Journal of Geographical Systems 15.3 (2013): 319-367

**DOI:** http://dx.doi.org/10.1007/s10109-013-0183-6

# Social networks and trade of services: modelling interregional flows with spatial and network autocorrelation effects

**Tamara de la Mata · Carlos Llano**

**Abstract** Recent literature on border effect has fostered research on informal barriers to trade and the role played by network dependencies. In relation to social networks, it has been shown that intensity of trade in goods is positively correlated with migration flows between pairs of countries/regions. In this article, we investigate whether such a relation also holds for interregional trade of services. We also consider whether interregional trade flows in services linked with tourism exhibit spatial and/or social network dependence. Conventional empirical gravity models assume the magnitude of bilateral flows between regions is independent of flows to/from regions located nearby in space, or flows to/from regions related through social/cultural/ethic network connections. With this aim, we provide estimates from a set of gravity models showing evidence of statistically significant spatial and network (demographic) dependence in the bilateral flows of the trade of services considered. The analysis has been applied to the Spanish intra- and interregional monetary flows of services from the accommodation, restaurants and travel agencies for the period 2000 2009, using alternative datasets for the migration stocks and definitions of network effects.

**Keywords** Social networks · Gravity models · Trade of services · Internal tourism · Bayesian spatial autoregressive regression model · Spatial connectivity of origin destination flows

**JEL Classification** C21 · F12 · F14 · L83 · R22

T. de la Mata
IESE Business School, Barcelona, Spain
e mail: tamara.delamata@uam.es; TDelamata@iese.edu

T. de la Mata C. Llano (✉)
Departamento de Análisis Económico: Teoría Económica e Historia Económica and Instituto L.R. Klein, Universidad Autónoma de Madrid, 28049 Madrid, Spain
e mail: carlos.llano@uam.es

## 1 Introduction

In spite of decreases in transportation costs, recent literature on border effect shows how countries still engage more in internal trade than external trade with other countries (McCallum 1995; Helliwell 1996; Wolf 2000; Chen 2004; Okubo 2004; Evans 2006). In an effort to explain this, research has increasingly focused on informal barriers to trade. One such barrier is a lack of information about international trade and investment opportunities (Rauch and Casella 2003). Social and business networks are seen as possible channels 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 mechanism is related to 'idiosyncratic' preferences of immigrants or 'taste effects', where the positive impact of immigrants on trade intensity reflects tastes for goods from their countries of origin. The second mechanism is the reduction of transaction costs or 'information effects', since immigration reduces transaction costs since migrants are familiar with preferences, social institutions, language and legal institutions of both countries, which reduces communication costs and cultural barriers. Moreover, communication between immigrants and those living in their country of origin is facilitated by social and business networks that is thought to be the explanation for higher levels of bilateral trade flows. Helliwell (1997) argued that given that institutions might be more different across countries than between regions within the same country, the trade creation effect of migrants should be bigger on international than on interregional trade. However, several papers (Combes et al. (2005), Millimet and Osang (2007), Garmendia et al. (2012)) have found that even at the regional level, the presence of networks can explain a part of the border effect puzzle. In fact, given that a higher percentage of both migration and trade takes place between regions within the same country, we could expect that this effect will be greater in absolute terms for domestic than for international trade.

Motivated by this literature, we investigate whether similar results exist for regional trade in services. We focus on the special case of interregional trade flows of some sectors related with tourism: accommodation, restaurants and travel agencies. Trade in these sectors usually implies a cross-border movement of people. The motivation for this focus is fourfold: first, it is well known that in all the developed countries, services account for the largest part of all economic activity; second, due to the lack of information on bilateral trade of services, it is difficult to find empirical work on quantification of border effects for services. Therefore, the relation between distance, the trade of services and the presence of informal barriers remains an open question. Third, we can expect that given the characteristics of services, information and tastes should affect more trade than for the case of goods. And finally, due to data restrictions, most studies have focused on the link between international migration and international trade, not taking into consideration that the bulk of people and trade flows between regions within countries.

Focusing on the link between tourism and migration at the international level, the network effects in absolute terms could be reduced by the limited number of foreign immigrants in a country given the restrictions to migrate, the low-income composition of the immigration structure, and the high cost of travel back to the home country. However, when the analysis focuses on the internal or interregional tourism flows, we might expect to see higher magnitudes of flows. According to a recent report by the World Bank (The World Bank 2008), the largest migration movements in the world are taking place nowadays within rather than between countries. According to this report, while 500,000 Chinese emigrated abroad in 2005, more than 150 million people moved internally in China itself. Similarly, in Brazil, during the 1960s and 1970s, almost 40 million people left the countryside for cities. However, these huge displacements are not just observed in developing countries where mass rural exodus are on course, but in OECD countries as well. For example, in the US cumulative moves over the 5-year period from 1995 to 2000 involved 112 million people for the United States, of which 22 million involved moves between states (Perry and Schachter 2003). Spain is a much smaller country, but with a strong tourist tradition, since Spain ranks 3rd in the world in terms of tourists inflows, and with a large tradition of interregional migration and intense internal movements during holidays and weekends. In 2001, there were 552 million overnight stays by Spanish citizens within Spain, despite the fact that Spain has only 42 million citizens. In addition, mobility of Spanish citizens is such that 16 % of the population live in a region different from that in which they were born. An important distinction between interregional and international movement of citizens is that lodging expenses may be lowered by ownership of ‘second residences’ or the ability to ‘share’ accommodations with relatives and friends in the case of interregional flows of visitors, augmenting potential savings on ‘transaction costs’ induced by the presence of ‘social networks’ that would apply in the case of international tourism flows.

Despite these intuitively appealing reasons to believe that the potential for significant relationships between trade flows in sectors linked with tourism and stocks of immigrants in the interregional case is greater than for international tourism, the lack of information has limited the ability to explore this type of interregional flows. To our knowledge, there have been no previous attempts to measure this type of relation for internal flows in service sectors linked with the touristic activity in Spain or worldwide.[1] In terms of social networks, there are several mechanisms that could induce positive correlation between trade and the intensity of the demographic linkages. In addition to the traditional trade creation effect of emigrants and immigrants found in the literature, we find that there are also potential sources of cross-sectional autocorrelation based on the regional concentration of the stocks of interregional emigration and immigration. This source of cross-sectional autocorrelation that we have labelled as ‘network autocorrelation’ or

---

[1] There are some studies analysing internal tourism flows, but they use input output models (Eriksen and Ahmt 1999), or time series approaches (Athanasopoulus and Hyndman 2008), but not a gravity model with cross sectional data or attention paid to network effects.

‘demographic-based autocorrelation’ could also affect the bilateral flows between two regions. These channels will be explained in Sect. 2.[2]

Recently, several articles have made use of spatial econometrics techniques when analysing different topics in international economics such as the determinants of foreign direct investment or the effects of entering in a bilateral agreement. This fact has highlighted the importance of including the geographic perspective in the analyses in order to control for the spatial dependence caused by spatial aggregation, spatial externalities, spillover effects and the spatial heterogeneity (Anselin 1988). Porojan (2001) revisited the gravity model of trade using the increasingly acknowledged findings of spatial econometrics. He examined the effect of being a member of a regional trade agreement incorporating the spatial effects in the analysis. He found that substantial changes occur in the magnitude and the statistical significance of the estimated parameters when the interdependence among countries is controlled. More recently, Egger and Larch (2008) examined the determinants of entering in a bilateral preferential trade agreement (PTA) making use of techniques drawn from spatial econometrics. They employ models for discrete choice panel data and a Bayesian spatial discrete choice model for interdependent cross-sectional data, paying attention on the interdependence of PTA memberships. Ledyaeva (2009) analysed empirically the determinants of the FDI in the Russian regions. This paper showed how adjacent regions have influenced FDI inflows to a particular region using a lag-dependent variable and the market potential. Finally, Behrens et al. (2010) derived a structural gravity equation system in which both trade flows and error terms are cross-sectionally correlated that can be estimated using techniques from the spatial econometrics literature. According to their findings, controlling directly for cross-sectional interdependence reduce measured border effects by capturing ‘multilateral resistance’ that is not totally controlled using origin and destination specific fixed effects.

Based on these recent approaches, in this paper, we study the relation between interregional trade flows of services linked to the tourism sector using a gravity model that relies on conventional distance measures thought to inhibit flows, plus spatial econometric methods for incorporating social network relationships between regions into the gravity model. The latter are based on use of the stock of interregional immigrants living in each region to form a spatial weight structure linking regions. This type of interregional dependence is contrasted with more conventional weight structures based on geographic proximity of the regions. We exploit recent estimates of the intra- and interregional trade flows of service sectors linked with tourism activity between the Spanish regions for the period 2000  2009 (De la Mata and Llano 2012), as well as efficient Bayesian econometric approaches based on Markov chain Monte Carlo (MCMC) estimation methods. Such methods are used for three alternative spatial model specifications, namely, a spatial lag model (SAR), a general spatial model (SAC) and a spatial Durbin model (SDM). These specifications have been defined in such a way that embed two different

[2] In previous versions, we described as ‘direct effects’ the trade creation effect of social networks that has been traditionally described in the literature and as ‘indirect of effect’ the spatial autocorrelation of the flows (based on the demographic structure). In this version, we have abandoned these concepts in order to be more consistent with the terms used in the spatial econometrics literature and in the trade literature.

weight matrices, which attempt to capture independently and simultaneously the two complementary autocorrelation effects described before, spatial and demographic. Additional robust analysis are also reported, using migration flows from previous years (census 1981) as well as alternative definitions of demographic neighbourhood.

We show that in the case of a simple gravity model, a strong 'internal border effects' exists, and trade of services linked with the tourism sector responds with a small negative but significant response to distance while controlling for intraregional trade flows. More sophisticated models that introduce an increasing number of autocorrelation effects tend to diminish the importance and significance played by geographic distance in the simpler models. These results are interpreted as an indication that people in their domestic trips express a preference for consumption of services from regions with which they have strong migration linkages. Spatial econometric methods draw upon the concept of 'neighbouring regions', where this is typically measured using geographic proximity. We broaden this concept to include regions that could be considered 'neighbours' based on the structure of emigration and immigration for each region. The role played by this type of regional connectivity could be labelled 'network effects', since past migration flows in conjunction with social networks represent an alternative to conventional geographic proximity of regions.

An interesting finding is that after taking into account conventional geographic proximity and network connectivity of regions, the role played by distance between exporting and importing regions drops. This means that the presence of social networks reduces the frictions that introduce distance.

In Sect. 2, we discuss some aspects of trade on services as well as network influences on trade flows of services. Section 3 presents an empirical gravity model, detailing a series of increasingly complex specifications that control for spatial/geographic as well as network dependencies. Empirical results obtained from applying the model to intra-and interregional trade flows associated with tourism in Spain are presented and discussed in Sect. 4.

## 2 Trade and social networks: background and definitions

### 2.1 Previous literature

An economic network has been defined as a group of agents that pursue repeated, enduring, exchange relations with one another (Podolny and Page 1998). Based on this definition, several authors have analysed the impact on bilateral trade between origin and destination regions of the stock of immigrants or emigrants from/to the importing and exporting region. As Rauch (2001) pointed out in his review, an immediate concern is 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 country of origin or destination characteristics that promote trade, for example geographic proximity. However, different authors have demonstrated that apart from these 'taste effects', there are also 'network effects' induced by the social linkages that immigrants maintain with their countries of origin. Such linkages may lead to important reductions in transaction cost resulting in increased bilateral trade flows.

Some authors have tried to quantify the relevance of social and business networks on trade in goods between countries. For example, Gould (1994), an early article analysed US trade with 47 other countries over the period from 1970 to 1986 arguing that immigration reduced information costs and or resistance due to border effects. Head and Ries (1998) carried out a similar analysis of Canadian bilateral trade involving 136 countries for the period 1980 to 1992. Dunlevy and Hutchinson (1999, 2001) studied US imports and exports over the period from 1870 to 1910, finding that immigration affected both imports and exports. They argue that for the case of imports 'taste effects' are larger than what they term 'information effects'. For exports, they contend that 'information effects' are more important because this facilitates knowledge needed to promote trade opportunities between both countries. Similarly, Wagner et al. (2002) studied the effects of immigration on the international trade of Canadian provinces, and Rauch and Trindade (2002) studied how the presence of Chinese ethnics affect bilateral trade. In countries where a large presence of Chinese ethnics who maintained connections with their home land, as in southeast Asia, the effects on the bilateral trade were found to be greater. Digging deeper into the historic causes of the social networks induced by stocks of immigrants, Girma and Yu (2002) carried out an analysis using data on immigration and trade for the United Kingdom. They distinguished between migration from countries with historic relations to the commonwealth and countries with no such relation. White and Tadesse (2008) measured the effect of immigration on trade, using state-level US data, 75 countries, and a novel indicator of cultural distance. They too confirmed that immigrants tend to counteract the negative effect on trade arising from cultural distance. However, their results indicated that the influence of immigrants on trade was not large enough to overcome resistance to trade associated with information costs induced by cultural distance or separation.

The role played by migration in determining patterns of trade flows within a single country has been examined by a reduced number of papers. Helliwell (1997) analysed the interregional and international trade of Canada and the US, finding that interregional migration played a minor role compared to that of international migration. The argument was that 'taste and information effects' are smaller between regions than between countries because differences in institutions are smaller. More recently, Combes et al. (2005) quantified the impact of social and business networks on the intensity of interregional trade between 94 French regions (departments). Using different gravity models, they verified that despite the traditional impediments to trade (distance and boundaries), networks facilitate bilateral trade, finding larger effects for business than for social networks. Finally, for the Spanish case, Garmendia et al. (2012) found out that the large border effect for the domestic Spanish trade disappear once the higher density of social and business networks within regions than between regions are considered.

As already noted, most of these studies focus on trade of goods, without considering interregional trade of services and the role played by interregional migration flows. To this regard, although the results found by Helliwell (1997) and others may point out to a less relevant effect of migration on trade of goods within a country than between countries (due to the lower differences within countries in terms of flavours, culture, institutions, etc.), there are also several reasons to expect larger effects when dealing with services: first, the magnitude of domestic trade in services is much larger than goods in all OCDE countries;[3] second, within countries immigration flows could be very intense and some times larger and more persistent over time than between countries; third, considering that information is more important for trade in services than for trade in goods (in relation with the 'face-to-face relation', also called the 'proximity burden'), the effect of a reduction in transaction costs driven by the presence of social networks is expected to be larger; finally, as we have commented before, when focussing on interregional trade flows of services related to the tourism sector, one has to consider that apart from the information and taste effects operating in goods, there is a potential reduction of lodging costs for those tourists that take advantage of second homes and accommodations owned by relatives and friends, a case that is more likely to occur within countries, when travelling back to the regions where they were born. Note that at least in some Mediterranean countries like Spain, Italy or France, this phenomenon is far from sporadic and may be repeated almost every weekend.

### 2.2 Relation between trade flows linked to tourism and migration

For generality and simplicity, in this section, we describe concepts related to both international and interregional trade and the role of past migration flows embodied in stocks of migrants from various origins. This approach might be more appealing to an international audience, despite the fact that our empirical application uses interregional data exclusively. More specifically, in our empirical application, we will just consider interregional trade and migration flows between the 17 Spanish regions (NUTS2).

For our purposes, an immigrant is defined as an individual who was born in a different region ('home land') from his current region of residence ('host region'). Note also that, when considering interregional monetary flows of sectors linked to touristic activity, an 'exporting region' is the one producing the service, in our case, the region receiving the tourists. Focusing on these sectors, there 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 in two groups to differentiate between relations affecting the trading regions ('emigrants and immigrants effects', as has been traditionally labelled in the literature) or relations affecting neighbours of the trading regions (cross-sectional autocorrelation).

Before going deeper in explaining the emigrants and immigrants effect on trade in services, it is useful to show that regarding trade on services, the movement of the people and the trade flow go in opposite directions. As an example, when one person travels from region $j$ to region $i$, and this person consumes services in region $i$, it will be a service provision of firms in regions $i$ to a resident in region $j$; that is, an

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

export of services from $i$ to $j$. Then, the origin of the monetary flow (export) corresponds with destination of the trip and vice versa.

Related to the channels considered in the empirical literature on the trade creation effect of social networks, two main ways can be described connecting our trade flows linked to tourism and the interregional migration stocks:

1. The destination choice of an internal touristic trip by immigrants is conditioned by familiar ties with their homeland. Since tourists take advantage of vacations to visit their homeland, they may own homes or have access to property in these regions. Then, the larger the stock of emigrants in a region, the larger the exports from the regions of origin of the emigrants (region where they were born) to the host regions. We label this as 'emigrants effect'.
2. Conversely, relatives and friends (that have not migrated) may tend to visit immigrants in their host regions, since these visits are made easier by access to information and less expensive dwelling options than other possible tourism destinations. Then, the larger the stock of immigrants in a region, the larger the exports from the host region to the homeland of the people that had migrated. We label this the 'immigrants effect'.

Apart from these two effects that would enhance bilateral flows and that have been traditionally analysed in trade literature, there are additional channels of influence that could impact bilateral trade flows of the sectors linked to tourism activity. These additional channels arise from what could be considered as cross-sectional autocorrelation based on 'spatial or demographic' neighbouring, and they tend to connect each bilateral trade flow of services with the outflows or/and inflows from/to the neighbouring locations of the exporting and 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 refers to the fact that a flow from $i$ to $j$ is associated with those flows from neighbours of $i$ to $j$; the latter (destination-based dependence) captures the relation between the flow from $i$ to $j$ and the flows from $i$ to the neighbours of $j$.[4] Then, in the case of bilateral trade flows between regions $i$ and $j$, exports from $i$ to $j$ could be associated with exports from $i$ to neighbours of $j$ (importer-based dependence) and with the exports from the neighbours of $i$ to $j$.

Moreover, the concept of 'neighbouring region' could be defined from a geographic proximity or spatial contiguity perspective as in Lesage and Pace (2008), or more generally using proximity measured in terms of population demographic composition.

There could be **cross-sectional dependence** between a given flow and a flow from the spatial neighbour (**contiguous regions**) of the neighbour of the exporting to the importing region (exporting-based dependence) and another flow from the

[4] In LeSage and Pace (2008) a third 'origin destination based dependence' was described, which captures the relation between the flows between the neighbours of $i$ and the neighbours of $j$. Like in Fisher and Griffith (2008), in this paper, this relationship is not considered.

exporting region to a neighbour of the importing region (importing-based dependence):

1. Export flows from a region *i* to a given region *j* can be correlated with exports from *i*'s neighbours to *j*. This spatial dependence could be caused because of different mechanisms:

    (a) Due to the 'taste effect', exports of service sectors linked to tourism from one region and the contiguous to a specific region may be related because people living in the importing region may choose one, the other or both destinations because these regions will have similar unobserved characteristics, such as weather, culture, etc.
    (b) In addition, it is easy to assume that people also have more information about the touristic options of any other region contiguous to the destination of the trip. Sharing common infrastructures can reinforce 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 neighbours of *j*. The mechanisms causing this type of spatial autocorrelation are equivalent to those described for the regions of origin of the flow (destination of the trips) but with forces acting in the opposite direction:

    (a) Due to the 'taste effect', people living in a specific region (importing region, j) may choose similar destinations than those people living in a spatial neighbour of this region (neighbours of the importing region), since the probability that they will have similar unobserved characteristics (tastes, culture, preferences, etc.) is higher than with people living in remote regions.
    (b) In addition, we can assume that people living in contiguous regions will have access to similar infrastructures and they could also have similar information about tourist options of any other region (exporting region, *i*).

For the case of **cross-sectional autocorrelation** based on the **demographic structure** (network dependence) of the regions, we can also delineate two of these mechanisms (based on the concentration of the emigration stocks of each region):

1. The first one relates to historic patterns of emigration in a region with the current tourist decisions through the 'importing-based dependence'. If emigrants from a given region have concentrated in a group of host regions, then it is likely that a social network between the home and the host regions appears. People in this social network (i.e. The members of a family all of them living in different regions) decide to travel periodically as tourist to the same region. Then, the imports of one region are not independent on the imports of its demographic neighbour. This cross-relation between demographic neighbours of a region may introduce enhancing or competing effects for the positive relation of migrants and trade of our three services sectors. As noted earlier, immigration is influenced by gravity so 'demographic neighbours' could

coincide with ‘spatial neighbours’. However, alternative situations might also arise. For example, one might consider the Jewish Diaspora in general terms, and specifically after WWII when strong Jewish communities were organized in countries such as Israel, the US or Argentina, which are considerable distant one from the other, have strong community links, intense network ties and tourism relations. For the case of Spanish regions, both Madrid and Cataluña have large shares of immigrants that were born in Andalucía or Extremadura.

2. A second type of situation could give rise to an ‘exporting-based dependence’. If the emigrants of one region are highly concentrated in other region, exports from the homeland to any other region *j* will be correlated to the exports from the host region to region *j*. The mechanisms that explain this dependence on the flows are similar to the one explained before, but acting in a different direction, affecting the destination of the trip (exporting region).

Finally, it is important to highlight that immigrants could also affect ‘tourism decisions’ of other non-immigrants living in the same region. For example, if we think of the large number of immigrants who form families with natives in a region, it is easy to suppose that there is an influence on immigrant tourism decisions arising from tastes and family ties that exert an influence on non-immigrants. For example, in the case of a ‘mixed couple’ (immigrant and non-immigrant) with two children, the decision to visit a relative in the homeland of one immigrant is conditioning travel decisions of three ‘non-immigrants’. Moreover, relatives and friends of the immigrants who are still living in the homeland (but could interact regularly with them) could also spread their travel experiences and tastes among their co-nationals in the homeland. Although the diffusion of information and preferences would mainly take place within each region (the homeland and the host region), it could also be progressively spread to neighbouring 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’ in the case of interregional trade of goods. In our case, this force is mixed and strengthened by the effects described above.

In conclusion, we have described how the stock of immigrants and emigrants can influence the bilateral flows between two regions through different channels, but also how a given trade flow can be related to the flows to and from the contiguous regions and the demographic neighbours (regions that are demographically related because there is a large concentration of emigrants from one region in the other one, or because of a large share of the immigrants living in one region were born in the other one). Furthermore, it could be assumed that all these influences could affect both immigrants and non-immigrant tourism decisions. These effects are summarized in Fig. 1 and in Fig. 2.

## 3 The empirical model

In this section, we first discuss the cross-sectional dependence of the flows based on spatial and demographic neighbouring and how they are related to our spatial econometric model. A series of alternative specifications of increasing

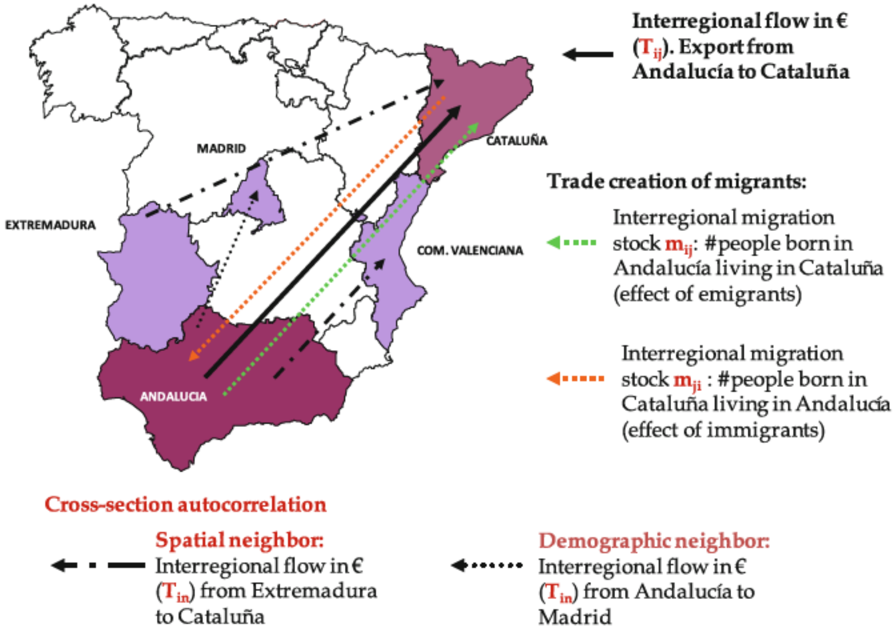


**Fig. 1** Intuitive scheme showing the relation between the trade flows of services and the migration stocks

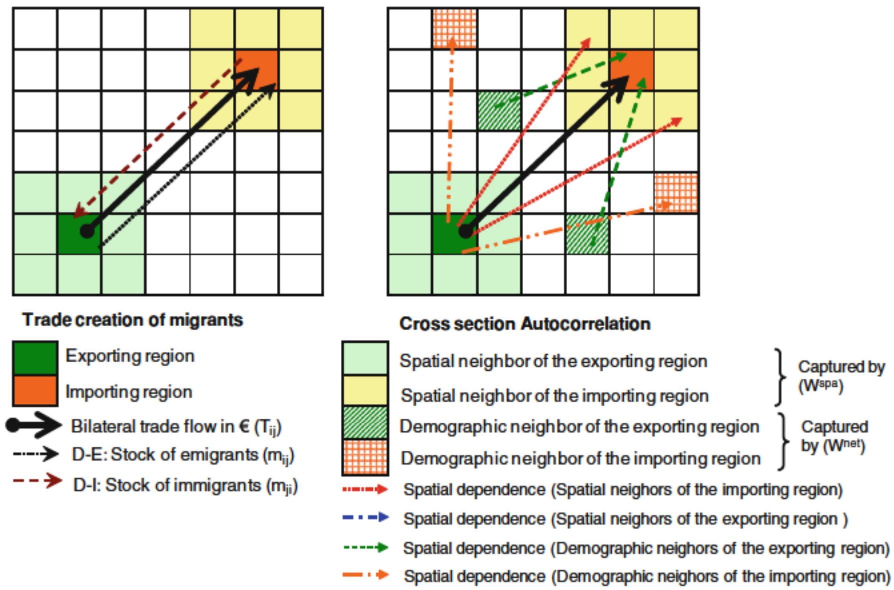


**Fig. 2** Scheme summarizing the spatial and network effects on bilateral flows

sophistication are set forth. These allow us to engage in a model comparison exercise that examines the alternative model specifications. The spatial econometric models introduced to accommodate spatial and network dependence in the flows follow from work by Autant-Bernard and LeSage (2011), LeSage and Pace (2008) and LeSage and Fisher (2008a, b).

### 3.1 Spatial and demographic dependence affecting gravity model estimates

Black (1992) suggested that network and spatial autocorrelation may bias classical estimation procedures typically used 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 socio-economic and network variables adjacent to the bilateral origin destination regions $i$ and $j$, arguing that these should also be incorporated in the relationship that attempts to explain flows ($T_{ij}$) between these regions. He emphasized that omission of neighbouring variable values gives rise to spatial autocorrelation in the regression errors. Sources of spatial autocorrelation among errors are model misspecification and omitted explanatory variables that capture effects related to the physical and economic characteristics (distances between zones, size of zones, lengths of frontiers between adjacent zones, etc.) of the region.

More recently, LeSage and Pace (2008) challenged the assumption that 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 use of distance alone in a gravity model may be inadequate for modelling spatial dependence between observations. For most of socio-economic spatial interactions (migration, trade, commuting, etc.), there are several explanations for these effects. For example, neighbouring origins (exporting regions) and destinations (importing region) may exhibit estimation errors of similar magnitude if underlying latent or unobserved forces are at work so that missing covariates exert a similar impact on neighbouring observations. Agents located at contiguous regions may experience similar transport costs and profit opportunities when evaluating alternative nearby destinations. This similar positive/negative influence among neighbours 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, neighbouring regions with similar factor endowments may be affected in a similar way 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 to find spatial autocorrelation in the sector specialization of production and trade of regions, when the spatial scale is fine enough.

As we have explained in the previous section, bilateral trade flows of services linked with the tourist sector could also 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 (demographic in our case) autocorrelation effects in interregional trade flows associated with tourism. The extended model subsumes models that exclude spatial and network dependence as special cases of the more elaborate model and provides a simple empirical test for the presence of significant spatial and network dependence.

Departing from this literature, our empirical model will be based on several alternative specifications that allow for considering two different weight matrices: the first one will be based on Autant-Bernard and LeSage (2011), which considers a spatial lag model with two different weight matrices; the second will be based on the SAC model described in LeSage and Pace (2009, pp. 32), which considers spatial dependence in both the dependent variable and the disturbances.

### 3.2 Introducing spatial and network effects in the gravity model

A conventional least-squares gravity model specification is shown in Eq. (1), where the bilateral flows ($T_{ij}$) between the exporting region $i$ and the importing $j$ are modelled as a function of a set of explanatory variables reflecting economic size of the two regions, and distance ($d_{ij}$) between the regions. $T_{ij}$ denotes the exports in monetary units (current Euros) of the services produced by restaurants + accommodation + travel agencies in region $i$ and imported by region $j$. The size of the origin of the flow (exporting region) is proxied by the gross value added of 'hotels and restaurants' in region $i$ ($\text{gva}_i$), while the size of the importing region, $j$, is modelled as depending on the population ($\text{pop}_j$) and income ($\text{inc}_j$).

$$T_{ij} = \alpha i_N + \text{gva}_i\beta_1 + \text{pop}_j\beta_2 + \text{inc}_j\beta_3 + d_{ij}\beta_4 + \varepsilon_{ij} \tag{1}$$

The next two specifications in Eqs. (2) and (3) include two alternative ways of controlling for the different nature of intraregional trade flows $T_{ii}$, which include expenses related to trips within each region as well as daily expenditures of residents on restaurants, coffee-shops and pubs. The model described in (2) adds a dummy variable $\text{ownreg}_{ij}$ that takes a value 1 when trade is intraregional and 0 otherwise. Past studies interpret the coefficient associated with this dummy variable as an 'internal border effect' or 'home bias' (McCallum 1995; Helliwell 1997; Wolf 2000; Chen 2004; Okubo 2004; Combes et al. 2005). The coefficient $\gamma$ is interpreted as how many times one region tends to trade more within itself than with any other region in the country after controlling for size and bilateral distance.

$$T_{ij} = \alpha i_N + \text{gva}_i\beta_1 + \text{pop}_j\beta_2 + \text{inc}_j\beta_3 + d_{ij}\beta_4 + \text{ownreg}_{ij}\gamma + \varepsilon_{ij} \tag{2}$$

An alternative approach in (3) is that proposed by LeSage and Pace (2008), who created a separate set of explanatory variables to model intra-and interregional trade flows, those on the main diagonal of the flow matrix versus the off-diagonal. Regressors corresponding to the intraregional flows are set to zero in the set of explanatory variables $X = (\text{gva}_i,\ \text{pop}_j,\ \text{inc}_j)$ and used to form a new set of explanatory variables that we label $X_\text{I} = (\text{gdp}_j)$ for the $i$th observation. This prevents the large magnitudes typically associated with intraregional flows from entering the interregional flow model explanatory variables and produces a separate set of explanatory variables to model variation in the intraregional flows ($T_{ii}$, $i = 1,\ldots,n$). Use of separate explanatory variables to explain variation in intraregional commodity flows should down-weight the impact of large intraregional flows on the main diagonal of the flow matrix, preventing them from exerting undue impact on the resulting estimates for $\beta_1$, $\beta_2$ and $\beta_3$ which are intended to explain interregional flow variation. Since the matrix $X_I$ contains only $n$ nonzero observations, we limit the number of explanatory variables used to explain variation in intraregional flows, using just the gdp of the region for this purpose. This suggests that the larger the economic activity in a region (gdp), the larger the intraregional flows of services, mainly due to daily expenditures in restaurants and the like services. Note that since interregional and intraregional trade flows are now modelled separately, the border dummy is meaningless and drops from this model. Note also that intraregional and interregional trade flows have also their corresponding intercept term.

$$T_{ij} = \alpha i_N + \alpha_i i_i + \mathrm{gva}_i\beta_1 + \mathrm{pop}_j\beta_2 + \mathrm{inc}_j\beta_3 + d_{ij}\beta_4 + X_I\beta_i + \varepsilon_{ij} \tag{3}$$

The next model described in Eq. (4) has been used to account for trade creation effect of social networks. They will be measured by introducing the variable $m_{ij}$ that captures variation in flows attributable to the stock of emigrants from region $i$ that are living in region $j$, and similarly, the variable $m_{ji}$ that captures the variation in flows due to the stock of immigrants from region $j$ living in region $i$. As in Combes et al. (2005), they can be introduced separately in such a way that if we set $\beta_5$ to be zero, we will just consider that there exist the immigrants effect, and similarly, if we force $\beta_6$ to be zero, we will only obtain the emigrants effect. Both effects can be estimated simultaneously if we impose no restrictions in coefficients $\beta_5$ and $\beta_6$.

$$T_{ij} = \alpha i_N + \alpha_i i_i + \mathrm{gva}_i\beta_1 + \mathrm{pop}_j\beta_2 + \mathrm{inc}_j\beta_3 + d_{ij}\beta_4 + X_I\beta_i + m_{ij}\beta_5 + m_{ji}\beta_6 + \varepsilon_{ij} \tag{4}$$

One may want to consider the presence of potential multicolinearity problems due to a high correlation between the emigrants and immigrants bilateral flows. In order to cope with this limitation, Eq. (5) will use a single vector of bilateral 'net migration' $\mathrm{mig\ net}_{ij} = (\mathrm{mig}_{ji} + \mathrm{mig}_{ij})$ for capturing the aggregate effect of immigrants + emigrants on trade. This specification will be considered also for the forthcoming augmented models including spatial and network effects.

$$T_{ij} = \alpha i_N + \alpha_i i_i + \mathrm{gva}_i\beta_1 + \mathrm{pop}_j\beta_2 + \mathrm{inc}_j\beta_3 + d_{ij}\beta_4 + X_I\beta_i + \mathrm{mig\_net}_{ij}\beta_5 + \varepsilon_{ij} \tag{5}$$

### *3.2.1 The spatial lag gravity model*

In order to figure out whether the spatial dependence on the bilateral flows that have been discussed in the previous sections are consistent with the data, the next spatial regression models rely on spatial lags of the dependent variable following the approach set forth in LeSage and Pace (2008). They also include all the explanatory variables from the previous models, allowing these models to subsume the non-spatial regression models as special cases. A spatial lag of the dependent variable ($W^{\mathrm{spa}}T_{ij}$) is introduced in Eq. (6), where $W^{\mathrm{spa}}$ represents a spatial weight matrix of the form suggested by LeSage and Pace (2008), $T$ is the $n^2 \times 1$ vector representing the $n \times n$ flows matrix transformed to a vector; $i_N$ is an $n^2 \times 1$ vector of ones; $d$ is the $n \times n$ matrix of interregional distances transformed to an $n^2 \times 1$ vector; gva, pop and inc are $n^2 \times 1$ vectors containing the explanatory variables appropriate for each bilateral flow; and $\varepsilon$ is an $n^2 \times 1$ vector of normally distributed constant variance disturbances.

In a typical cross-sectional model with $n$ regions, where each pair of regions represent an observation, spatial regression models rely on an $n \times n$ non-negative weight matrix that describes the connectivity structure between the n regions. For example, $W_{ij} > 0$ if region $i$ is contiguous to region $j$. By convention, $W_{ii} = 0$ to prevent an observation from being defined as a neighbour to itself, and the matrix $W$ is typically row standardized. In the case of bilateral flows, where we are working with $N = n^2$ observations, LeSage and Pace (2008), Chun (2008), Chun and Griffith (2011) and Fischer and Griffith (2008) suggest using $W^{\text{spa}} = W_j^{\text{spa}} + W_i^{\text{spa}}$, where $W_j^{\text{spa}} = I_n \otimes W_s$ represents an $N \times N$ connectivity between the importing region and its neighbour and $W_i^{\text{spa}} = W_s \otimes I_n$ is another $N \times N$ spatial weight matrix that captures connectivity between the exporting region and its neighbour.[5] We row standardize the matrix $W^{\text{spa}}$ to form a spatial lag of the $N \times 1$ 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 neighbours 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 neighbours to this origin to the same destination, a situation labelled origin-based dependence by LeSage and Pace (2008). The spatial lag matrix, $W^{\text{spa}}$, 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 neighbouring regions of the destination region.

We take a similar approach to produce a network dependence weight matrix, $W^{\text{net}}$, which captures network autocorrelation effects. As in the case of $W^{\text{spa}}$, the $W^{\text{net}}$ matrix was formed as a sum of two matrices that specify 'demographic neighbours' to the origin and destination regions, specifically $W^{\text{net}} = W_i^{\text{net}} + W_j^{\text{net}}$. The matrix $W_j^{\text{net}} = I_n \otimes W_m$ where $W_m$ was constructed using the stock of emigrants from each region living in each other region, with details provided in the next section. Similarly, $W_i^{\text{net}} = W_m \otimes I_n$ and the matrix $W^{\text{net}}$ was row standardized. This allows us to include in the model a network lag of the dependent variable shown in Eqs. (4) and (5).

In the case of 'network autocorrelation', the 'tastes and information' could flow in both directions, which resulted in use of the two explanatory variables ($m_{ij}$, $m_{ji}$). Moreover, the additional 'lodging savings' could also work in both directions: a person could take advantage of a second home (or a lodging owned by friends and relatives) located in the region where she was born (home region), but also this person can be visited by these friends and relatives in his house located in the region where he lives (host region), Thus, a rotated network weight matrix $W^{\text{net}\prime} = W_i^{\text{net}\prime} + W_j^{\text{net}\prime}$ can be used to capture the network autocorrelation acting in the

[5] We use the symbol $\otimes$ to denote a Kronecker product.

opposite direction. This matrix could be used to replace the spatial lag $W^{\mathrm{net}}$ in Eq. (6).

We can include the two types of autocorrelation simultaneously, then a spatial lag as well as a network lag is included to account for the presence of both spatial and network dependence for origins and destinations. For the case of the spatial lag models (SAR), following Autant-Bernard and LeSage (2011) and LeSage and Fisher (2008a, b), we adjust the weight matrices to produce row standardization across both of these, accomplished by scaling each matrix by 0.5. Then, the scalar parameter $\rho$ denotes the strength of spatial dependence in flows, and when this parameter takes a value of zero in the model in Eq. (6), it 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. If both types of autocorrelation are not statistical significant, then the model in Eq. (6) becomes the one in Eq. (4).

$$
\begin{aligned}
T_{ij} = {} & \alpha i_N + \alpha_i i_i + \rho_1 W^{\mathrm{spa}} T_{ij} + \rho_2 W^{\mathrm{net}} T_{ij} + \mathrm{gva}_i \beta_1 + \mathrm{pop}_j \beta_2 + \mathrm{inc}_j \beta_3 + d_{ij} \beta_4 \\
& + X_i \beta_i + m_{ij} \beta_5 + m_{ji} \beta_6 + \varepsilon_{ij}
\end{aligned}
\tag{6}
$$

Then, as in Eq. (5), a new Eq. (7) can be defined, where immigrants and emigrant effects are added in a single net migration vector.

$$
\begin{aligned}
T_{ij} = {} & \alpha i_N + \alpha_i i_i + \rho_1 W^{\mathrm{spa}} T_{ij} + \rho_2 W^{\mathrm{net}} T_{ij} + \mathrm{gva}_i \beta_1 + \mathrm{pop}_j \beta_2 + \mathrm{inc}_j \beta_3 \\
& + d_{ij} \beta_4 + X_i \beta_i + \mathrm{mig\_net}_{ij} \beta_5 + \varepsilon_{ij}
\end{aligned}
\tag{7}
$$

### 3.2.2 Alternative specifications and robustness checks

In this section, a number of alternative specifications are described:

The first alternative specification is based on the spatial general model (SAC) described in LeSage and Pace (2009, p. 32). Such model, which considers spatial dependence in both the dependent variable and the disturbances, is described in Eq. (8):

$$
\begin{aligned}
T_{ij} &= \alpha i_N + \alpha_i i_i + \rho_1 W_1 T_{ij} + \mathrm{gva}_i \beta_1 + \mathrm{pop}_j \beta_2 \\
&\quad + \mathrm{inc}_j \beta_3 + d_{ij} \beta_4 + X_i \beta_i + m_{ij} \beta_5 + m_{ji} \beta_6 + u_{ij} \\
u_{ij} &= (I_N - \theta W_2) \varepsilon_{ij} \\
\varepsilon_{ij} &\sim (0, \sigma^2 I_N)
\end{aligned}
\tag{8}
$$

Note that the model described in Eq. (8) considers two different weight matrices $W_1$ and $W_2$, each of them will capture the effects affecting the dependent variable and the disturbance. Following the recommendations by LeSage and Pace (2009, pp. 32), in the next section, we will consider 4 alternative cases, without imposing a preferred structure to the data in advance: (1) ($W_1 = W^{\mathrm{spa}}$; $W_2 = W^{\mathrm{net}}$); (2) ($W_1 = W^{\mathrm{net}}$; $W_2 = W^{\mathrm{spa}}$); (3) ($W_1 = W_2 = W^{\mathrm{spa}}$); and (4) ($W_1 = W_2 = W^{\mathrm{net}}$).

The second alternative specification is based on the spatial Durbin model (SDM). This model is described in LeSage and Fischer (2008a, b) among others and 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 the independent variables as it is described in Eq. (9):

$$T_{ij} = \alpha i_N + \rho_1 W_1 T_{ij} + X\beta + W_1 X\gamma + \varepsilon_{ij} \quad (9)$$

where $W_1 X\gamma$ is the spatial lag of all the dependent variables included in $X$. Note that, in contrast to previous specifications included in this paper, just one constant term and one weight matrix $W_1$ will be used for lagging both groups of variables. A SDM gravity model with two alternative $W$ matrices has not been reported in the literature. However, departing from this common specification, three alternative models have been estimated using the following weight matrices: (1) ($W_1 = W^{spat}$); (2) ($W_2 = W^{net}$); and (3) ($W_3 = W^{spa} + W^{net}$).

For briefness, we omit including a new equation for describing the corresponding models in which the 'net migration' vector is used instead of their emigrant and immigrant counterparts. However, the corresponding results are also analysed in the next section.

Finally, some robustness checks are also developed in this section. The first robust exercise is an attempt to tackle with the endogeneity problem that is likely to arise when considering trade and migration flows. In addition, we have also computed two alternative weight matrices for capturing the network effects derived from similar demographic structures. With this aim, we proceed to the following robust checks:

1. All the models (SAR, SAC and SDM) have been re-estimated using the average flows for the period 2000 2009 (as before), but with a time-lagged set of variables for the migration stocks. Now, the migration variables ($m_{ij}$, $m_{ji}$, and mig net$_{ij}$) and the weight matrix capturing the demographic structure ($W^{net}$ or $W^{net\prime}$) were obtained based on the interregional migration stocks of the Spanish census in 1981, instead of the corresponding ones for the period 2000 2009.
2. Furthermore, all the models (SAR, SAC and SDM) have been re-estimated again using the previous dataset (average flows versus migration stocks in 1981), but using two alternative method for computing the demographic weight matrices ($W^{net}$ or $W^{net\prime}$). These two alternative weight matrices consider specific thresholds for narrowing the concept of demographic neighbours and will be labelled $W^{net}_{81\_born}$ and $W^{net}_{81\_residence}$.

The two new weight matrices were obtained following the following steps: (1) We take the matrix containing the stock of interregional migrants in 1981 according to the Spanish Census; (2) For $W^{net}_{81\_born}$, we get the share of every home region with respect to the total interregional immigrants in each host region (shares along the rows), while for $W^{net}_{81\_residence}$, we obtain the share of each host region with respect to the total interregional emigrants from each home region (shares along the columns). (3) Next, we compute the percentile 90 in the distribution of the shares of the interregional migration for each *home region* and *host region*.

Therefore, two regions will be considered as neighbours when the threshold defined by the percentile 90 is lower than the corresponding share. In this case, the corresponding $W$ matrix will contain this share and a value 0 otherwise. Then, departing from each of these two matrices, we obtain the corresponding $W^{net}_{81\_born} = W^{net}_{81_{born}i} + W^{net}_{81_{born}j}$ as the addition of the origin-based and destination-based matrices, row normalized as usual. The same procedure is used for obtaining $W^{net}_{81\_residence} = W^{net}_{81\_residence\ i} + W^{net}_{81\_residence\ j}$.

Note that by defining the $W$ matrix in this way, it is assured that every region has a positive number of neighbours and this relation will not depend on the sizes of both region, but on the weight that each region represent in the demographic structure of the rest of the regions.[6]

## 4 An application to the Spanish domestic trade of some services sectors

### 4.1 The data

As in most of the countries, there are no official data on monetary interregional trade flows associated with the 3 sectors related to tourism in Spain that we are considering here: restaurants, accommodation and travel agencies. Our application takes advantage of recent estimates of intra- and interregional trade flows for the grouping of these sectors between the Spanish regions. The dataset has been obtained for the period 2000 2009 (De la Mata and Llano 2012) based on an improved methodology presented for the year 2001 in Llano and de la Mata (2009a). This dataset has been constructed as part of a larger research project (www.c-intereg.es). Schematically, the methodology used can be summarized in two steps:

1. The estimation of output in each region consumed by Spanish citizens, that is to say, that is not exported internationally;
2. Determining for each region the bilateral distribution of the output not exported internationally. This last step is based on existing information regarding daily expenses of national travellers in the destination region and origin and destination matrices (Familitur surveys and Occupancy Surveys) that capture overnight stays and displacements of Spanish residents, depending on the type of dwelling options at the destination of the trip. The estimation uses different daily expenses in 'accommodation' and 'restaurants and the like' for hotels, apartments, campings, rural tourism, friends and relatives homes, second residences and excursions, covering all possible trip motives (leisure, work, education, etc.). The estimation has been done separately for accommodation, restaurants and travel agencies. Therefore, our data does not include expenses

[6] For example, emigrants from Islas Canarias do not represent more than 2 % over the interregional immigrants living in any other region, given its small size in terms of population. The largest shares are found in Andalucía, Baleares and Murcia. In these regions, people from Islas Canarias represent a 1.4, 1.2 and 1.3 % in respect to the total interregional immigrants. Then, their relative weight is higher than in Madrid (although in absolute terms are higher) where immigrants from Islas Canarias represent just the 0.2 % of the total interregional immigrants. Then, according to our definition, Canarias is a demographic neighbour of Andalucía, Baleares and Murcia and not of Madrid, because its relative magnitude is higher in the former group of regions than in Madrid.

related to transportation, shopping or any other good or service bought during the stay. This fact avoids endogeneity problems between the interregional trade flows of the tourist services and the transport cost linked to the bilateral distance.

3. The bilateral flows of accommodation is proportionally adjusted to the total output; the sum of the interregional exports of 'restaurants and the like' are adjusted to the output assuming that the difference is the daily consumption in this sector, and travel agencies are considered to be an intraregional consumption.[7]

In summary, the estimates for the interregional monetary flows of the three service sectors analysed (accommodation, restaurants and travel agencies) 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 2001).

Regarding remaining variables, we used gross value added of the 'hotels and restaurants' sector, the regional income (inc) obtained from the Spanish Regional Accounts (INE) and population (pop) from the Spanish Register (INE). Similarly, the interregional migration matrices are also obtained from the Spanish Register (INE), which offer information on the stock of people living in a region born other regions. The direct effects captured by the $m_{ij}$ and the $m_{ji}$ terms enter as two independent column vectors. In order to avoid collinearity problems between the population and the intraregional migration stock (number of people born in a region living in that region), the latter is considered to be null for individuals that live in the same place where they were born ($m_{ii} = 0$). Following this strategy, this analysis differs from others that include the stock of people born in the same region and that measure how this produces a reduction in the coefficient related with the border effect (Garmendia et al. 2012).

The spatial weight matrices are built taking into account first order contiguity relations based on shared borders, with islands treated as having no adjacent regions. The demographic network weight matrix is built using a row-standardized OD matrix of immigrants born in one region who are living in another, with diagonal elements set to zero values.[8]

Finally, the distance used was obtained from the Movilia survey 2001 (Ministerio de Fomento 2001), which is the actual distance travelled by the Spanish residents in their displacements, both within and between regions. One of the most interesting features of this measure is that it includes not just interregional distance but also

---

[7] The econometric analysis has been also done without considering the daily consumption in restaurants and without the consumption in travel agencies and similar results has been found. Note that these two types of flows just increase the intraregional flows.

[8] In previous versions in which the empirical application used a previous dataset for 2001, alternative specifications of the $W^{net}$ matrix were explored based on percentages of the destination region population, or a binary matrix used in conjunction with a threshold (i.e. 5 % of the population in the destination region). In the final analysis, since our trade flows are measured in levels, we choose the current specification. This specification showed stronger results and avoids subjective decisions regarding a threshold level.

intraregional. Thus, in the line of Head and Mayer (2010), 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 by each of the more than 500 million displacements estimated by the Movilia survey in 2001. These displacements cover all motives, so that the distance reported is not constrained by distance between capitals, which could be predominant for business trips, but not distances between tourist spots (beaches, skiing resorts, countryside, etc.) located in the periphery.

As an overview of internal flows of the sectors considered in this work in Spain, Fig. 3 shows the largest average interregional monetary flows in accommodation and restaurants,[9] as well as the distribution of the population and the location coefficient for the 'hotels and restaurants' sector (LCRegion = Regional Hostel Industry GVA/National Hostel Industry GVA). Arrows between east-coastal regions (Andalucía, C. Valenciana and Cataluña) to the landlocked region of Madrid show that there are a large part of the interregional exports (in current Euros) of accommodation and restaurants from these regions to Madrid. These are the consequence of a large number of travels from Madrid to Andalucía. From the figure, it is easy to see that the major exporting regions are located along the coast, with the largest importers located in the most populated high-income regions. There are also large exports from the islands to highly populated regions (Canarias to Madrid and Baleares to Madrid and Cataluña). In addition, there is a large share of the flows between the largest regions such as the exports from Cataluña to Madrid and Madrid to Cataluña or Andalucía. Note also that some of the largest interregional flows are 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 firstly because of the size of the regions (in terms of population and income or gross domestic product) and secondly by important social networks that have arisen as a result of historic bilateral migration flows (Table 1).

### 4.2 Estimation results

We compare estimation results from the sequence of models beginning with non-spatial models that assume no spatial or network dependence.

The alternative model specifications were estimated using 17 NUTS2 level Spanish regions with Ceuta and Melilla excluded.[10] This results in dependent and independent variable vectors having $N = 17 \times 17 = 289$ observations based on the average of the flows in the period 2000 2009. All the variables were averaged and log-transformed (except the dummy variables) as is traditional when estimating gravity models. The same specifications have been estimated for each year (the

[9] Note that Travel Agencies are not included in this analysis because according to the methodology used, it is considered that this type of expense is done in the region of residence. Then, the whole part of the output not internationally exported is part of the intraregional flows.

[10] Ceuta and Melilla are not regions, but autonomous cities. Their relevance from the spatial and touristic view point is very small. The data for these cities has not the required quality. In order to avoid noise in the estimation, they are omitted in the sample.

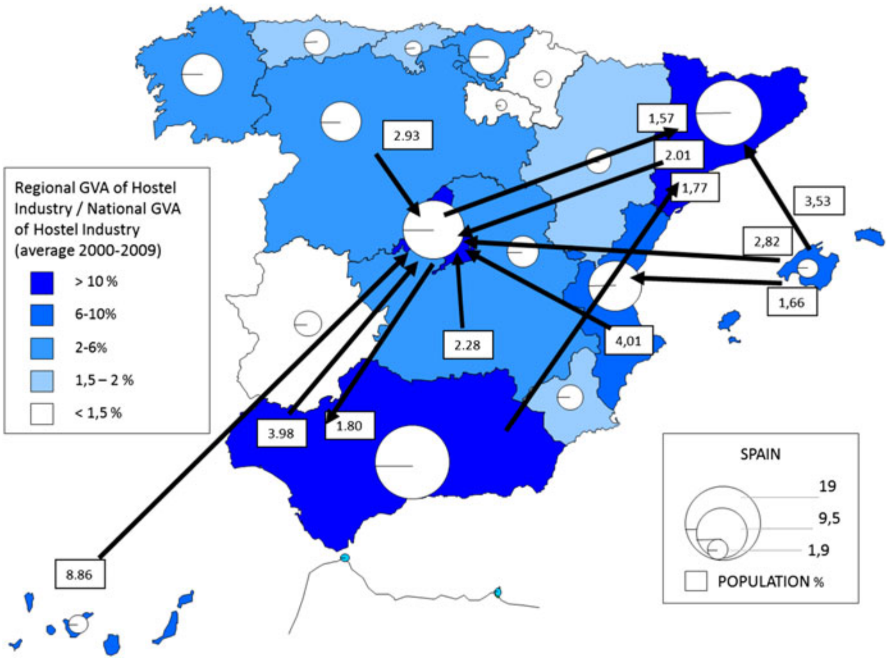


**Fig. 3** Main interregional flows (€) of accommodation and restaurants. % of total interregional flows. (Average 2000 2009)

**Table 1** Description and source of the *X* variables

| Variable | Abbreviation | Description | Source |
|---|---|---|---|
| Gross domestic product | $gdp_i$ | Regional GDP. Average 2000 2009 | INE |
| Population | $pop_j$ | Regional population. Average 2000 2009 | INE |
| Income per capita | $inc_j$ | Regional income per capita. Average 2000 2009 | INE |
| Gross value added | $gva_i$ | G. V. A. of Hostel industry. Average 2000 2009 | INE |
| Interregional migration stock | $m_{ij}$, $m_{ji}$ | Municipal register. Average 2000 2009 | INE |
| Distance | $d_{ij}$ | Actual distance in km travelled between regions. 2001 | Movilia (2001) |

*Source*: Own elaboration

results for 2000 and 2009 each year are shown in the Appendix, and the results for the rest of the period are available upon request), but in this section, we will comment the results with the averaged data that will reduce the effect of outliers.

Table 2 shows least-squares estimation results for six different model specifications that we have labelled M1 to M7 in the table. Model M1 in the first column of the table shows estimates for the simplest gravity model, which attempts to explain variation in the 289 bilateral (Euro) flows between regions ($T_{ij}$) using $gva_i$, $pop_j$, $inc_j$

**Table 2** Ordinary least-squares

| | M1 | M2 | M3 | M4 | M5 | M6 | M7 |
|---|---|---|---|---|---|---|---|
| $R^2$ | 0.703 | 0.893 | 0.903 | 0.907 | 0.930 | 0.931 | 0.920 |
| $R\text{bar}^2$ | 0.698 | 0.891 | 0.901 | 0.905 | 0.929 | 0.929 | 0.918 |
| Sigma 2 | 0.954 | 0.344 | 0.313 | 0.300 | 0.225 | 0.226 | 0.260 |
| Const | −20.977*** | −26.36*** | −28.643*** | −26.127*** | −29.335*** | −29.533*** | −25.663*** |
| | −6.374 | −13.236 | −14.573 | −12.788 | −17.584 | −16.333 | −14.02 |
| log(gva$_i$) | 0.937*** | 0.838*** | 0.882*** | 0.83*** | 0.54*** | 0.54*** | 0.675*** |
| | 16.964 | 25.02 | 26.74 | 23.506 | 12.601 | 12.562 | 16.745 |
| log(pop$_j$) | 0.987*** | 0.931*** | 0.979*** | 0.863*** | 0.671*** | 0.676*** | 0.703*** |
| | 15.227 | 23.876 | 25.477 | 17.546 | 15.333 | 14.411 | 14.049 |
| log(inc$_j$) | 1.002*** | 1.377*** | 1.479*** | 1.32*** | 1.978*** | 1.996*** | 1.476*** |
| | 3.33 | 7.585 | 8.3 | 7.346 | 12.488 | 11.672 | 9.102 |
| log($d_{ij}$) | −1.087*** | −0.469*** | −0.478*** | −0.393*** | −0.131** | −0.133** | −0.226*** |
| | −16.153 | −9.586 | −10.253 | −7.677 | −2.544 | −2.555 | −4.228 |
| ownreg$_{ij}$ | | 3.984*** | | | | | |
| | | 22.45 | | | | | |
| intra_const | | | −2.266 | −2.407 | −2.842 | −2.839 | −2.684 |
| | | | −0.865 | −0.939 | −1.279 | −1.276 | −1.125 |
| log(intra_gdp) | | | 1.099*** | 1.088*** | 1.052*** | 1.052*** | 1.065*** |
| | | | 7.289 | 7.366 | 8.217 | 8.205 | 7.752 |
| log($m_{ij}$) | | | | 0.108*** | | −0.008 | |
| | | | | 3.656 | | −0.286 | |
| log($m_{ji}$) | | | | | 0.344*** | 0.348*** | |
| | | | | | 10.537 | 9.644 | |
| log(mig_net$_{ij}$) | | | | | | | 0.14*** |
| | | | | | | | 7.702 |

*Source* Own elaboration. *T* statistics below the coefficients. Significance *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$. All variables are averages in the period 2000–2009

Dependent variable interregional monetary flows of accommodation, restaurants and travel agencies. Average flows 2000–2009 and the distance $d_{ij}$ as explanatory variables. The simplest model based on these four explanatory variables is able to explain 70 % of the variation in flows. All the explanatory variables are highly significant and have expected signs. For example, there are positive coefficients associated with the measures of economic size of importing and exporting regions involved in the bilateral flow, and a negative coefficient for distance between origin and destination regions.

In the second column, the intraregional flows are controlled including the border effect dummy 'ownreg'. The 'border effect' coefficient estimate (3.984) is very large and consistent with other empirical findings regarding border effects in Spain, for industries such as 'Chemical products' or 'Non-metallic minerals' (Ghemawat et al. 2010; Requena and Llano 2010). In this case, this large border effect is not expected to be driven by an external barrier to trade. By contrast, as discussed in Llano and de la Mata (2009b), a large coefficient of the border effect for the services sectors analysed likely arises from the importance of 'restaurants' within the grouping of sectors considered (more than the 50 % of the output), which is heavily oriented towards intraregional trade flows.[11] An interesting consequence of introducing the border dummy is that the negative coefficient on the distance variable decreases in absolute value from −1.087 to −0.469. As a robustness check, model M3 produced similar estimates when the border dummy variable in Eq. (2) is replaced by the $X_I$ matrix as explained in the discussion surrounding Eq. (3). The stability of the results obtained for these two last models points out to the validity of both methods for controlling for the different nature of intraregional/interregional flows.

Next, models M4, M5 separately include the two variables regarding the stock of migrants in order to measure the trade creation effect of social networks. The coefficient estimates for these two variables point to a positive (and significant) relation between the bilateral stocks of emigrants and immigrants and domestic flows when they are considered separately. It is noteworthy that the coefficient of distance drops to −0.393 when the stock of emigrants is included and to −0.131 when we include the stock of immigrants. Finally, it is important to highlight that although both emigrants and immigrants are significant when they are included separately, when we include both together, it is just the stock of immigrants the one that is significant. In addition to the control variables, $m_{ij}$ and $m_{ji}$ lead to a higher $R^2 = 92\ \%$ than the simpler model specifications.

At this point, it is interesting to discuss in more detail the results obtained regarding the relation between the trade flows and the stock of interregional emigrants and immigrants. Although the inclusion of these two variables is standard in the literature (Combes et al. 2005), both are highly correlated (87 % between $m_{ij}$ and $m_{ji}$, when both vectors include '0' values for the intraregional flows). In order to avoid multicolinearity problems, an additional model (M7) is included, where the two variables are added together as net migration vector $\text{mig net}_{tij} = (m_{ji} + m_{ij})$.

[11] This is partially a result of own region holiday spending in restaurants and pubs which accounts for a large share of income spent relative to expenditures on hotels, travel agencies, restaurants and similar businesses in other regions.

As we can see, now the coefficient for the new variable of net migration is positive and significant, but the rest of the results are not altered.

Departing from these first estimates, and with the aim of motivating the inclusion of spatial lag and/or spatial error terms, several statistical tests are considered. 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 7 models. In all of them, the spatial structure based on three different spatial weight matrices were considered (each one of them row normalized): (1) $W_i^{\text{spa}}$: for capturing the 'spatial-origin-based' autocorrelation; (2) $W_j^{\text{spa}}$: for capturing the 'spatial-destination-based' autocorrelation; and ($W^{\text{spa}} = W_i^{\text{spa}} + W_j^{\text{spa}}$): for capturing the aggregate spatial autocorrelation (omitting, as said before, the origin-to-destination-based element). The results for these 7 models, 5 tests and 3 spatial autocorrelation matrices are reported in Table 3, showing that all cases show spatial autocorrelation in the residuals (Moran I-analysis). Such result is found for the 'origin-based' and 'destination-based' weight matrices, as well as when both are mixed in a single spatial matrix ($W^{\text{spa}} = W_i^{\text{spa}} + W_j^{\text{spa}}$). Regarding the LM tests, in all cases but 1 (Model 1, LM error tests for spatial correlation in the dependent variable) the test confirmed the suitability of a spatial lag model (SAR) as well as a spatial autoregressive error model (SEM). However, when the robust version of these two previous tests is used, non-significant results are obtained for models 3 to 7 in the Robust LM error tests for spatial autocorrelation in the dependent variable when using $W = W_i + W_j$.

Then, a similar exercise is conducted using the network (demographic) weight matrices for analysing the results for the same 7 models. Now, the results are reported in Table 4, considering three alternative demographic base weight matrices, namely, the origin-based demographic neighbour structure ($W_i^{\text{net}}$), the destination-based demographic neighbour structure ($W_j^{\text{net}}$) and the aggregate origin + destination based demographic neighbour structure ($W^{\text{net}} = W_i^{\text{net}} + W_j^{\text{net}}$). Like in the previous table, the results confirm the presence of 'network' autocorrelation in the residuals (Moran I analysis test). Although the majority of the tests confirm the presence of network (demographic) autocorrelation effects when using the origin-based and destination-based weight matrices, some tests are non-significant for some models and weight matrices.[12]

In conclusion, although there are some non-significant cases,[13] the significant results obtained when considering $W_i$ and $W_j$ separately, both for spatial and demographic weight matrices, point out to the convenience of estimating a number of alternative specifications, which, preferably, may be able to consider two potential sources of autocorrelation (spatial and demographic), affecting the dependent variable and/or the disturbance term. For this reason, we now proceed

[12] For $W_i$: M1 (for the LM error in the dependent variable and the robust LM error in the dependent variable and the residuals) and M4 (for the robust LM error in the residuals); For $W_j$: M2 and M3 just in the robust LM error in the dependent variable; For $W = W_i + W_j$: M4 7 for the the robust LM error in the dependent variable.

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

**Table 3** Spatial autocorrelation tests

| | M1 | M2 | M3 | M4 | M5 | M6 | M7 |
|---|---|---|---|---|---|---|---|
| *Spatial 'origin based' autocorrelation with row normalized 'Wo' (neighbours of the exporting region i)* | | | | | | | |
| Moran I test for spatial correlation in residuals (SD = 0.041) | | | | | | | |
| Moran I | 0.087 | 0.239 | 0.229 | 0.220 | 0.192 | 0.186 | 0.191 |
| Moran I statistic | 2.414 | 6.137 | 5.868 | 5.686 | 5.012 | 4.918 | 4.976 |
| Marginal probability | 0.016 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| LM error tests for spatial correlation in residuals [$\chi(1)$ 0.01 value = 6.635] | | | | | | | |
| LM value | 4.432 | 33.233 | 30.379 | 28.180 | 21.377 | 20.210 | 21.240 |
| Marginal probability | 0.035 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| LM error tests for spatial correlation in the dependent variable [$\chi(1)$ 0.01 value = 6.640] | | | | | | | |
| LM value | 32.189 | 12.480 | 15.470 | 54.866 | 42.891 | 65.461 | 72.477 |
| Marginal probability | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Robust LM error tests for spatial correlation in the residuals [$\chi(1)$ 0.01 value = 6.640] | | | | | | | |
| LM value | 12.185 | 40.172 | 37.291 | 42.667 | 30.385 | 32.851 | 34.605 |
| Marginal probability | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Robust LM error tests for spatial correlation in the dependent variable [$\chi(1)$ 0.01 value = 6.640] | | | | | | | |
| LM value | 39.943 | 19.419 | 22.383 | 69.354 | 51.899 | 78.101 | 85.842 |
| Marginal probability | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| *Spatial 'destination based' autocorrelation with row norm. 'Wd' (neighbours of the importing region j)* | | | | | | | |
| Moran I test for spatial correlation in residuals (SD = 0.041) | | | | | | | |
| Moran I | 0.234 | 0.369 | 0.350 | 0.402 | 0.385 | 0.397 | 0.424 |
| Moran I statistic | 5.938 | 9.236 | 8.758 | 10.120 | 9.668 | 10.062 | 10.643 |
| Marginal probability | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| LM error tests for spatial correlation in residuals [$\chi(1)$ 0.01 value = 6.635] | | | | | | | |
| LM value | 31.786 | 79.218 | 71.183 | 93.929 | 86.294 | 91.780 | 104.618 |
| Marginal probability | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| LM error tests for spatial correlation in the dependent variable [$\chi(1)$ 0.01 value = 6.640] | | | | | | | |
| LM value | 0.630 | 37.456 | 31.881 | 40.069 | 19.728 | 24.095 | 32.775 |
| Marginal probability | 0.427 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Robust LM error tests for spatial correlation in the residuals [$\chi(1)$ 0.01 value = 6.640] | | | | | | | |
| LM value | 35.529 | 65.811 | 59.888 | 79.719 | 77.318 | 81.219 | 91.750 |
| Marginal probability | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Robust LM error tests for spatial correlation in the dependent variable [$\chi(1)$ 0.01 value = 6.640] | | | | | | | |
| LM value | 4.373 | 24.050 | 20.586 | 25.859 | 10.752 | 13.534 | 19.907 |
| Marginal probability | 0.037 | 0.000 | 0.000 | 0.000 | 0.001 | 0.000 | 0.000 |
| *Spatial autocorrelation using row normalized first contiguity matrix 'W = (Wo + Wd)' (neighbours of ij)* | | | | | | | |
| Moran I test for spatial correlation in residuals (SD = 0.033) | | | | | | | |
| Moran I | 0.186 | 0.339 | 0.327 | 0.406 | 0.352 | 0.372 | 0.421 |
| Moran I statistic | 5.954 | 10.578 | 10.205 | 12.705 | 11.029 | 11.763 | 13.133 |
| Marginal probability | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| LM error tests for spatial correlation in residuals [$\chi(1)$ 0.01 value = 6.635] | | | | | | | |
| LM value | 29.820 | 99.117 | 92.312 | 142.119 | 106.882 | 119.307 | 152.844 |

**Table 3** continued

| | M1 | M2 | M3 | M4 | M5 | M6 | M7 |
|---|---|---|---|---|---|---|---|
| Marginal probability | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| LM error tests for spatial correlation in the dependent variable [$\chi(1)$ 0.01 value = 6.635] | | | | | | | |
| LM value | 3.907 | 21.024 | 11.789 | 10.209 | 5.578 | 5.597 | 7.200 |
| Marginal probability | 0.048 | 0.000 | 0.001 | 0.001 | 0.018 | 0.018 | 0.007 |
| Robust LM error tests for spatial correlation in the residuals [$\chi(1)$ 0.01 value = 6.640] | | | | | | | |
| LM value | 45.373 | 82.310 | 81.592 | 131.971 | 101.307 | 113.744 | 145.716 |
| Marginal probability | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Robust LM error tests for spatial correlation in the dependent variable [$\chi(1)$ 0.01 value = 6.640] | | | | | | | |
| LM value | 19.461 | 4.216 | 1.069 | 0.062 | 0.003 | 0.035 | 0.072 |
| Marginal probability | 0.000 | 0.040 | 0.301 | 0.803 | 0.956 | 0.852 | 0.788 |

*Source*: Own elaboration. All variables are averages in the period 2000 2009

Dependent variable: interregional monetary flows of accommodation, restaurants and travel agencies. Average flows 2000 2009

to analyse the results obtained using the spatial lag model (SAR), the spatial general model (SAC) and the spatial Durbin model (SDM).

In addition, Fig. 4 reports the Moran scatterplots for the residuals of the main 6 models using the row-normalized spatial ($W^{spa} = W_i^{spa} + W_j^{spa}$), for capturing the aggregate spatial autocorrelation of both exporting and importing regions. As in LeSage and Pace (2009) each graph is divided in 4 quadrants: Q-I (red points): *ij* flows that have residuals above the mean, where the average neighbouring *ij* flows (orgin-based + destination-based) is also greater than the mean; Q-II (green points): *ij* flows that have residuals below the mean, but the average of neighbouring *ij* flows is above the mean; Q-III (blue points): *ij* flows with residuals below the mean and the average of the neighbouring *ij* flows is also below the mean; Q-IV (purple points): *ij* flows that have residuals above the mean, and the average neighbouring *ij* flows is below the mean. In a similar way, Fig. 5 reports the Moran scatterplots for the residuals of the main 6 models using the row-normalized network (demographic) weight matrix ($W^{net} = W_i^{net} + W_j^{net}$).

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 will be greater the shorter the number of green and purple points and the larger the number of blue and red ones. Conversely to other papers using scatterplot, since our dataset is referred to origin destination flows, the residuals cannot be plotted in a map. Such graphical analysis will require the use of specialized GIS systems for transport modelling (Berglund and Karström 1999a, b; Berglund 2001), which is beyond the scope of this paper. The results shown in Figs. 4 and 5 suggest the presence of a positive association between the residuals of the 6 main models obtained by a simple OLS estimate procedure and the two different cross-sectional autocorrelation structures one pure spatial and the other pure demographic under consideration. It is also worth mentioning the differences in the shapes of the dot clouds obtained with each weight matrix, which indicates the

**Table 4** Testing demographic dependence

| | M1 | M2 | M3 | M4 | M5 | M6 | M7 |
|---|---|---|---|---|---|---|---|
| *Demographic 'origin based' autocorrelation using row norm 'Wo' (neighbours of exporting region i)* | | | | | | | |
| Moran I test for 'network' correlation in residuals (SD = 0.030) | | | | | | | |
| Moran I | 0.068 | 0.074 | 0.109 | 0.107 | 0.066 | 0.063 | 0.072 |
| Moran I statistic | 2.582 | 2.764 | 3.864 | 3.832 | 2.531 | 2.474 | 2.712 |
| Marginal probability | 0.010 | 0.006 | 0.000 | 0.000 | 0.011 | 0.013 | 0.007 |
| LM error tests for 'network' correlation in residuals [$\chi(1)$ 0.01 value = 6.635] | | | | | | | |
| LM value | 4.361 | 5.105 | 11.044 | 10.781 | 4.049 | 3.728 | 4.916 |
| Marginal probability | 0.037 | 0.024 | 0.001 | 0.001 | 0.044 | 0.054 | 0.027 |
| LM error tests for 'network' correlation in the dependent variable [$\chi(1)$ 0.01 value = 6.640] | | | | | | | |
| LM value | 1.833 | 60.136 | 60.750 | 52.951 | 39.417 | 38.765 | 41.739 |
| Marginal probability | 0.176 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Robust LM error tests for 'network' correlation in the residuals [$\chi(1)$ 0.01 value = 6.640] | | | | | | | |
| LM value | 2.564 | 6.940 | 2.892 | 2.432 | 2.950 | 3.501 | 3.932 |
| Marginal probability | 0.109 | 0.008 | 0.089 | 0.119 | 0.086 | 0.061 | 0.047 |
| Robust LM error tests for 'network' correlation in the dependent variable [$\chi(1)$ 0.01 value = 6.640] | | | | | | | |
| LM value | 0.035 | 61.971 | 52.598 | 44.602 | 38.318 | 38.538 | 40.755 |
| Marginal probability | 0.851 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| *Demographic 'destination based' autocorrelation. Row norm 'Wd' (neighbours of importing region j)* | | | | | | | |
| Moran I test for 'network' correlation in residuals (SD = 0.031) | | | | | | | |
| Moran I | 0.238 | 0.357 | 0.368 | 0.441 | 0.402 | 0.421 | 0.470 |
| Moran I statistic | 7.771 | 11.541 | 11.880 | 14.450 | 13.027 | 13.883 | 15.295 |
| Marginal probability | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| LM error tests for 'network' correlation in residuals [$\chi(1)$ 0.01 value = 6.635] | | | | | | | |
| LM value | 52.803 | 119.074 | 126.545 | 182.193 | 151.505 | 165.831 | 207.204 |
| Marginal probability | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| LM error tests for 'network' correlation in the dependent variable [$\chi(1)$ 0.01 value = 6.640] | | | | | | | |
| LM value | 1.536 | 30.837 | 34.952 | 28.108 | 14.631 | 14.390 | 17.292 |
| Marginal probability | 0.215 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Robust LM error tests for 'network' correlation in the residuals [$\chi(1)$ 0.01 value = 6.640] | | | | | | | |
| LM value | 88.290 | 89.191 | 93.450 | 176.766 | 163.223 | 188.897 | 239.238 |
| Marginal probability | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Robust LM error tests for 'network' correlation in the dependent variable [$\chi(1)$ 0.01 value = 6.640] | | | | | | | |
| LM value | 37.022 | 0.954 | 1.857 | 22.681 | 26.350 | 37.456 | 49.325 |
| Marginal probability | 0.000 | 0.329 | 0.173 | 0.000 | 0.000 | 0.000 | 0.000 |
| *Demographic autocorrelation using row normalized 'W = (Wo + Wd)' (neighbours of ij)* | | | | | | | |
| Moran I test for 'network' correlation in residuals (SD = 0.026) | | | | | | | |
| Moran I | 0.191 | 0.251 | 0.275 | 0.368 | 0.290 | 0.317 | 0.382 |
| Moran I statistic | 7.634 | 9.939 | 10.844 | 14.550 | 11.491 | 12.694 | 15.036 |
| Marginal probability | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| LM error tests for 'network' correlation in residuals [$\chi(1)$ 0.01 value = 6.635] | | | | | | | |
| LM value | 47.371 | 82.022 | 98.469 | 176.726 | 109.485 | 131.075 | 190.143 |
| Marginal probability | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |

**Table 4** continued

| | M1 | M2 | M3 | M4 | M5 | M6 | M7 |
|---|---|---|---|---|---|---|---|
| LM error tests for 'network' correlation in the dependent variable [$\chi(1)$ 0.01 value = 6.640] | | | | | | | |
| LM value | 2.630 | 36.057 | 35.653 | 34.856 | 17.258 | 18.176 | 24.885 |
| Marginal probability | 0.105 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Robust LM error tests for 'network' correlation in the residuals [$\chi(1)$ 0.01 value = 6.640] | | | | | | | |
| LM value | 54.835 | 52.136 | 66.655 | 141.872 | 92.309 | 113.436 | 166.678 |
| Marginal probability | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Robust LM error tests for 'network' correlation in the dependent variable [$\chi(1)$ 0.01 value = 6.640] | | | | | | | |
| LM value | 10.094 | 6.171 | 3.839 | 0.001 | 0.082 | 0.537 | 1.420 |
| Marginal probability | 0.001 | 0.013 | 0.050 | 0.971 | 0.775 | 0.464 | 0.233 |

*Source*: Own elaboration. All variables are averages in the period 2000 2009

Dependent variable: interregional monetary flows of accommodation, restaurants and travel agencies. Average flows 2000 2009

complementary nature of both structures. Such differences would also be observed when running the 4 alternative SAC models.

Next, we analyse the results obtained for the augmented gravity models that consider the presence of spatial and/or network (demographic in our case) effects. Before doing that, it is important to have in mind that the coefficient estimates on the explanatory variables in these models are not interpretable in the same fashion as those from the non-spatial models, a point made in LeSage and Pace (2009), Chapter 8. However, as we will see, the sign of the coefficient estimates reflect the correct direction of impact on flows that would arise from changes in the explanatory variables.[14]

Estimation results for the spatial lag model (SAR) specifications are shown in Table 5. These models were estimated using maximum likelihood methods (see LeSage and Pace (2009), Chapter 3). As opposed to the non-spatial least-squares estimates, these models allow for the spatial spillover effects to neighbouring regions as well as network spillover influences, both of which were motivated in the previous section. The non-spatial models restrict spatial and network spillover influences to be zero, since each bilateral flow is treated as independent of all other flows.

In model M8, the M1 is extended by including the 2 autocorrelation terms $\rho_1$ (spatial effects) $\rho_2$ (network effects) without the immigration variables. All the coefficients are significant and with the expected signs, including the ones indicating the presence of spatial and demographic autocorrelation effects in the bilateral trade flows. Then, models M9 and M10 add separately the variables capturing the emigrant ($m_{ij}$) and immigrant ($m_{ji}$) effects. In this case, all the new variables have positive and significant coefficients, with the exception of the spatial

[14] 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 an issue studied in Lesage and Thomas Agnan (2012).

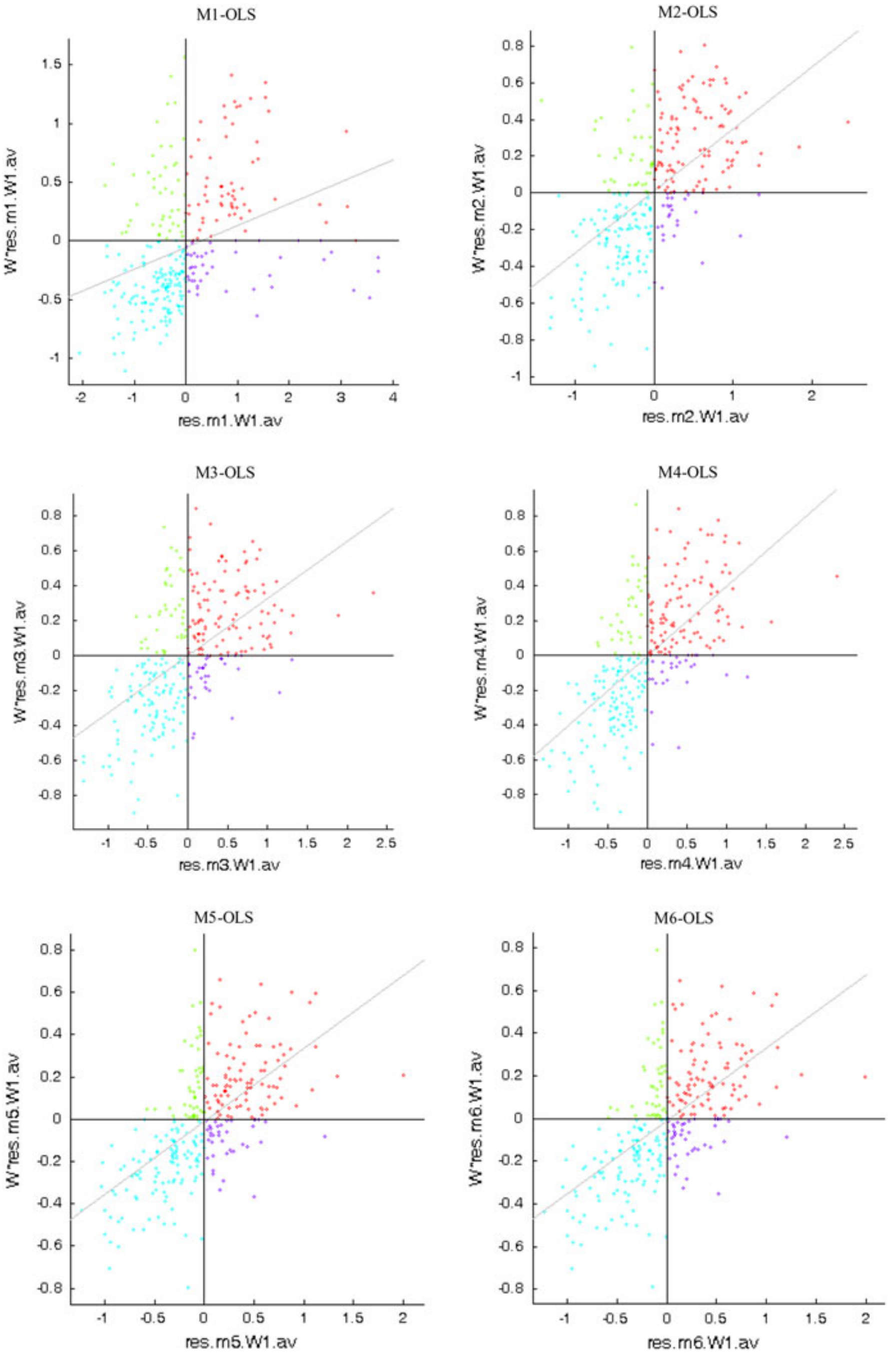


**Fig. 4** I Moran scatterplot on residuals from OLS estimates. $Y =$ Residuals from Models 1 6. $W^{spa} = (W_i^{spa} + W_j^{spa})$ 1st order contiguity matrix row normalized

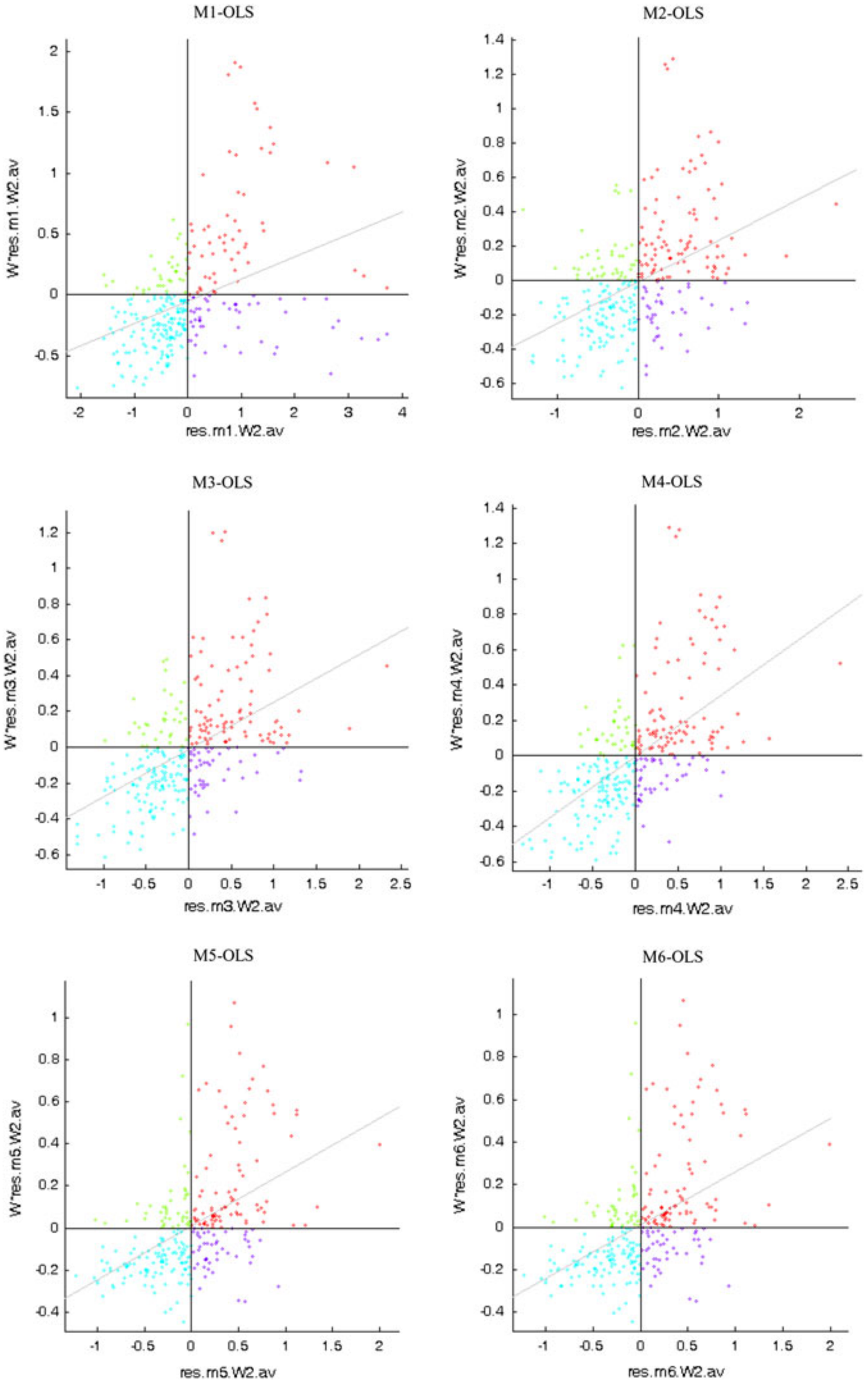


**Fig. 5** I Moran scatterplot on residuals from OLS estimates. $Y =$ Residuals. Models 1 6. $W^{net} = (W_i^{net} + W_j^{net})$ 1st order demographic matrix row normalized

**Table 5** Spatial autoregressive model

| | M8 | M9 | M10 | M11 | M12 | M13 | M14 |
|---|---|---|---|---|---|---|---|
| Pseudo $R^2$ | 0 916 | 0 919 | 0 933 | 0 933 | 0 934 | 0 926 | 0 925 |
| $R$bar$^2$ | 0 915 | 0 917 | 0 932 | 0 931 | 0 932 | 0 924 | 0 924 |
| Sigma 2 | 0 264 | 0 256 | 0 211 | 0 211 | 0 208 | 0 233 | 0 235 |
| Log likelihood | −624 503 | −619 881 | −591 052 | −591 036 | −589 562 | −605 741 | −607 321 |
| Const | −28 51*** | −26 561*** | −29 176*** | −29 291*** | −30 586*** | −26 13*** | −27 316*** |
| | −15 815 | −14 089 | −18 097 | −16 791 | −17 630 | −15 085 | −15 686 |
| log(gva$_i$) | 0 714*** | 0 683*** | 0 502*** | 0 502*** | 0 51*** | 0 592*** | 0 624*** |
| | 23 584 | 20 972 | 12 115 | 12 108 | 12 362 | 15 517 | 16 267 |
| log(pop$_j$) | 0 809*** | 0 729*** | 0 627*** | 0 63*** | 0 637*** | 0 632*** | 0 652*** |
| | 22 950 | 16 055 | 14 831 | 13 932 | 14 146 | 13 334 | 13 682 |
| log(inc$_j$) | 1 554*** | 1 425*** | 1 947*** | 1 958*** | 2 05*** | 1 53*** | 1 588*** |
| | 9 506 | 8 592 | 12 725 | 11 870 | 12 495 | 9 972 | 10 291 |
| log($d_{ij}$) | −0 385*** | −0 323*** | −0 131*** | −0 132*** | −0 136*** | −0 204*** | −0 212*** |
| | −9 001 | −6 838 | −2 630 | −2 632 | −2 736 | −4 036 | −4 156 |
| intra_const | −1 507 | −1 653 | −2 38 | −2 383 | −2 217 | −2 045 | −1 862 |
| | −0 627 | −0 699 | −1 108 | −1 110 | −1 038 | −0 906 | −0 821 |
| log(intra_gdp) | 0 834*** | 0 84*** | 0 925*** | 0 926*** | 0 897*** | 0 878*** | 0 868*** |
| | 6 027 | 6 165 | 7 473 | 7 484 | 7 293 | 6 756 | 6 642 |
| log($m_{ij}$) | | 0 084*** | | −0 005 | −0 021 | | |
| | | 3 092 | | −0 171 | −0 778 | | |
| log($m_{ji}$) | | | 0 297*** | 0 3*** | 0 306*** | | |
| | | | 9 426 | 8 617 | 8 833 | | |

**Table 5** continued

| | M8 | M9 | M10 | M11 | M12 | M13 | M14 |
|---|---|---|---|---|---|---|---|
| log(mig_net$_{ij}$) | | | | | | 0 114*** | 0 109*** |
| | | | | | | 6 622 | 6 317 |
| $\rho_1$ (spat) | 0 091* | 0 089* | 0 047 | 0 046 | 0 054* | 0 07 | 0 093** |
| | 1 936 | 1 896 | 1 102 | 1 083 | 0 000 | 1 589 | 2 115 |
| $\rho_2$ (demo) | 0 557*** | 0 52*** | 0 279*** | 0 277*** | 0 342*** | 0 399*** | 0 393*** |
| | 5 617 | 4 435 | 2 924 | 2 903 | 2 637 | 4 114 | 2 785 |

*Source*: Own elaboration  *T* statistics below the coefficients  Significance: *** $p < 0\ 01$; ** $p < 0\ 05$; * $p < 0\ 1$  All variables are averages in the period 2000–2009

Dependent variable: interregional monetary flows of accommodation, restaurants and travel agencies  Average flows 2000–2009 autocorrelation effect that appears to be non-significant when it is included with the immigrant vector in M10. The difference between the fully saturated models M11 and M12 (that include the full set of explanatory variables) is the use of the rotated version $W^{net\prime}$ in model M12 in place of $W^{net}$ for model M11. This alternative specification of the network effect is supported by the idea that the demographic linkages are bi-directional, that is, they can produce pull and push effects (through taste and information channels) in the 'demographic' neighbours of the exporting and importing regions, both based on the historic patterns of emigration and immigration. As before, in M11 and M12, the emigrant effect ($m_{ij}$) is non-significant when it is included together with the immigrants ($m_{ji}$). The spatial effect appears to be non-significant for M11 but it is for M12. According to the likelihood function values, the higher pseudo $R^2$ and lower noise variance estimate ($\hat{\sigma}^2$)[15] model M11 has the best goodness of fit. Finally, two more models (*M13* and *M14*) are included, with the aim of testing to what extent the results are sensible to the inclusion of one single vector of net migration instead of the 2 previous ones for emigrants and immigrants. It is worth mentioning that like in M11, the spatial effect also appears to be non-significant in M13. The rest of the results do not vary too much.

After confirming the presence of spatial and demographic autocorrelation of the flows, it is interesting to test whether similar patterns exist in the residuals of the model and if a SAC model could beat the SAR specification capturing such effects and explaining the bilateral trade flows.

Now, we focus on the results using the general spatial model and the 4 specifications described before: SAC-I: ($W_1 = W^{spa}$; $W_2 = W^{net}$); SAC-II: ($W_1 = W^{net}$; $W_2 = W^{spa}$), SAC-III: ($W_1 = W_2 = W^{spa}$); and SAC-IV: ($W_1 = W_2 = W^{net}$). For brevity, we will focus on the results for M11 and M13  the two with the better fits in the SAR model  , which are reported in Table 6.

The first thing to note is the strong similarity between M11 and M13 in the four cases. In addition, it is important to make notice that the spatial and network effects appear to be significant for all the models and specifications with the exception of the spatial effects in the dependent variable for M11 and M13 in SAC-I. Surprisingly, the lag of the dependent variable in SAC-II-III and IV is significant but negative, that is, the opposite sign that the one found in the SAR specifications. To this regard, it is worth mentioning that the negative coefficient for this element in SAC-III is very low (M11: −0.055**; M13: −0.056**) compared to the one on SAC-II and SAC-III when the lag is based on the 'network' (demographic structure). i.e.: SAC-II-M11: −0.157***; SAC-II-M13: −0.154***. Another remarkable difference is found on the coefficient of the log of distance: when the trade flows are modelled in the SAC-I and the SAC-IV version of Eq. (7), which both have in common the use of $W^{net}$ on the disturbance term, the negative coefficient is around −0.2, that is, a value that is close to the one obtained for M13 in the SAR specification. However, the negative value of distance in SAC-II and

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

**Table 6** Bayesian Spatial General Model

| | SAC-I | | SAC-II | | SAC-III | | SAC-IV | |
|---|---|---|---|---|---|---|---|---|
| | $W_1 = W^{spa}$; $W_2 = W^{net}$ | | $W_1 = W^{net}$; $W_2 = W^{spa}$ | | $W_1 = W_2 = W^{spa}$ | | $W_1 = W_2 = W^{net}$ | |
| | M11 | M13 | M11 | M13 | M11 | M13 | M11 | M13 |
| Pseudo $R^2$ | 0 951 | 0 951 | 0 964 | 0 964 | 0 962 | 0 962 | 0 955 | 0 955 |
| $R\text{bar}^2$ | 0 950 | 0 950 | 0 963 | 0 963 | 0 961 | 0 961 | 0 954 | 0 954 |
| Sigma 2 | 0 158 | 0 158 | 0 117 | 0 117 | 0 122 | 0 122 | 0 147 | 0 146 |
| Const | −27 551*** | −26 25*** | −22 692*** | −22 846*** | −24 746*** | −24 74*** | −25 19*** | −23 993*** |
| | 1 840 | 1 554 | 2 545 | 2 392 | 2 328 | 2 200 | 1 920 | 2 284 |
| log(gva$_i$) | 0 56*** | 0 6*** | 0 519*** | 0 516*** | 0 513*** | 0 513*** | 0 548*** | 0 583*** |
| | 0 049 | 0 040 | 0 042 | 0 041 | 0 042 | 0 041 | 0 047 | 0 040 |
| log(pop$_j$) | 0 623*** | 0 613*** | 0 576*** | 0 575*** | 0 564*** | 0 562*** | 0 581*** | 0 567*** |
| | 0 058 | 0 058 | 0 052 | 0 053 | 0 053 | 0 053 | 0 063 | 0 063 |
| log(inc$_j$) | 1 865*** | 1 704*** | 1 528*** | 1 542*** | 1 663*** | 1 665*** | 1 833*** | 1 689*** |
| | 0 187 | 0 150 | 0 248 | 0 227 | 0 235 | 0 217 | 0 177 | 0 150 |
| log($d_{ij}$) | −0 233*** | −0 249*** | −0 082* | −0 08* | −0 099** | −0 098** | −0 211*** | −0 221*** |
| | 0 053 | 0 052 | 0 051 | 0 051 | 0 053 | 0 053 | 0 050 | 0 049 |
| intra_const | −4 649*** | −4 894*** | −2 98** | −2 968** | −3 992*** | −4 019*** | −2 742* | −2 864* |
| | 1 853 | 1 860 | 1 692 | 1 659 | 1 662 | 1 700 | 1 932 | 2 434 |
| log(intra_gdp) | 1 177*** | 1 196*** | 1 165*** | 1 16*** | 1 136*** | 1 137*** | 1 176*** | 1 186*** |
| | 0 109 | 0 110 | 0 097 | 0 093 | 0 096 | 0 098 | 0 104 | 0 106 |
| log($m_{ij}$) | 0 133*** | | 0 257*** | | 0 223*** | | 0 175*** | |
| | 0 038 | | 0 046 | | 0 046 | | 0 04 | |
| log($m_{ji}$) | 0 241*** | | 0 237*** | | 0 225*** | | 0 269*** | |

**Table 6** continued

| | SAC-I | | SAC-II | | SAC-III | | SAC-IV | |
|---|---|---|---|---|---|---|---|---|
| | $W_1 = W^{spa}$; $W_2 = W^{net}$ | | $W_1 = W^{net}$; $W_2 = W^{spa}$ | | $W_1 = W_2 = W^{spa}$ | | $W_1 = W_2 = W^{net}$ | |
| | M11 | M13 | M11 | M13 | M11 | M13 | M11 | M13 |
| | 0 041 | | 0 047 | | 0 049 | | 0 041 | |
| log(mig_net$_{ij}$) | | 0 185*** | | 0 247*** | | 0 224*** | | 0 221*** |
| | | 0 017 | | 0 019 | | 0 018 | | 0 019 |
| $\rho$ | 0 008 | 0 007 | −0 157*** | −0 154*** | −0 055*** | −0 056*** | −0 199*** | −0 206*** |
| | 0 019 | 0 020 | 0 047 | 0 047 | 0 023 | 0 021 | 0 065 | 0 062 |
| $\theta$ | 0 77*** | 0 798*** | 0 901*** | 0 894*** | 0 861*** | 0 854*** | 0 879*** | 0 895*** |
| | 0 067 | 0 057 | 0 034 | 0 035 | 0 041 | 0 037 | 0 053 | 0 050 |

*Source*: Own elaboration  $T$ statistics below the coefficients  Significance: *** $p < 0\ 01$; ** $p < 0\ 05$; * $p < 0\ 1$  All variables are averages in the period 2000–2009

Dependent variable: interregional monetary flows of accommodation, restaurants and travel agencies  Average flows 2000–2009

SAC-III, that is, when $W^{spa}$ is used for the disturbance term, drops to −0.08 or −0.09, reaching the smallest values of all the specifications tested in this article. However, the rest of the coefficients  even the ones referred to migration effects  remain almost invariant in the four alternative specifications.

Next, in Fig. 6, we show the Moran scatterplots for the residuals obtained in M11 using the SAR, SAC-I-IV estimation procedures, and a row-normalized weight matrix obtained as a sum over all the weight matrices described here ($W_3 = W^{spa} + W^{net}$).[16] The use of such approach is an attempt to show in a single picture whether after using these 5 spatial models the residuals still show a significant association with a lag based on spatial and demographic structure. The interpretation is like the one in Figs. 4 and 5. Based on these graphs, just the scatter plot for the first quadrant (M11-SAR)  and less clear for the M11-SAC-I and the M11-SAC-IV  still shows a positive relation. This result can be interpreted as if the SAC specifications  specially SAC-II and SAC-III  did a better job on eliminating all the positive association between the residuals and the spatial and demographic lags plotted in Fig. 4 and in Fig. 5.

We now proceed with the alternative specifications and robustness analysis described in Sect. 3.2.2. The main results are reported in Table 7, 8, 9, 10. The rest of the results are available upon request.

Briefly, the results reported in Table 7 for the SDM are complementary to the ones offered by the SAR and the SAC estimates: the coefficients for the spatial and network (demographic) autocorrelation terms are positive and significant for the dependent variable obtaining high values for ρ in the 6 specifications reported. Moreover, the coefficients for the spatial and network (demographic) autocorrelation terms for the explanatory variables are not always significant and the signs varied depending on each variable. For example, variables such as $W$-gva$_i$ or $W$-pop$_j$ show negative and significant coefficients for all the specifications, suggesting that on average the flows between the trading regions decreases when the value of population and gross value added in the touristic sector of their neighbours increases (considering neighbourhood in a spatial, demographic or both terms). Such results would be pointed out to some kind of competing effect between regions, which deserves further research.

Another aspect that should be noticed is the difference in the significance of the coefficients of the migration variables depending on the model estimated. When a SAR model is estimated, there is not a significant effect of the stock of emigrants, but it does of the stock of immigrants (0.3 in M11 in Table 5), while a significant positive effect of both variables is found when a SAC model is estimated.[17] Finally, when a SDM is estimated, the significant effect is found for the stock of emigrants

[16] The Moran scatterplots for the residuals of each model and weight matrix is available upon request.

[17] In Table 6, the effect of emigrants is: 0.133 in SAC I, 0.257 in SAC II, 0.223 in SAC III and 0.175 in SAC IV; and the effect of immigrants: 0.241 in SAC I, 0.237 in SAC II, 0.225 in SAC III and 0.269 in SAC IV.

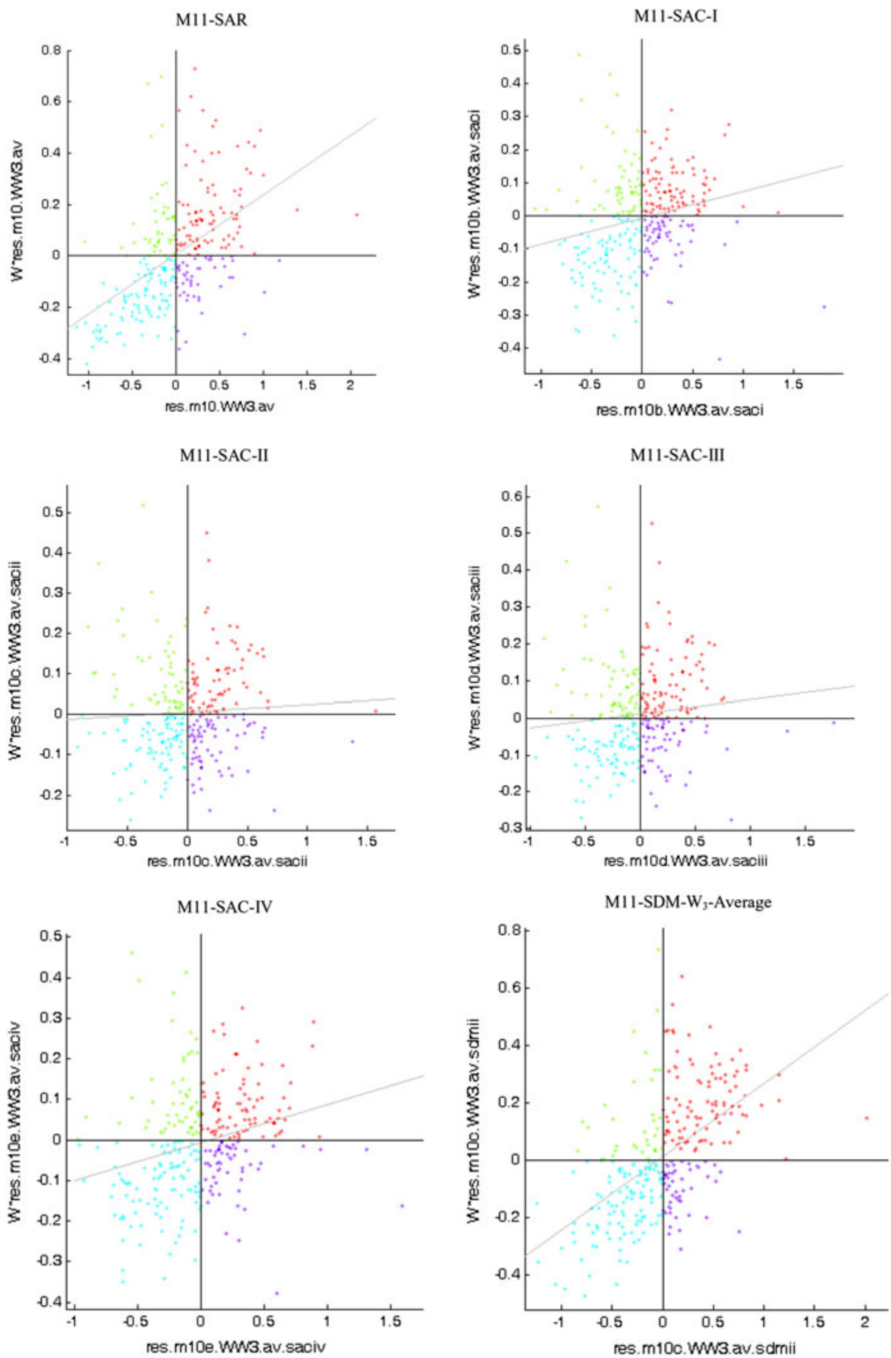


**Fig. 6** I Moran scatterplot on residuals from SAR and SAC estimates. $Y =$ Residuals from M10. $(W_3 = W^{spa} + W^{net})$

**Table 7** Bayesian spatial Durbin model

| | $W^{spa}$ | | $W^{net}$ | | $W^{spa} + W^{net}$ | |
|---|---|---|---|---|---|---|
| | M11 | M13 | M11 | M13 | M11 | M13 |
| $R^2$ | 0.940 | 0.922 | 0.929 | 0.894 | 0.935 | 0.913 |
| Mean sige draws | 0.145 | 0.151 | 0.183 | 0.197 | 0.159 | 0.168 |
| Sige, epe/($n$ $k$) | 0.199 | 0.257 | 0.237 | 0.350 | 0.216 | 0.286 |
| const | 11.245*** | 9.831*** | 0.601 | 8.392** | 4.097 | 1.323 |
| | 1.348 | 1.291 | 4.388 | 4.162 | 3.541 | 3.233 |
| log(gva$_i$) | 0.514*** | 0.461*** | 0.676*** | 0.573*** | 0.634*** | 0.543*** |
| | 0.051 | 0.050 | 0.059 | 0.048 | 0.058 | 0.053 |
| log(pop$_j$) | 0.612*** | 0.587*** | 0.578*** | 0.659*** | 0.67*** | 0.697*** |
| | 0.064 | 0.064 | 0.084 | 0.083 | 0.080 | 0.081 |
| log(inc$_j$) | 0.194* | 0.152 | 0.64*** | 0.856*** | 0.425*** | 0.562*** |
| | 0.144 | 0.137 | 0.153 | 0.147 | 0.152 | 0.151 |
| log($d_{ij}$) | 0.064 | 0.073 | 0.215*** | 0.212*** | 0.129** | 0.121** |
| | 0.061 | 0.063 | 0.059 | 0.061 | 0.062 | 0.063 |
| log(intra gdp) | 1.556*** | 1.48*** | 1.884*** | 1.99*** | 1.807*** | 1.844*** |
| | 0.076 | 0.074 | 0.090 | 0.091 | 0.096 | 0.097 |
| log($m_{ij}$) | 0.385*** | | 0.366*** | | 0.397*** | |
| | 0.052 | | 0.048 | | 0.048 | |
| log($m_{ji}$) | 0.069 | | 0.039 | | 0.006 | |
| | 0.058 | | 0.05 | | 0.053 | |
| log(mig net$_{ij}$) | | 0.238*** | | 0.203*** | | 0.207*** |
| | | 0.023 | | 0.024 | | 0.025 |
| $W$ gva$_i$ | 0.379*** | 0.23*** | 0.685*** | 0.476*** | 0.597*** | 0.406*** |
| | 0.091 | 0.081 | 0.126 | 0.117 | 0.116 | 0.109 |
| $W$ pop$_j$ | 0.399*** | 0.351*** | 0.333** | 0.543*** | 0.485*** | 0.57*** |
| | 0.091 | 0.089 | 0.161 | 0.153 | 0.142 | 0.136 |
| $W$ inc$_j$ | 0.743*** | 0.525*** | 0.717** | 1.668*** | 0.017 | 0.467* |
| | 0.151 | 0.141 | 0.387 | 0.367 | 0.341 | 0.324 |
| $W$ intra gdp | 0.591*** | 0.643*** | 1.481*** | 2.137*** | 1.238*** | 1.505*** |
| | 0.063 | 0.059 | 0.317 | 0.292 | 0.283 | 0.254 |
| $W$ $d_{ij}$ | 0.027 | 0.052 | 0.245** | 0.101 | 0.105 | 0.004 |
| | 0.088 | 0.085 | 0.106 | 0.107 | 0.101 | 0.100 |
| $W$ $m_{ij}$ | 0.48*** | | 0.575*** | | 0.58*** | |
| | 0.062 | | 0.074 | | 0.072 | |
| $W$ $m_{ji}$ | 0.076 | | 0.273*** | | 0.155* | |
| | 0.082 | | 0.093 | | 0.095 | |
| $W$ mig net$_{ji}$ | | 0.259*** | | 0.222*** | | 0.268*** |
| | | 0.032 | | 0.043 | | 0.039 |
| $\rho$ | 0.675*** | 0.751*** | 0.573*** | 0.76*** | 0.726*** | 0.831*** |
| | 0.055 | 0.050 | 0.091 | 0.072 | 0.078 | 0.059 |

Dependent variable: Interregional monetary flows of accommodation, restaurants and travel agencies and Average flows 2000 2009. Interregional migration stock: Average 2000 2009

**Table 8** Robustness checks: SAR and SAC models with the 1981 census

| | SAR | | SAC-I | | SAC-II | | SAC-III | | SAC-IV | |
|---|---|---|---|---|---|---|---|---|---|---|
| | $W_1 = W^{spa}$; $W_2 = W^{net}$ | | $W_1 = W^{spa}$; $W_2 = W^{net}$ | | $W_1 = W^{net}$; $W_2 = W^{spa}$ | | $W_1 = W_2 = W^{spa}$ | | $W_1 = W_2 = W^{net}$ | |
| | M11 | M13 | M11 | M13 | M11 | M13 | M11 | M13 | M11 | M13 |
| $R^2$ | 0 925 | 0 923 | 0 950 | 0 950 | 0 963 | 0 963 | 0 961 | 0 960 | 0 954 | 0 953 |
| $R\text{bar}^2$ | 0 923 | 0 922 | 0 948 | 0 948 | 0 962 | 0 962 | 0 960 | 0 959 | 0 952 | 0 952 |
| Sigma 2 | 0 236 | 0 241 | 0 164 | 0 163 | 0 119 | 0 122 | 0 126 | 0 129 | 0 151 | 0 152 |
| Const | −28 777*** | −26 146*** | −26 461*** | −26 717*** | −21 653*** | −23 824*** | −23 104*** | −25 247*** | −25 514*** | −25 902*** |
| | −14 597 | −14 953 | 1 978 | 1 608 | 2 499 | 2 371 | 2 501 | 2 341 | 2 194 | 2 447 |
| log(gva$_i$) | 0 563*** | 0 615*** | 0 625*** | 0 616*** | 0 592*** | 0 557*** | 0 581*** | 0 549*** | 0 625*** | 0 616*** |
| | 12 790 | 16 391 | 0 048 | 0 040 | 0 043 | 0 041 | 0 045 | 0 042 | 0 049 | 0 039 |
| log(pop$_j$) | 0 667*** | 0 655*** | 0 635*** | 0 637*** | 0 605*** | 0 617*** | 0 593*** | 0 605*** | 0 597*** | 0 602*** |
| | 14 311 | 13 884 | 0 058 | 0 057 | 0 052 | 0 052 | 0 054 | 0 054 | 0 063 | 0 061 |
| log(inc$_j$) | 1 799*** | 1 492*** | 1 677*** | 1 71*** | 1 346*** | 1 596*** | 1 408*** | 1 65*** | 1 757*** | 1 792*** |
| | 9 409 | 9 542 | 0 201 | 0 152 | 0 248 | 0 229 | 0 253 | 0 229 | 0 201 | 0 149 |
| log($d_{ij}$) | −0 154*** | −0 195*** | −0 238*** | −0 236*** | −0 09** | −0 087** | −0 107** | −0 105** | −0 216*** | −0 216*** |
| | −2 765 | −3 628 | 0 055 | 0 055 | 0 053 | 0 052 | 0 055 | 0 054 | 0 053 | 0 053 |
| intra_const | −2 275 | −2 139 | −5 118*** | −5 006*** | −2 947** | −2 659* | −4 563*** | −4 252*** | −3 085* | −3 188** |
| | −1 001 | −0 931 | 1 892 | 1 893 | 1 721 | 1 760 | 1 688 | 1 719 | 2 198 | 2 649 |
| log(intra_gdp) | 0 897*** | 0 881*** | 1 21*** | 1 202*** | 1 177*** | 1 161*** | 1 173*** | 1 154*** | 1 194*** | 1 194*** |
| | 6 849 | 6 651 | 0 112 | 0 112 | 0 096 | 0 097 | 0 098 | 0 099 | 0 106 | 0 104 |
| log($m_{ij}$) | 0 036 | | 0 185*** | | 0 313*** | | 0 284*** | | 0 221*** | |
| | 1 262 | | 0 033 | | 0 04 | | 0 041 | | 0 033 | |
| log($m_{ji}$) | 0 184*** | | 0 168*** | | 0 145*** | | 0 127*** | | 0 202*** | |

**Table 8** continued

| | SAR | | SAC-I | | SAC-II | | SAC-III | | SAC-IV | |
|---|---|---|---|---|---|---|---|---|---|---|
| | $W_1 = W^{spa}$; $W_2 = W^{net}$ | | $W_1 = W^{spa}$; $W_2 = W^{net}$ | | $W_1 = W^{net}$; $W_2 = W^{spa}$ | | $W_1 = W_2 = W^{spa}$ | | $W_1 = W_2 = W^{net}$ | |
| | M11 | M13 | M11 | M13 | M11 | M13 | M11 | M13 | M11 | M13 |
| | 5 202 | | 0 035 | | 0 042 | | 0 041 | | 0 037 | |
| log(mig_net$_{ij}$) | 0 | 0 096*** | | 0 177*** | | 0 231*** | | 0 206*** | | 0 21*** |
| | 0 | 5 76 | | 0 017 | | 0 019 | | 0 018 | | 0 019 |
| $\rho_1$ (spa) | 0 063** | 0 07 | | | | | | | | |
| | 0 000 | 1 548 | | | | | | | | |
| $\rho_2$ (net) | 0 349*** | 0 399*** | | | | | | | | |
| | 3 015 | 4 100 | | | | | | | | |
| $\rho$ | | | 0 009 | 0 011 | −0 17*** | −0 173*** | −0 06*** | −0 059*** | −0 18*** | −0 17*** |
| | | | 0 020 | 0 020 | 0 048 | 0 049 | 0 021 | 0 023 | 0 054 | 0 059 |
| $\theta$ | | | 0 775*** | 0 775*** | 0 916*** | 0 911*** | 0 872*** | 0 857*** | 0 887*** | 0 874*** |
| | | | 0 052 | 0 053 | 0 028 | 0 031 | 0 035 | 0 038 | 0 051 | 0 055 |

Dependent variable: interregional monetary flows of accommodation, restaurants and travel agencies Average flows 2000–2009 Interregional migration stock: from the Spanish Census 1981

**Table 9** Robustness checks: SAR and SAC estimation of M11 with alternative datasets

| | C81_born | C81_resid | Census 81_percentile 90_born | | | | Census 81_ percentile 90_residence | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | SAR | SAR | SAC-I | SAC-II | SAC-III | SAC-IV | SAC-I | SAC-II | SAC-III | SAC-IV |
| $R^2$ | 0 931 | 0 926 | 0 946 | 0 961 | 0 961 | 0 945 | 0 936 | 0 960 | 0 961 | 0 946 |
| $R\text{bar}^2$ | 0 929 | 0 923 | 0 945 | 0 959 | 0 960 | 0 943 | 0 935 | 0 959 | 0 960 | 0 945 |
| Sigma 2 | 0 219 | 0 235 | 0 176 | 0 128 | 0 126 | 0 181 | 0 207 | 0 129 | 0 126 | 0 176 |
| Const | −31 679*** | −29 629*** | −29 207*** | −23 872*** | −23 102*** | −29 886*** | −29 819*** | −23 918*** | −23 163*** | −30 596*** |
| | −16 673 | −15 060 | 1 994 | 2 628 | 2 459 | 2 192 | 2 162 | 2 602 | 2 433 | 2 171 |
| log(gva$_i$) | 0 603*** | 0 596*** | 0 639*** | 0 595*** | 0 584*** | 0 634*** | 0 578*** | 0 589*** | 0 584*** | 0 578*** |
| | 14 229 | 13 569 | 0 046 | 0 044 | 0 044 | 0 046 | 0 049 | 0 045 | 0 044 | 0 048 |
| log(pop$_j$) | 0 731*** | 0 713*** | 0 692*** | 0 601*** | 0 592*** | 0 697*** | 0 755*** | 0 594*** | 0 593*** | 0 759*** |
| | 16 258 | 15 317 | 0 055 | 0 054 | 0 053 | 0 055 | 0 053 | 0 053 | 0 053 | 0 052 |
| log(inc$_j$) | 2 013*** | 1 832*** | 1 913*** | 1 407*** | 1 406*** | 1 936*** | 1 922*** | 1 426*** | 1 413*** | 1 968*** |
| | 10 923 | 9 602 | 0 212 | 0 256 | 0 248 | 0 215 | 0 214 | 0 256 | 0 247 | 0 211 |
| log($d_{ij}$) | −0 16*** | −0 124** | −0 194*** | −0 09* | −0 11** | −0 182*** | −0 165*** | −0 08* | −0 11** | −0 162*** |
| | −2 989 | −2 236 | 0 057 | −0 090 | 0 054 | 0 057 | 0 060 | 0 054 | 0 055 | 0 058 |
| intra_const | −2 159 | −1 131 | −4 642*** | −4 514*** | −4 515*** | −4 481** | −2 987* | −4 343*** | −4 507*** | −3 207* |
| | −0 986 | −0 499 | 1 918 | 1 754 | 1 695 | 1 972 | 2 058 | 1 706 | 1 704 | 2 096 |
| log(intra_gdp) | 0 908*** | 0 873*** | 1 171*** | 1 138*** | 1 171*** | 1 135*** | 1 052*** | 1 127*** | 1 17*** | 1 046*** |
| | 7 199 | 6 684 | 0 112 | 0 102 | 0 098 | 0 113 | 0 120 | 0 101 | 0 098 | 0 122 |
| log($m_{ij}$) | 0 001 | 0 028 | 0 105*** | 0 276*** | 0 285*** | 0 093*** | 0 073** | 0 275*** | 0 283*** | 0 064** |
| | 0 04 | 0 986 | 0 032 | 0 042 | 0 04 | 0 035 | 0 032 | 0 042 | 0 04 | 0 032 |
| log($m_{ji}$) | 0 186*** | 0 195*** | 0 177*** | 0 114*** | 0 125*** | 0 026 | 0 202*** | 0 116*** | 0 126*** | 0 197*** |
| | 5 451 | 5 518 | 0 037 | 0 041 | 0 041 | 0 035 | 0 038 | 0 042 | 0 042 | 0 037 |
| $\rho_1^{\dagger}$ | 0 04 | 0 084* | | | | | | | | |
| | 0 922 | 1 921 | | | | | | | | |

**Table 9** continued

| | C81_born | C81_resid | Census 81_percentile 90_born | | | | Census 81_ percentile 90_residence | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | SAR | SAR | SAC-I | SAC-II | SAC-III | SAC-IV | SAC-I | SAC-II | SAC-III | SAC-IV |
| $\rho_2^{\dagger}$ | 0 324*** | 0 187*** | | | | | | | | |
| | 5 899 | 3 754 | | | | | | | | |
| $\rho$ | | | −0 022 | 0 02 | −0 06*** | 0 177*** | 0 018 | 0 017 | 0 126*** | 0 197*** |
| | | | 0 020 | 0 025 | 0 023 | 0 037 | 0 021 | 0 019 | 0 042 | 0 037 |
| $\theta$ | | | 0 591*** | 0 878*** | 0 872*** | 0 026 | 0 414*** | 0 873*** | −0 06*** | 0 051** |
| | | | 0 055 | 0 039 | 0 035 | 0 035 | 0 066 | 0 042 | 0 022 | 0 026 |

Dependent variable: interregional monetary flows of accommodation, restaurants and travel agencies Average flows 2000–2009 Interregional migration stock: from the Spanish Census 1981

For SAR: $\rho_1^{\dagger}$ is the coefficient associated with the spatial weight matrix; $\rho_2^{\dagger}$ is the one for the demographic network; For SAC: $\rho$ is the coefficient for the lag of the dependent variable, while $\theta$ is the one for the lag in the residuals In SAC, each one of these weight matrix will be spatial or demographic depending on the models: SAC-I: $(W_1 = W^{spa}; W_2 = W^{net})$; SAC-II: $(W_1 = W^{net}; W_2 = W^{spa})$, SAC-III: $(W_1 = W_2 = W^{spa})$; and SAC-IV: $(W_1 = W_2 = W^{net})$

**Table 10** Robustness checks: SDM estimation of model M11 with alternative datasets

| | Census 81 | | | Census 81_percentile 90_born | | | Census 81_percentile 90_residence | | |
|---|---|---|---|---|---|---|---|---|---|
| | $W^{spa}$ | $W^{net}$ | $W^{spa}+W^{net}$ | $W^{spa}$ | $W^{net}$ | $W^{spa}+W^{net}$ | $W^{spa}$ | $W^{demo}$ | $W^{spa}+W^{net}$ |
| $R^2$ | 0 9395 | 0 9216 | 0 9314 | 0 9394 | 0 9115 | 0 9248 | 0 9394 | 0 9064 | 0 9174 |
| Mean sige draws | 0 1448 | 0 1879 | 0 1558 | 0 1448 | 0 2268 | 0 1805 | 0 1448 | 0 2504 | 0 1842 |
| Sige, epe/$(n-k)$ | 0 2012 | 0 2604 | 0 228 | 0 2012 | 0 294 | 0 2499 | 0 2013 | 0 3112 | 0 2745 |
| Const | −10 794*** | 1 728 | −1 742 | −10 801*** | −8 568*** | −7 66*** | −10 783*** | −14 951*** | −7 803*** |
| | 1 369 | 4 696 | 3 476 | 1 376 | 2 673 | 3 005 | 1 366 | 1 615 | 2 886 |
| log(gva$_i$) | 0 602*** | 0 738*** | 0 707*** | 0 602*** | 0 66*** | 0 644*** | 0 603*** | 0 582*** | 0 584*** |
| | 0 052 | 0 059 | 0 056 | 0 051 | 0 058 | 0 057 | 0 051 | 0 059 | 0 058 |
| log(pop$_j$) | 0 627*** | 0 591*** | 0 689*** | 0 627*** | 0 753*** | 0 692*** | 0 627*** | 0 782*** | 0 75*** |
| | 0 062 | 0 081 | 0 075 | 0 062 | 0 075 | 0 075 | 0 061 | 0 07 | 0 072 |
| log(inc$_j$) | 0 053 | 0 519*** | 0 274** | 0 052 | 0 422*** | 0 274** | 0 048 | 0 435*** | 0 226 |
| | 0 146 | 0 155 | 0 151 | 0 144 | 0 18 | 0 162 | 0 143 | 0 173 | 0 169 |
| log($d_{ij}$) | −0 068 | −0 23*** | −0 131** | −0 067 | −0 2*** | −0 141** | −0 066 | −0 163** | −0 098* |
| | 0 061 | 0 061 | 0 062 | 0 062 | 0 065 | 0 064 | 0 061 | 0 072 | 0 072 |
| log(intra_gdp) | 1 533*** | 1 865*** | 1 773*** | 1 533*** | 1 827*** | 1 71*** | 1 531*** | 1 79*** | 1 686*** |
| | 0 078 | 0 093 | 0 095 | 0 078 | 0 09 | 0 092 | 0 077 | 0 094 | 0 099 |
| log($m_{ij}$) | 0 412*** | 0 354*** | 0 377*** | 0 413*** | 0 222*** | 0 315*** | 0 413*** | 0 171*** | 0 286*** |
| | 0 044 | 0 038 | 0 04 | 0 044 | 0 035 | 0 039 | 0 044 | 0 037 | 0 04 |
| log($m_{ji}$) | −0 005 | 0 033 | −0 025 | −0 006 | 0 077** | 0 029 | −0 005 | 0 118*** | 0 056 |
| | 0 049 | 0 041 | 0 043 | 0 048 | 0 043 | 0 045 | 0 049 | 0 044 | 0 046 |
| $W$-gva$_i$ | −0 438*** | −0 692*** | −0 649*** | −0 434*** | −0 345*** | −0 439*** | −0 435*** | −0 225*** | −0 405*** |
| | 0 092 | 0 116 | 0 105 | 0 093 | 0 089 | 0 098 | 0 09 | 0 092 | 0 106 |
| $W$-pop$_j$ | −0 412*** | −0 248* | −0 499*** | −0 411*** | −0 453*** | −0 481*** | −0 411*** | −0 429*** | −0 581*** |

**Table 10** continued

| | Census 81 | | | Census 81_percentile 90_born | | | Census 81_percentile 90_residence | | |
|---|---|---|---|---|---|---|---|---|---|
| | $W^{spa}$ | $W^{net}$ | $W^{spa} + W^{net}$ | $W^{spa}$ | $W^{net}$ | $W^{spa} + W^{net}$ | $W^{spa}$ | $W^{demo}$ | $W^{spa} + W^{net}$ |
| | 0 088 | 0 154 | 0 13 | 0 089 | 0 101 | 0 112 | 0 087 | 0 098 | 0 116 |
| $W$-inc$_j$ | 0 817*** | −0 785** | −0 087 | 0 816*** | −0 029 | 0 205 | 0 817*** | 0 566*** | 0 373 |
| | 0 149 | 0 422 | 0 339 | 0 149 | 0 229 | 0 281 | 0 148 | 0 164 | 0 294 |
| $W$-intra_gd$p$ | −0 594*** | −1 535*** | −1 35*** | −0 59*** | −0 861*** | −0 939*** | −0 59*** | −0 362*** | −0 891*** |
| | 0 063 | 0 329 | 0 264 | 0 064 | 0 178 | 0 22 | 0 063 | 0 067 | 0 215 |
| $W$-$d_{ij}$ | 0 013 | 0 136 | 0 033 | 0 009 | 0 166** | 0 119 | 0 009 | 0 132 | 0 1 |
| | 0 09 | 0 108 | 0 103 | 0 091 | 0 095 | 0 1 | 0 09 | 0 101 | 0 115 |
| $W$-$m_{ij}$ | −0 499*** | −0 543*** | −0 54*** | −0 499*** | −0 229*** | −0 373*** | −0 499*** | −0 181*** | −0 353*** |
| | 0 053 | 0 07 | 0 065 | 0 053 | 0 047 | 0 054 | 0 053 | 0 05 | 0 058 |
| $W$-$m_{ji}$ | 0 107* | 0 134* | 0 087 | 0 106* | 0 061 | 0 07 | 0 106* | 0 037 | 0 038 |
| | 0 069 | 0 083 | 0 081 | 0 068 | 0 061 | 0 07 | 0 069 | 0 058 | 0 071 |
| $\rho$ | 0 691*** | 0 617*** | 0 774*** | 0 689*** | 0 481*** | 0 666*** | 0 689*** | 0 372*** | 0 659*** |
| | 0 054 | 0 086 | 0 069 | 0 055 | 0 06 | 0 062 | 0 053 | 0 054 | 0 062 |

Dependent variable: Interregional monetary flows of accommodation, restaurants and travel agencies Average flows 2000–2009 Interregional immigration stock: Spanish Census 1981 and not for the immigrants (between 0.366 and 0.397 depending on the $W$ considered in Table 7).[18] Independently on whether the effect goes in one direction (effect of emigrants) or in the other (effect of immigrants) it seems that there is an effect of these variables on the bilateral trade flows that does not disappear when the spatial autocorrelation of the flows is controlled for and this has been tested for different kinds of autocorrelation.

Finally, regarding the effect of distance on bilateral trade flows when a SDM is estimated, it is remarkable that the coefficient is negative and significant when the pattern of the spatial autocorrelation considered includes the $W^{net}$ matrix (in Table 7, −0.215 and −0.212 with the $W^{net}$ and −0.129 and −0.121 with $W^{spa} + W^{net}$), while it seems not to have a significant effect when we use $W^{spa}$ based on contiguity.

The results obtained when using the 1981 Spanish census for computing the migration variables as well as the weight matrix capturing the demographic linkages between the regions do not alter significantly the results for all the models and specifications. The same conclusions can be derived from the results obtained using two alternative matrices for computing the demographic neighbours based on 1981 census stocks which strongly reduce the number of neighbours in 'demographic terms' for each trading pair. The main findings are reported in Tables 8, 9, 10 and can be summarized in tow main ideas: (1) interestingly, when using the data from the 1981 census for migrants and the demographic links, the SAR models reach to same non-significant results for emigrants $(m_{ij})$ than the ones obtained when using the stocks for the average period 2000 2009. In these models, the spatial and demographic cross-sectional effects are significant and positive but like in Table 5, the spatial effects are non-significant for the model M13 (Table 8). Such effects are also non-significant for the model M11 (Table 9) when using $W^{net}_{81\_born}$ matrix. (2) The SAC models also show non-significant or significant and negative coefficients for the autocorrelation terms, both when the 1981 census stocks are used with no constrains and when they are used subjected to the thresholds considered in $W^{net}_{81\_born}$ and $W^{net}_{81\_residence}$ matrices.

As a final step, Fig. 7 shows the Moran scatterplots for the residuals obtained in the most notable alternative specifications. Such plots were obtained in the same way than in Fig. 6. As before, just the Moran scatterplots for the SAC-II and SAC-III seem to better control for the whole autocorrelation effects (spatial and demographic), showing no significant relation (random dot cloud and a flat fit lane) between the residuals and its lags using a row-standardized weight matrix such as $W_3 = W^{spa} + W^{net}$. These results are in line with the ones obtained in Fig. 6 using the same specifications but alternative migration stocks and network weight matrices.

[18] Two exceptions in Table 10 columns 5 and 8 when both the emigration and immigration variables have a positive and significant effect.

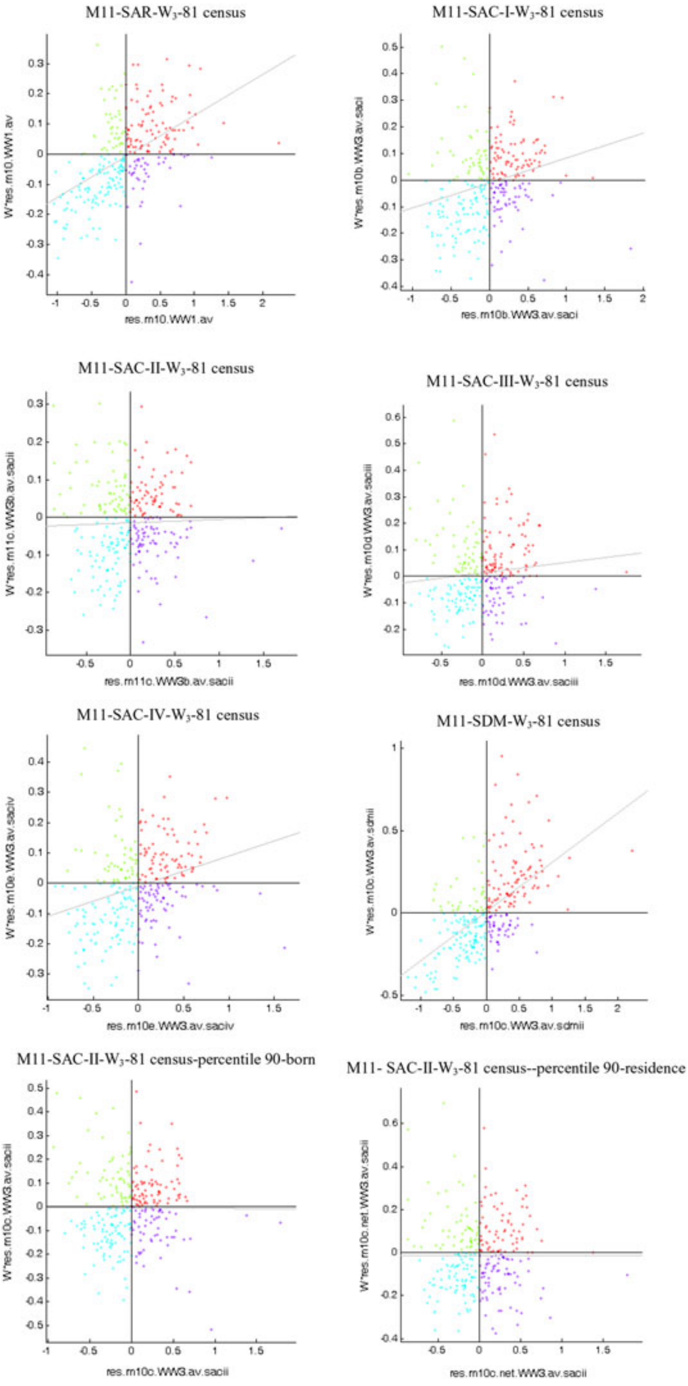


**Fig. 7** I Moran scatterplot on residuals from SAR and SAC estimates. $Y =$ Residuals from M10. ($W_3 = W^{\mathrm{spa}} + W^{\mathrm{net}}$)

## 5 Conclusions

In this article, we analyse the relation between interregional trade of services and social networks. We also considered whether interregional trade flows in services linked with tourism exhibit spatial and/or social network dependence. Conventional empirical gravity models assume the magnitude of bilateral flows between regions are independent of flows to/from regions located nearby in space or flows to/from regions related through social/cultural/ethic network connections.

We provide an extended empirical specification that relaxes the assumption of independence between bilateral flows which is inherent in any least-squares regression. Our argument is that bilateral flows between an exporting region $i$ and an exporting region $j$ may exhibit dependence on (1) flows to regions that are spatially near the exporting and importing regions $i$ and $j$ (spatial dependence) and (2) flows to regions that are socially/demographically 'related' to the exporting and importing regions $i$ and $j$. A spatial weight matrix elaborated in the way suggested by LeSage and Pace (2008) was used to quantify the spatial structure of connectivity between regions involved in bilateral flows. A novel social network matrix was constructed using information on the bilateral stock of interregional migrants between the 17 Spanish regions.

Estimates from a set of nested models show evidence of statistically significant spatial and network (demographic) dependence in the bilateral flows of the trade of services considered. The analysis has been applied to average data for the period 2000 2009, using alternative datasets for the migration stocks and definitions of network effects, finding robust results. The significant social network dependence can be interpreted as an indication that people exhibit preferences for destinations in or near their homeland regions, or destination regions in or near where co-nationals have settled heavily. Significant spatial dependence is an indication that people consider intervening opportunities taking the form of visits to regions nearby the origin of their vacation trip, as well as competing destinations, represented by regions nearby the destination trip.

One finding of interest is that introduction of explanatory variables that control for the stock of emigrants and immigrants as well as spatial and network dependence (and the conventional measures of origin and destination economic size) results in a low coefficient estimate for bilateral distance between origin and destination regions. This suggests that cultural/social as well as intervening opportunities and competing destinations considerations may exert an important enough influence on destination trip decisions to overcome the traditional resistance role played by distance that typically diminishes the magnitude of bilateral flows.

Departing from these results, a number of extensions could be considered in the future agenda. First, it is convenient to explore alternative specifications of spatial models such as the SLX. Then, based on Fischer and Griffith (2008), it will be interesting to explore the sensibility of the results obtained here with the ones that could be obtained through the combination of spatial filtering techniques and PPML estimators. Finally, although such routines are still under development, our current analysis could be enriched by considering the dynamic dimension exploiting the panel data and including the spatial autocorrelation effects.

**Acknowledgments** The authors want to express their gratitude to James LeSage for his help on improving previous versions of this paper. We also want to thank the helpful comments received from Giovanni Peri, Vicente Blanes and the other participants in the INTECO meeting in 2010. This paper has been developed in the context of different research projects: TransporTrade S2007/HUM/497, (www.uam.es/transportrade), funded by the Education Department of the Madrid Regional Govern ment; the Project (ECO2010 21643/ECON) by the Spanish Ministry of Science and Innovation, as well as the DESTINO Project (Ministerio de Fomento). T. de la Mata also acknowledges the fund received from the Universidad Autónoma de Madrid (Programa FPI UAM). Carlos Llano also thanks the support received by the New York University Economics Department, where part of this work was also accomplished during an academic stay in the Fall semester 2012.

## References

Angulo AM, Mtimet N, Dhehibi B, Atwi M, Ben Youssef O, Gil JM, Sai MB (2011) A revisited gravity equation in trade flow analysis: an application to the case of Tunisian olive oil exports. Investig Reg (21):225 239

Anselin L (1988) Spatial econometrics: methods and models. Kluwer, Berlin

Athanasopoulos G, Hyndman RJ (2008) Modelling and forecasting Australian domestic tourism. Tour Manag 29(1):19 31

Autant Bernard C, LeSage J (2011) Quantifying knowledge spillovers using spatial econometric Models. J Reg Sci 51(3):471 496

Behrens K, Ertur C, Koch W (2010) 'Dual' gravity: using spatial econometrics to control for multilateral resistance. J Appl Economet. first published online: 12 Dec 2010

Belderbos R, Sleuwaegen L (1998) Tariff jumping FDI and export substitution: Japanese electronics firms in Europe. Int J Ind Organ 16(5):601 638

Berglund S (2001) Gis in transport modelling. Royal Institute of Technology, Department of Infrastructure. Report.

Berglund S, Karström A (1999a) Identifying local spatial association in flow data. J Geogr Syst 1(3):219 236

Berglund S, Karström A (1999b) TECHNICAL REPORT: computing Gi and Gij. Program Documen tation. Mimeo

Black WR (1992) Network autocorrelation in transport network and flow systems. Geograph Anal 24(3):207 222

Bolduc D, Laferriere R, Santarossa G (1992) Spatial autoregressive error components in travel flow models. Reg Sci Urban Econ 22(3):371 385

Chen N (2004) Intra national versus international trade in the European Union: why do national borders matter? J Int Econ 63(1):93 118

Chun Y (2008) Modeling network autocorrelation within migration flows by eigenvector spatial filtering. J Geogr Syst 10(4):317 344

Chun Y, Griffith DA (2011) Modeling network autocorrelation in space time migration flow data: an eigenvector spatial filtering approach. Ann Assoc Am Geogr 101(3):523 536

Combes PP, Lafourcade M, Mayer T (2005) The trade creating effects of business and social networks: evidence from France. J Int Econ 66(1):1 29

De la Mata T, Llano C (2012) How tradable are non tradables? Measuring interregional flows of accommodation, restaurants and travel agencies in Spain. Mimeo

Dunlevy JA, Hutchinson WK (1999) The impact of immigration on American import trade in the late nineteenth and early twentieth centuries. J Econ Hist 59(4):1043 1062

Dunlevy JA, Hutchinson WK (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. J Int Econ 76(2):384 399

Eriksen L, Ahmt T (1999) Measuring and modelling the regional impact of tourism in Denmark. Int J Tour Res 1(5):313 327

Evans CL (2006) Border effects and the availability of domestic products abroad. Can J Econ 39(1):211 246

Fischer MM, Griffith DA (2008) Modeling spatial autocorrelation in spatial Interaction data: an application to patent Citation data in the European Union. J Reg Sci 48(5):969 989

Garmendia A, Minondo A, Llano C, Requena F (2012) Networks and the disappearance of the intranational home bias. Econ Lett 116(2):178 182

Ghemawat P, Llano C, Requena F (2010) Competitiveness and interregional as well as international trade: the case of Catalonia. Int J Ind Organ 28(4):415 422

Girma S, Yu ZH (2002) The link between immigration and trade: evidence from the United Kingdom. Weltwirtschaftliches Archiv/World Econ 138(1):115 130

Gould DM (1994) Immigrant links to the home country empirical implications for United States bilateral trade flows. Rev Econ Stat 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, Cambridge

Head K, Ries J (1998) Immigration and trade creation: econometric evidence from Canada. Can J Econ 31(1):47 62

Helliwell JF (1996) Do national borders matter for Quebec's trade? Can J Econ 29(3):507 522

Helliwell JF (1997) National borders, trade and migration. Pac Econ Rev 2(3):165 185

Ledyaeva S (2009) Spatial econometric analysis of foreign direct investment determinants in Russian regions. World Econ 32(4):643 666

LeSage JP, Fischer MM (2009) The impact of knowledge capital on regional total factor productivity (April 20,2009). Available at SSRN: http://ssrn.com/abstract 1088301 or doi:10.2139/ssrn.1088301

Lesage JP, Fischer MM (2008b) Spatial growth regressions: model specification, estimation and interpretation. Spatial Econ Anal 3(3):275 304

LeSage JP, Pace RK (2008) Spatial econometric modeling of origin destination flows. J Reg Sci 48(5):941 967

LeSage JP, Pace RK (2009) Introduction to Spatial Econometrics. Chapman & Hall/CRC Press, London

Lesage JP, 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 (2009a) El comercio interregional en España: una estimación de los flujos bilaterales del sector turismo. Revista ICE 848:67 87

Llano C, de la Mata T (2009b) El comercio intra e interregional del sector turismo en España. Documento de Trabajo de FUNCAS 446:1 46

McCallum J (1995) National borders matter: Canada U.S. regional trade patterns. Am Econ Rev 85(3):615 623

Millimet DL, Osang T (2007) Do state borders matter for U.S. intranational trade?The role of history and internal migration. Can J Econ 40(1):93 126

Okubo T (2004) The border effect in the Japanese market: a gravity model analysis. J Jpn Int Econ 18(1):1 11

Perry MJ, Schachter J (2003) Migration of natives and the foreign born: 1995 to 2000, Technical report, U.S. Census Bureau

Podolny JM, Page KL (1998) Network forms of organization. Annu Rev Sociol 24:57 76

Porojan A (2001) Trade flows and spatial effects: the gravity model revisited. Open Econ Rev 12(3):265 280

Portes R, Rey H (2005) The determinants of cross border equity flows. J Int Econ 65(2):269 296

Rauch JE (2001) Business and social networks in international trade. J Econ Lit 39(4):1177 1203

Rauch JE, Casella A (2003) Overcoming informational barriers to international resource allocation: prices and ties. Econ J 113(484):21 42

Rauch JE, Trindade V (2002) Ethnic Chinese networks in international trade. Rev Econ Stat 84(1):116 130

Requena F, Llano C (2010) The border effects in Spain: an industry level analysis. Empirica 37(4):455 476

The World Bank (2008) World development report 2009: reshaping economic geography. WB report. http://econ.worldbank.org/external/default/main?pagePK 64165259&theSitePK 469372&piPK 64165421&menuPK 64166322&entityID 000333038 20081203234958

Wagner D, Head K, Ries J (2002) Immigration and the trade of provinces. Scott J Polit Econ 49(5):507 525

White R, Tadesse B (2008) Cultural distance and the US immigrant trade link. World Econ 31(8):1078 1096

Wolf HC (2000) Intranational home bias in trade. Rev Econ Stat 82(4):555 563