(1.28)	(3.053)	(2.972)
$W\text{-}d_{ij}$	-0.022	-0.087	0.18*	0.137	0.031	-0.025
	(-0.245)	(-0.967)	(1.895)	(1.441)	(0.302)	(-0.272)
$W\text{-}m_{ij}$	-0.449***		-0.111*		-0.39***	
	(-8.267)		(-1.862)		(-6.577)	
$W\text{-}m_{ji}$	0.072		-0.035		0.105	
	(1.036)		(-0.494)		(1.446)	
$W\text{-}m_net_{ij}$		-0.239***		-0.081**		-0.186***
		(-7.551)		(-2.42)		(-5.613)
rho	0.584***	0.657***	0.494***	0.54***	0.575***	0.741***
	(9.507)	(11.492)	(7.405)	(8.42)	(8.523)	(12.551)
W matrix	Contiguity	Contiguity	Demography	Demography	Contiguity + Demography	Contiguity + Demography

Source: Authors' calculations. T statistics in brackets. Significance:. *** p<0.01, ** p<0.05, * p<0.1. Dependent variable: Interregional monetary flows of Accommodations and Restaurants generated by trips. (Average 2005–2009.)

Table 8. Alternative Spatial General Model (SAC-III: $W_1 = W_2 = W^{spa)}$)

Social-network measure used for elements m_{ij} & m_{ji}	R-squared	Rbar-squared	sigma^2	Log likelihood	i_N	gva_i	pop_j	$pcincome_j$	$ownreg_{ij}$	d_{ij}	m_{ij} = *Social networks*	m_{ji} = *Social networks'*	rho	lambda
Soc_net_2	0.9386	0.937	0.1385	-48.454998	-24.304***	0.471***	0.51***	1.707***	0.028	-0.064	0.228***	0.252***	-0.07***	0.836***
Soc_net_3	0.9518	0.9506	0.1088	-12.525703	-17.87***	0.529***	0.544***	1.063***	0.63***	-0.015	0.314***	0.114***	-0.062***	0.816***
Soc_net_4	0.9376	0.936	0.1408	-51.877311	-24.44***	0.499***	0.531***	1.711***	0.257*	-0.057	0.235***	0.221***	-0.076***	0.844***
Soc_net_5	0.9368	0.9352	0.1424	-53.131846	-24.701***	0.508***	0.536***	1.722***	0.204	-0.062	0.245***	0.216***	-0.073***	0.837***
Soc_net_6	0.9386	0.9371	0.1384	-48.555903	-22.713***	0.473***	0.515***	1.563***	-0.128	-0.107**	0.25***	0.231***	-0.069***	0.833***
Soc_net_7	0.9458	0.9444	0.1223	-25.723318	-18.626***	0.406***	0.372***	1.408***	-1.634***	-0.071	0.119**	0.492***	-0.06***	0.763***
Soc_net_8	0.9391	0.9376	0.1373	-47.640128	-22.986***	0.447***	0.488***	1.661***	-0.006	-0.06	0.221***	0.278***	-0.066***	0.84***
Soc_net_9	0.9361	0.9345	0.144	-49.762395	-22.51***	0.523***	0.6***	1.456***	0.09	0.038	0.201***	0.154***	-0.046**	0.772***
Soc_net_10	0.9375	0.9359	0.1409	-52.324179	-23.53***	0.502***	0.533***	1.585***	0.1	-0.066	0.248***	0.206***	-0.076***	0.844***
Soc_net_11	0.9403	0.9388	0.1346	-40.297177	-18.066***	0.421***	0.419***	1.307***	0.386***	-0.089*	0.044	0.502***	-0.06***	0.775***
Soc_net_12	0.9404	0.9389	0.1344	-41.140492	-18.702***	0.422***	0.424***	1.353***	-1.137***	-0.098*	0.061	0.493***	-0.062***	0.777***
Soc_net_13	0.939	0.9375	0.1375	-49.257076	-23.329***	0.512***	0.521***	1.585***	0.172	-0.054	0.274***	0.201***	-0.078***	0.857***
Soc_net_14	0.9384	0.9368	0.139	-50.961368	-23.105***	0.513***	0.526***	1.553***	0.279*	-0.042	0.264***	0.193***	-0.075***	0.846***
Soc_net_15	0.9268	0.925	0.165	-72.119997	-32.622***	0.622***	0.66***	2.225***	0.741***	-0.069	-0.127	0.493*	-0.066***	0.812***
Soc_net_16	0.9559	0.9548	0.0995	3.1876671	-16.369***	0.4***	0.503***	0.841***	0.618***	-0.112**	0.11***	0.414***	-0.043**	0.78***
Soc_net_17	0.9618	0.9608	0.0862	23.316959	-15.942***	0.417***	0.443***	0.721***	0.374***	-0.055	0.087***	0.48***	-0.056***	0.791***
Soc_net_18	0.9706	0.9699	0.0663	58.039691	-6.513***	0.158***	0.108**	0.304*	0.55***	-0.09**	0.138***	0.784***	-0.058***	0.826***
Soc_net_19	0.904	0.9016	0.2164	-109.23021	-26.75***	0.8***	0.948***	1.347***	1.564***	-0.276***	0.011	0.019*	-0.058**	0.781***

Source: Authors' calculations. T statistics in brackets. Significance:. *** p<0.01, ** p<0.05, * p<0.1. Dependent variable: Interregional monetary flows of Accommodations and Restaurants generated by trips. (Average 2005–2009.)

Appendix

Table A1. Alternative Spatial General Model (SAC-III: $W_1 = W_2 = W^{spa)}$)

$(m_{ji} + m_{ij})$ Social-network measure	R-squared	Rbar-squared	sigma^2	Log likelihood	i_N	gva_i	pop_j	$pcincome_j$	$ownreg_{ij}$	d_{ij}	$m_{ij} + m_{ji}$ = *Social networks+ Social networks'*	rho	lambda
Soc_net_2	0.9387	0.9374	0.1381	-49.048119	-24.067***	0.474***	0.51***	1.68***	0.026	-0.064	0.24***	-0.072***	0.842***
Soc_net_3	0.9487	0.9476	0.1157	-21.299598	-22.416***	0.491***	0.542***	1.572***	0.619***	-0.01	0.217***	-0.063***	0.813***
Soc_net_4	0.9371	0.9358	0.1417	-52.893313	-24.618***	0.498***	0.532***	1.726***	0.267*	-0.057	0.228***	-0.071***	0.833***
Soc_net_5	0.9368	0.9355	0.1424	-53.274376	-25.171***	0.502***	0.534***	1.781***	0.195	-0.061	0.232***	-0.074***	0.838***
Soc_net_6	0.9352	0.9338	0.1461	-54.70218	-23.107***	0.484***	0.515***	1.526***	0.013	-0.086	0.235***	0.004	0.81***
Soc_net_7	0.9454	0.9442	0.1231	-30.728987	-19.87***	0.376***	0.406***	1.528***	-1.638***	-0.07	0.306***	-0.064***	0.825***
Soc_net_8	0.939	0.9377	0.1375	-48.170558	-22.387***	0.455***	0.493***	1.586***	0.005	-0.062	0.247***	-0.066***	0.84***
Soc_net_9	0.936	0.9346	0.1444	-49.787451	-21.801***	0.53***	0.599***	1.377***	0.093	0.037	0.177***	-0.045**	0.771***
Soc_net_10	0.9371	0.9358	0.1417	-52.500915	-24.027***	0.494***	0.535***	1.645***	0.095	-0.066	0.228***	-0.078***	0.836***
Soc_net_11	0.9389	0.9376	0.1377	-46.622531	-19.566***	0.398***	0.433***	1.468***	0.377***	-0.084	0.274***	-0.063***	0.823***
Soc_net_12	0.9395	0.9382	0.1364	-45.094657	-19.931***	0.403***	0.439***	1.481***	-1.144***	-0.093*	0.278***	-0.064***	0.813***
Soc_net_13	0.9382	0.9369	0.1393	-50.176938	-24.795***	0.491***	0.523***	1.753***	0.169	-0.05	0.239***	-0.075***	0.842***
Soc_net_14	0.938	0.9367	0.1397	-50.642191	-24.427***	0.494***	0.527***	1.707***	0.271*	-0.039	0.23***	-0.074***	0.843***
Soc_net_15	0.9262	0.9247	0.1663	-73.29523	-31.876***	0.634***	0.658***	2.138***	0.751***	-0.073	0.181***	-0.064***	0.807***
Soc_net_16	0.9527	0.9517	0.1067	-10.272406	-18.867***	0.404***	0.491***	1.106***	0.616***	-0.112**	0.261***	-0.048***	0.824***
Soc_net_17	0.9561	0.9551	0.099	-0.79809748	-21.111***	0.38***	0.437***	1.295***	0.361***	-0.05	0.286***	-0.061***	0.842***
Soc_net_18	0.9611	0.9603	0.0877	1.2536318	-11.097***	0.099**	0.155***	0.795***	0.53***	-0.087**	0.458***	-0.089***	0.965***
Soc_net_19	0.904	0.9019	0.2164	-109.11979	-26.691***	0.8***	0.948***	1.34***	1.565***	-0.275***	0.015***	-0.058**	0.782***

Source: Authors' calculations. T statistics in brackets. Significance:. *** p<0.01, ** p<0.05, * p<0.1. Dependent variable: Interregional monetary flows of Accommodations and Restaurants generated by trips. (Average 2005–2009.)

Table A2. Alternative Spatial General Model (SAC-II: $W_1 = W^{net}$; $W_2 = W^{spa)}$)

Social-network measure used for elements m_{ij} & m_{ji}	R-squared	Rbar-squared	sigma^2	Log likelihood	i_N	gva_i	pop_j	$pcincome_j$	$ownreg_{ij}$	d_{ij}	m_{ij} = *Social networks*	m_{ji} = *Social networks'*	rho	lambda
Soc_net_2	0.9361	0.9345	0.144	-53.799	-24.598***	0.483***	0.51***	1.653***	0.161	-0.044	0.24***	0.228***	0.013	0.832***
Soc_net_3	0.9497	0.9485	0.1133	-17.638	-18.863***	0.531***	0.535***	1.072***	0.75***	0.009	0.113***	0.304***	0.043	0.806***
Soc_net_4	0.936	0.9344	0.1443	-57.039	-24.32***	0.511***	0.53***	1.625***	0.36**	-0.039	0.205***	0.245***	0.005	0.869***
Soc_net_5	0.9349	0.9332	0.1469	-58.750	-24.434***	0.522***	0.536***	1.631***	0.303*	-0.045	0.203***	0.254***	-0.009	0.853***
Soc_net_6	0.9354	0.9338	0.1456	-54.168	-23.54***	0.485***	0.517***	1.537***	0.059	-0.084	0.222***	0.236***	0.038	0.803***
Soc_net_7	0.9431	0.9417	0.1283	-30.291	-19.136***	0.42***	0.372***	1.372***	-1.442***	-0.05	0.494***	0.099*	0.012	0.731***
Soc_net_8	0.9368	0.9352	0.1425	-52.733	-23.3***	0.458***	0.488***	1.614***	0.116	-0.042	0.268***	0.22***	0.012	0.836***
Soc_net_9	0.9342	0.9325	0.1484	-51.505	-23.302***	0.527***	0.593***	1.464***	0.207	0.056	0.148***	0.199***	0.029	0.732***
Soc_net_10	0.9353	0.9337	0.1458	-58.648	-23.645***	0.517***	0.534***	1.51***	0.23	-0.047	0.189***	0.253***	0.013	0.857***
Soc_net_11	0.9374	0.9358	0.1411	-44.377	-18.926***	0.436***	0.426***	1.282***	0.544***	-0.068	0.491***	0.029	0.032	0.738***
Soc_net_12	0.9382	0.9367	0.1393	-44.842	-19.448***	0.433***	0.424***	1.337***	-0.959***	-0.075	0.483***	0.054	0.02	0.769***
Soc_net_13	0.9365	0.9349	0.1431	-56.332	-22.801***	0.528***	0.522***	1.472***	0.269	-0.038	0.19***	0.282***	-0.021	0.862***
Soc_net_14	0.9365	0.935	0.1431	-55.804	-22.853***	0.528***	0.525***	1.453***	0.386**	-0.025	0.178***	0.272***	0.003	0.865***
Soc_net_15	0.9226	0.9206	0.1746	-76.889	-32.887***	0.633***	0.666***	2.14***	0.94***	-0.058	0.482*	-0.151	0.048	0.754***
Soc_net_16	0.9545	0.9534	0.1025	0.141	-16.392***	0.402***	0.495***	0.81***	0.678***	-0.097**	0.416***	0.11***	-0.005	0.764***
Soc_net_17	0.9596	0.9586	0.0912	16.755	-16.361***	0.423***	0.435***	0.699***	0.477***	-0.033	0.476***	0.084***	0.014	0.765***
Soc_net_18	0.9687	0.9679	0.0705	50.812	-7.654***	0.164***	0.103**	0.329*	0.661***	-0.064*	0.771***	0.135***	0.044	0.804***
Soc_net_19	0.9029	0.9005	0.2189	-103.665	-28.687***	0.75***	0.869***	1.461***	1.714***	-0.249***	0.017	0.006	0.197***	0.622***

Source: Authors' calculations. T statistics in brackets. Significance:. *** p<0.01, ** p<0.05, * p<0.1. Dependent variable: Interregional monetary flows of Accommodations and Restaurants generated by trips. (Average 2005–2009.)

Table A3. Alternative Spatial General Model (SAC-II: $W_1 = W^{net}$; $W_2 = W^{spa)}$)

$(m_{ji} + m_{ij})$ Social-network measure	R-squared	Rbar-squared	sigma^2	Log likelihood	i_N	gva_i	pop_j	$pcincome_j$	$ownreg_{ij}$	d_{ij}	$m_{ij} + m_{ji}$ = *Social networks+ Social networks'*	rho	lambda
Soc_net_2	0.9357	0.9344	0.1448	-54.440	-24.527***	0.487***	0.512***	1.635***	0.179	-0.044	0.232***	0.017	0.821***
Soc_net_3	0.9465	0.9453	0.1207	-24.947	-23.48***	0.492***	0.53***	1.563***	0.765***	0.019	0.208***	0.068*	0.783***
Soc_net_4	0.9348	0.9334	0.1469	-58.161	-24.545***	0.507***	0.53***	1.672***	0.35**	-0.038	0.228***	-0.023	0.843***
Soc_net_5	0.9341	0.9327	0.1485	-59.944	-25.076***	0.512***	0.533***	1.72***	0.288*	-0.043	0.231***	-0.025	0.839***
Soc_net_6	0.9354	0.934	0.1457	-53.950	-23.57***	0.484***	0.516***	1.545***	0.054	-0.084	0.23***	0.035	0.802***
Soc_net_7	0.9434	0.9422	0.1275	-36.195	-20.19***	0.384***	0.403***	1.496***	-1.522***	-0.05	0.303***	0.002	0.829***
Soc_net_8	0.9369	0.9356	0.1422	-53.356	-22.617***	0.463***	0.491***	1.547***	0.104	-0.044	0.245***	0.001	0.843***
Soc_net_9	0.9343	0.9329	0.1481	-51.806	-22.78***	0.532***	0.59***	1.391***	0.226	0.055	0.171***	0.049	0.74***
Soc_net_10	0.9344	0.933	0.1478	-58.535	-24.648***	0.507***	0.537***	1.608***	0.255	-0.045	0.219***	0.022	0.836***
Soc_net_11	0.9363	0.9349	0.1436	-51.330	-20.428***	0.412***	0.436***	1.449***	0.518***	-0.062	0.264***	0.032	0.804***
Soc_net_12	0.9364	0.935	0.1435	-50.302	-20.899***	0.419***	0.444***	1.46***	-0.911***	-0.071	0.264***	0.038	0.776***
Soc_net_13	0.9358	0.9344	0.1448	-56.460	-25.017***	0.502***	0.524***	1.703***	0.283*	-0.033	0.235***	0	0.853***
Soc_net_14	0.9362	0.9349	0.1437	-56.586	-24.663***	0.501***	0.525***	1.665***	0.37**	-0.022	0.228***	0.006	0.867***
Soc_net_15	0.9232	0.9216	0.173	-77.162	-32.175***	0.644***	0.66***	2.078***	0.904***	-0.058	0.17***	0.027	0.785***
Soc_net_16	0.9507	0.9496	0.1112	-13.550	-19.063***	0.406***	0.483***	1.079***	0.69***	-0.097**	0.259***	0.012	0.785***
Soc_net_17	0.9537	0.9527	0.1043	-5.7959	-21.833***	0.385***	0.429***	1.283***	0.48***	-0.026	0.28***	0.042	0.812***
Soc_net_18	0.9585	0.9576	0.0936	3.138	-12.67***	0.104**	0.144**	0.85***	0.647***	-0.064	0.45***	0.073**	0.888***
Soc_net_19	0.903	0.901	0.2186	-103.802	-28.58***	0.752***	0.87***	1.448***	1.712***	-0.248***	0.011**	0.195***	0.63***

Source: Authors' calculations. T statistics in brackets. Significance:. *** p<0.01, ** p<0.05, * p<0.1. Dependent variable: Interregional monetary flows of Accommodations and Restaurants generated by trips. (Average 2005–2009.)

FIGURES

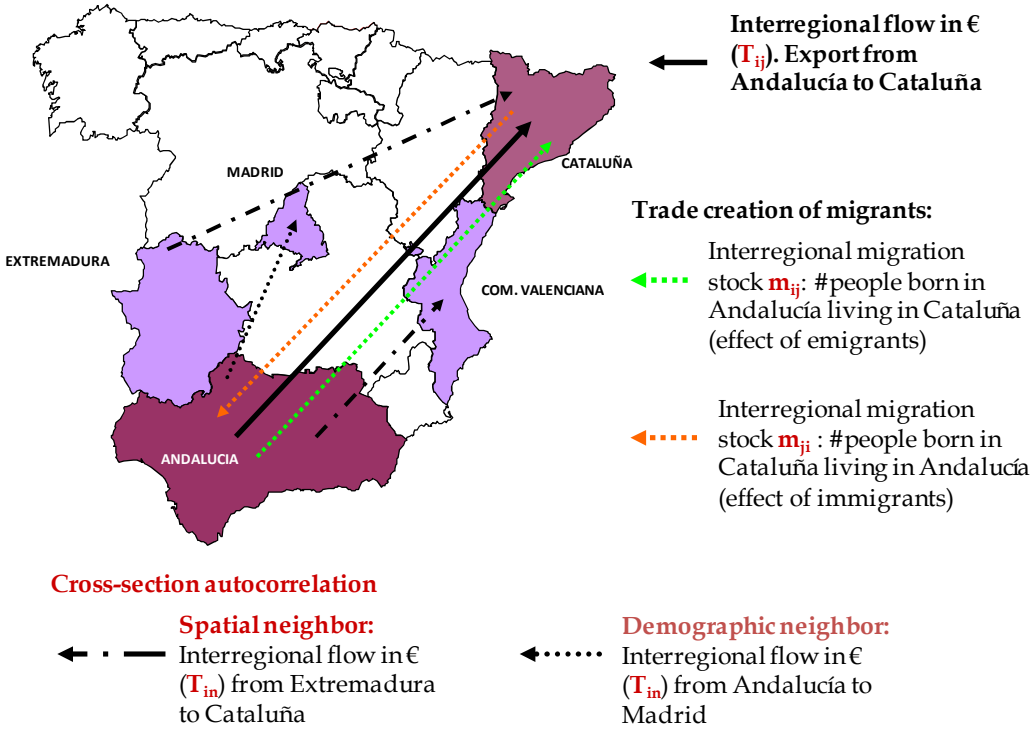

Figure 1: Intuitive scheme showing the relation between trade flows in services and migration stocks.

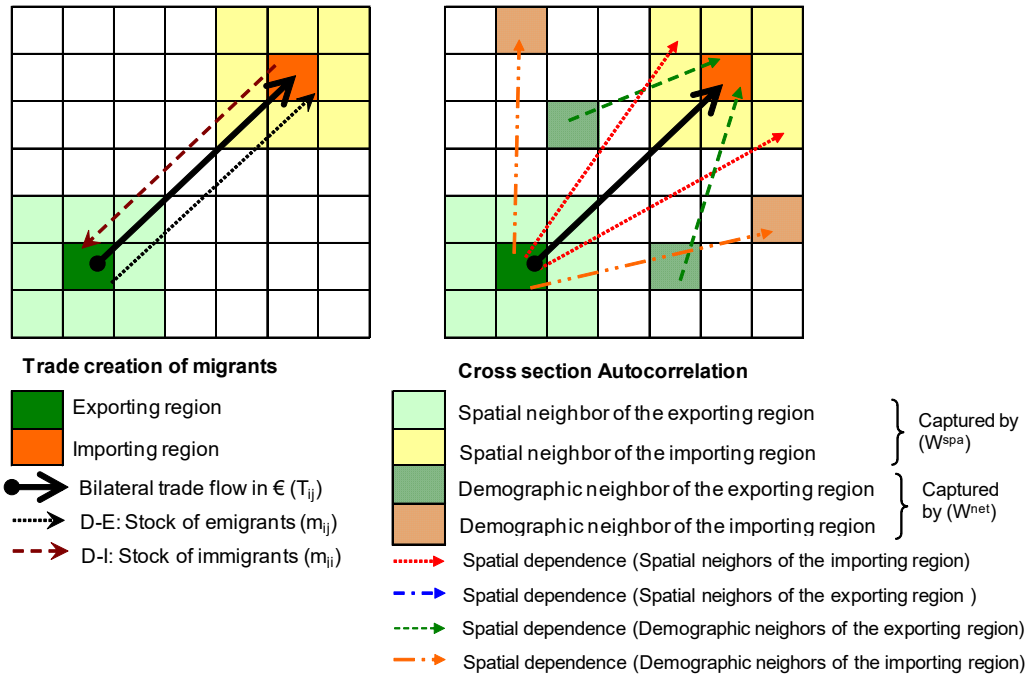

Figure 2: Scheme summarizing spatial and network effects on bilateral flows.

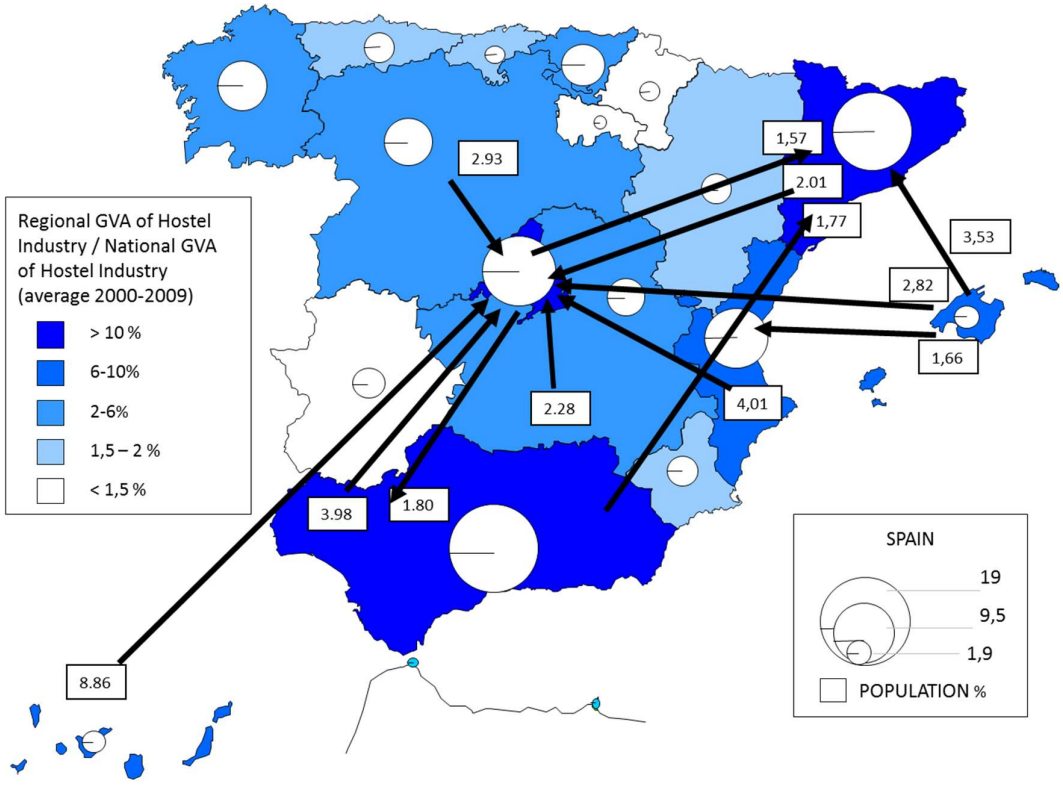

Figure 3: Main interregional flows (€) for Accommodations and Restaurants
% of total interregional flows. (Average for 2000–2009)

Region (NUTS 2)	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1				X	X			O	X		⊗			O			
2							O	O	⊗	O					⊗		O
3						⊗	⊗					⊗					
4	X				X				X	X				X			
5	X			X								X	X				
6			⊗				⊗									⊗	
7		O	⊗			⊗		O			O	⊗	⊗			⊗	O
8	O	O					O			⊗	⊗		⊗	O			
9	X	⊗		X						O							
10		O		X				⊗	O					⊗			
11	⊗						O	⊗					X			X	
12			⊗		X		⊗										
13					X		⊗	⊗			X						
14	O			X				O		⊗							
15		⊗														⊗	⊗
16						⊗	⊗				X				⊗		⊗
17							O								⊗	⊗	

Region (NUTS 2)	Code	Region (NUTS 2)	Code	Region (NUTS 2)	Code
Andalucía	1	Castilla y León	7	Madrid (Comunidad de)	13
Aragón	2	Castilla-La Mancha	8	Murcia (Región de)	14
Asturias (Principado de)	3	Cataluña	9	Navarra (Comunidad Foral de)	15
Baleares (Islas)	4	Comunidad Valenciana	10	País Vasco	16
Canarias	5	Extremadura	11	Rioja (La)	17
Cantabria	6	Galicia	12		

Figure 4: Comparison of the neighboring pattern with the contiguity matrix and the demography-link matrix

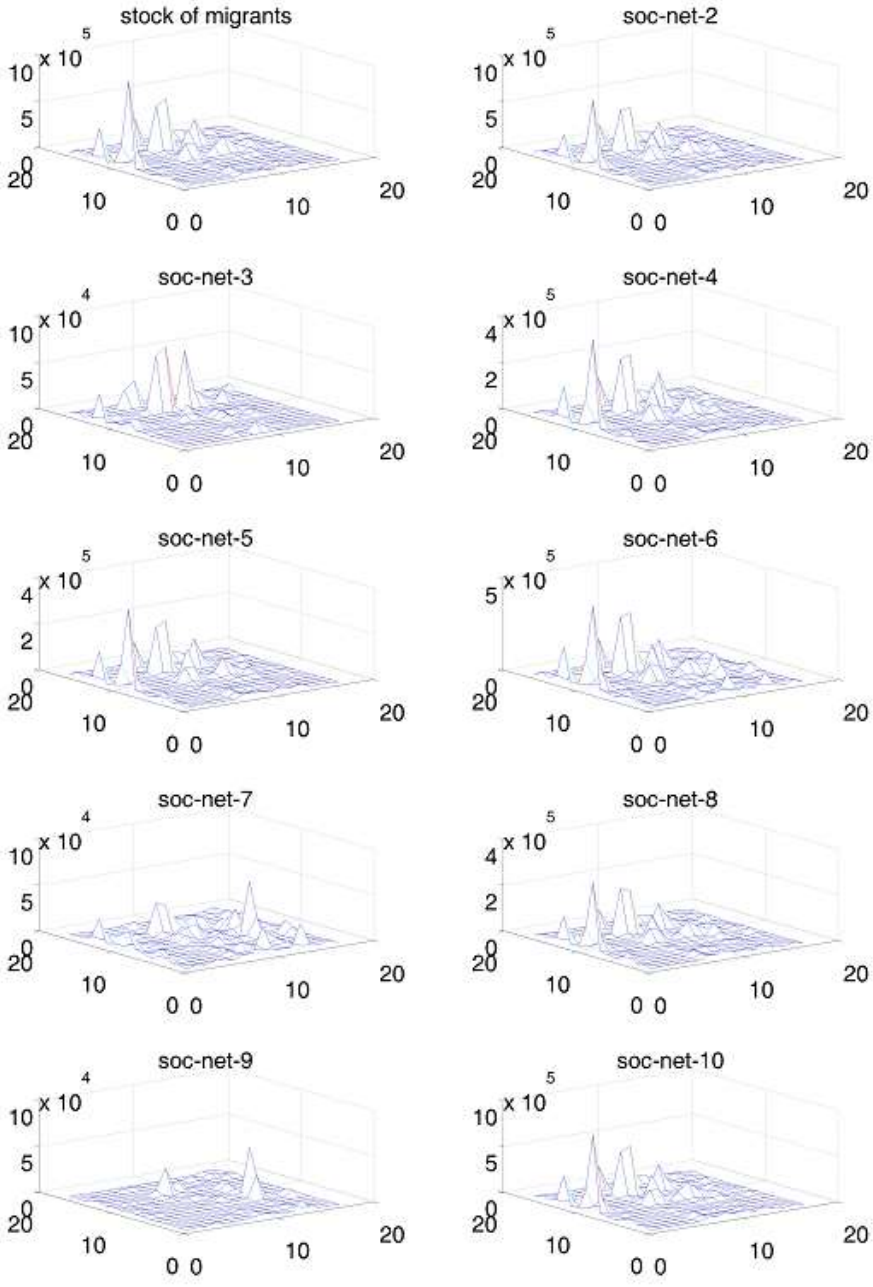

Figure 5a. Geographical pattern of alternative social-network measures.

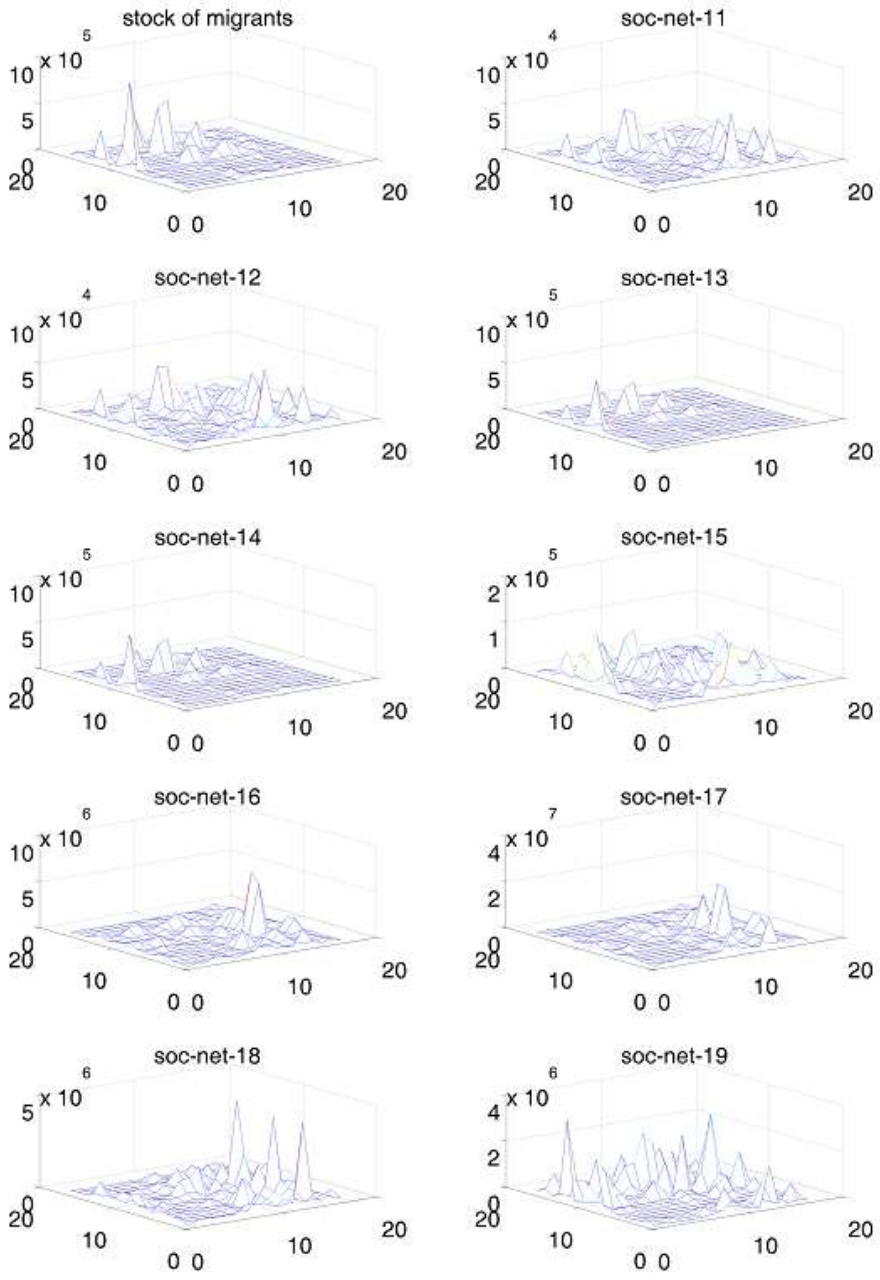

Figure 5b. Geographical pattern of alternative social-network measures.

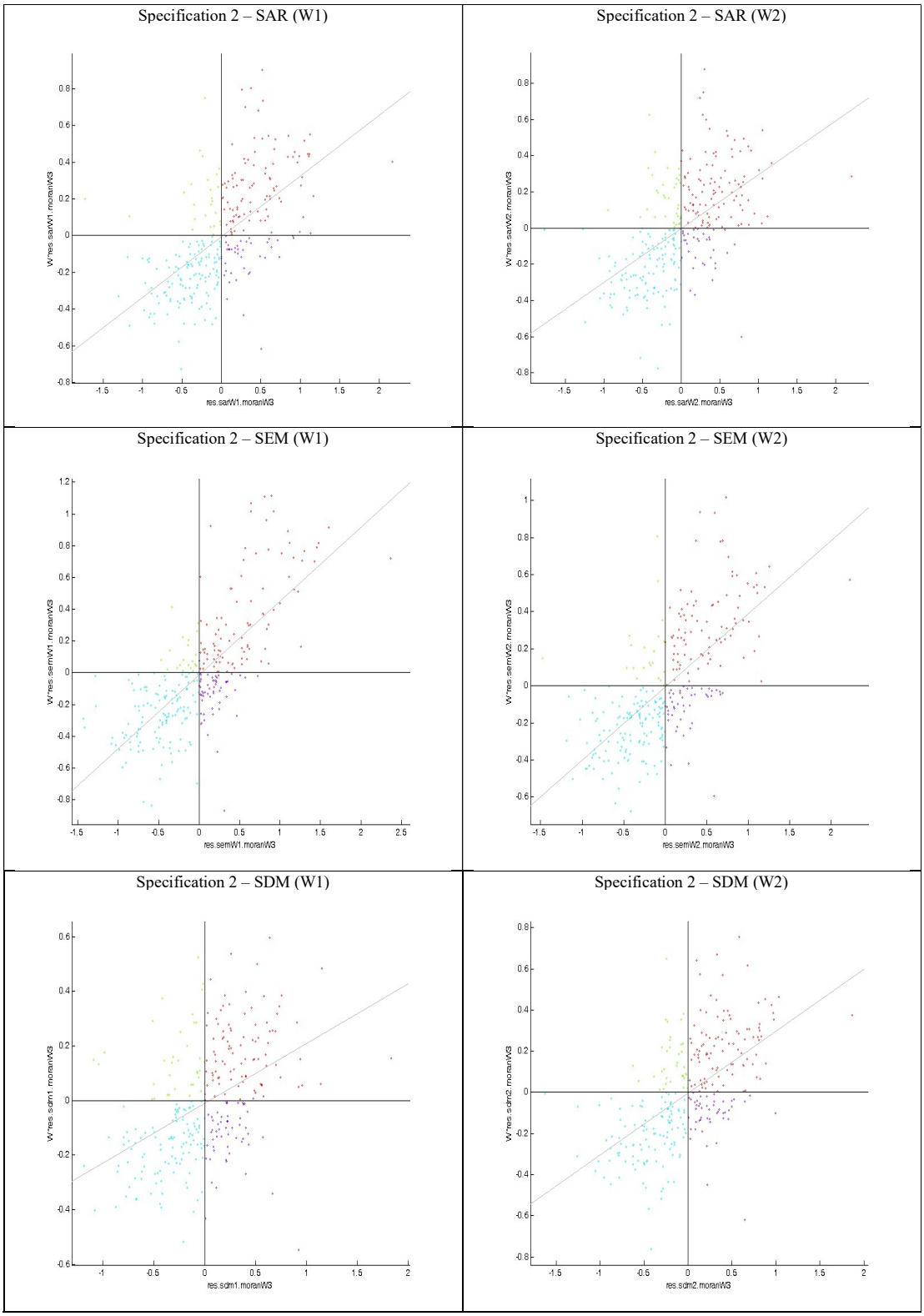

Figure 6a. I-Moran scatterplot on residuals from SAR, SEM and SDM estimates. Y = Residuals with "average" flows and stocks for 2000–2009. Scatterplot uses $W_3 = W^{spa} + W^{net}$.

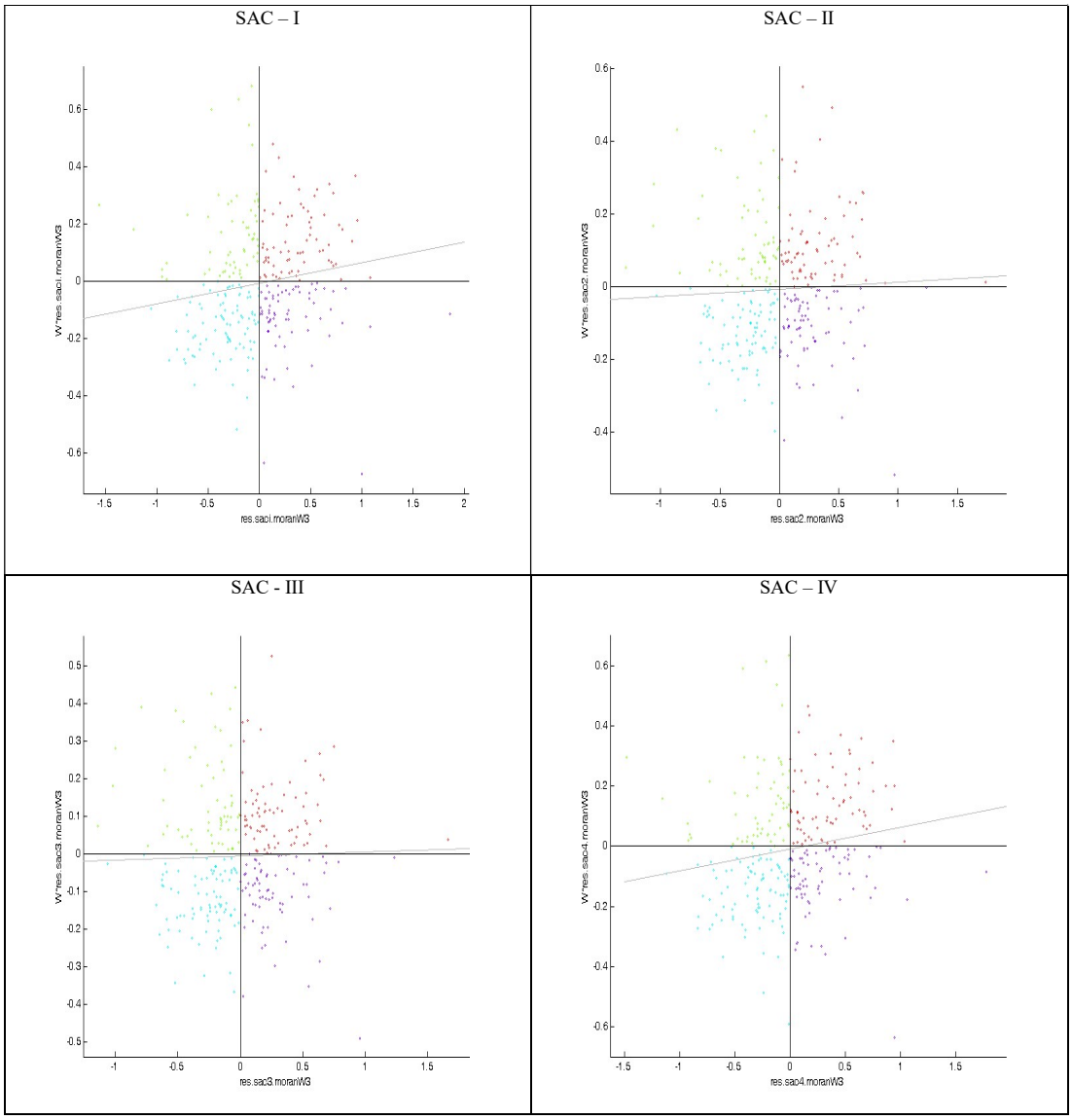

Figure 6b. I-Moran scatterplot on residuals from SAC estimates. Y = Residuals with average flows and stocks 2000–2009. Scatterplot uses $W_3 = W^{spa} + W^{net}$.