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Modeling the effects of dyadic spatial dependence structures in policy-based gravity models of international trade

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1 Introduction

Over the years, the so-called *gravity model* – derived from Newton's *law of universal gravitation* ([1713] 1999) – has become the workhorse model of economists and political scientists alike when analyzing volumes of trade, migration or capital flows based on two countries' factor endowments and transaction costs. Despite its robustness and wide applicability, researchers still face multiple methodological and empirical challenges when applying the gravity equation to model interaction flows. While issues such as an enhanced consistency between formal theoretical frameworks and empirical strategies or endogeneity bias in the econometric specification of the gravity equation are discussed widely (see De Benedictis & Taglioni, 2011 for an overview), one pivotal methodological issue has received little attention to date: spatial dependence.[1] The notion of spatial dependence – sometimes referred to as *Galton's problem* in political science – builds on Tobler's (1970, p. 236) first law of geography which posits that "*[e]verything is related to everything else, but near things are more related than distant things.*" Put more formally, spatial dependence occurs whenever the observed values of social or economic phenomena at one location depend on the values observed at nearby locations.

Although both spatial econometricians (e.g., Curry, 1972; Griffith & Jones, 1980; Fotheringham, 1981; Anselin, 1988; LeSage & Pace 2008, 2009) and political economists (e.g., Beck, Gleditsch, & Beardsley; Ward & Gleditsch, 2008; Neumayer & Plümper, 2010) alike emphasize the importance of spatial dependence among observations, only few dyadic data analyses explicitly account for the role of spatial processes, whereas the bulk of articles (implicitly) assumes independence of observations.[2] Since gravity equations explain economic or social interactions between two countries, they are interdependent by construction and, thus, the assumption of independence among observations will not hold. Conventional gravity models in economics address this concern by either controlling for geodesic distances between the two trading partners or, following the seminal work of Anderson & van Wincoop (2003), by including unit fixed

[1] *Spatial dependence* is not to be confused with *spatial heterogeneity*. While both concepts can be subsumed under the more general term *spatial effects*, spatial dependence refers to spatial interactions between nearby geographical units, whereas spatial heterogeneity refers to the unequal distribution of spatial processes across space (Anselin, 1988).

[2] Notable exceptions are, among others, the articles by Baltagi, Egger, & Pfaffermayr (2007) and LeSage & Llano-Verduras (2014) on third-country effects in foreign direct investment and commodity flows, respectively.

effects.

LeSage & Pace (2008, 2009) and Behrens, Ertur, & Koch (2012), however, argue that relying on great-circle distances or fixed effects estimators for capturing spatial dependence does not suffice for unbiased point estimates as both approaches disregard multilateral dependence structures between each dyad and third countries. Consequently, ignoring spatial dependence when modeling interaction flows will lead to either inefficient or biased and inconsistent OLS estimates, depending on whether incorporating spatial error autocorrelation or a spatially lagged dependent variable captures the data-generating spatial process properly.[3]

Controlling for spatial dependence is particularly important when assessing the effects of regional trade agreements (hereafter: RTAs) as the formation of trade agreements tends to be geographically clustered by nature. Hence, if spatial mechanisms such as spatial competition or spillover processes are at work and not explicitly accounted for in the econometric model, causal inferences on the effects of trade agreements are invalid.

Despite this substantial importance of spatial processes, to date there are – to the best of the author's knowledge – only two cross-sectional analyses accounting for spatial dependence when estimating the effects of EU-NAFTA bloc membership on trade flows among OECD member states (Porojan, 2001) and, more recently, the effects of free trade agreements on global trade flows (Krisztin & Fischer, 2015). One reason for this is the complex spatial dependence structure when dealing with dyadic data as both origin- and destination-based spatial effects are present. Thus, estimating the effects of trade agreements – or, for that matter, policy interventions in general – requires modeling multiple types of spatial dependence structures within a unified framework.

Bringing together research methods from spatial econometrics and political economy, this paper attempts to fill the aforementioned gap by modeling the effects of multilateral spatial dependence within a theoretically grounded gravity framework. In doing so, the paper serves two purposes. Methodologically, it introduces the notion of cross-sectional spatial autoregressive dependence to longitudinal gravity models using origin- and destination-specific connectivity

[3] Put simply, the main difference between these two types of spatial dependence is the respective conceptualization of spatial dependence as either a statistical nuisance in the error term in the presence of spatial error autocorrelation or substantively as an explanatory variable reflecting some kind of spatial mechanism in terms of spatially lagged dependent and/or independent variables.

matrices as initially proposed by LeSage & Pace (2008, 2009). In other words, bilateral trade flows are modeled as a function of both two countries' bilateral trading characteristics *and* trading volumes of neighboring countries to account for omitted variable bias resulting from the omission of spatial lags. Empirically, the paper reestimates the effects of trade-enhancing and trade-reducing factors on aggregate trade flows among countries located in the Americas and Europe for a five year time period (2002-2006) when controlling for the underlying spatial mechanisms.

The remainder of the paper is organized as follows. Section 2 outlines the theoretical foundations of the gravity equation derived from international trade theory and introduces a spatially augmented equation which captures both origin- and destination-based dependence among neighboring countries to account for the hypothesized spatial competition effects. Section 3 then describes data sources, the use of graph-based connectivity matrices for capturing dependence structures and specifications for the spatial autoregressive panel models employed in this paper. After presenting the preliminary empirical results of the spatial analyses in section 4, section 5 discusses implications as well as limitations of the empirical findings, followed by concluding remarks.

2 Theoretical framework

2.1 The gravity equation in international trade theory

As already mentioned, the workhorse model for explaining bilateral trade flows is referred to as gravity equation for its analogy with Newton's *law of universal gravitation* (1)

$$F_{ij} = G\frac{(M_i \times M_j)}{D_{ij}} \tag{1}$$

which postulates that the force F_{ij} between two objects i and j is proportional to their masses M_i and M_j and inversely proportional to the square of distance D_{ij} between them. G denotes the gravitational constant.

Initially set forth by Tinbergen (1962) and Pöyhönen (1963) to explain patterns of international bilateral trade between two countries i and j, Anderson (1979) was the first to provide formal theoretical foundations for the empirical gravity equation based on similar trade preferences and transport cost structures within preferential trade groups.

Hence, building on equation (1), the empirical gravity equation in its most basic form can be written as

$$X_{ij} = C\frac{(Y_i \times Y_j)}{D_{ij}} \tag{2}$$

where X_{ij} denotes the volume of aggregate trade flows from an exporter i to an importer j and the mass coefficients Y_i and Y_j, respectively, reflect both countries' trade-generating factors. In other words, (2) states that trade flows between two countries are directly proportional to the product of their trade potentials, proxied by GDP, and negatively related to the distance and further restrictions to spatial interaction D_{ij} between them, i.e., trade will decrease as distance – or, more generally, resistance to cross-border interaction flows – increases.

Transforming (2) into its conventionally applied log-linear form for any time period t and replacing Y_i (Y_j) with GDP_i (GDP_j), (3) is obtained

$$\ln X_{ijt} = \beta_0 + \beta_1 \ln GDP_{it} + \beta_2 \ln GDP_{jt} + \beta_3 \ln D_{ijt} + \varepsilon_{ijt} \tag{3}$$

with ε_{ijt} as an *i.i.d.* error term. In applied econometrics and international political economy alike, this traditional gravity equation is augmented with (usually binary) measures accounting for the similarity of two trading partners, reflecting the idea that sharing a common border or having a common official language increases interaction flows.

Similar reasoning applies when controlling for the effects of regional trade agreements. Generally speaking, RTAs are either bi- or multilateral reciprocal trade agreements which reduce or even eliminate tariffs among signatory states while, at the same time, maintaining tariffs on trade flows to and from non-member third countries. Following the theoretical argumentation of Viner (1950), the removal of internal barriers to cross-border economic interaction leads to trade creation, that is, increased volumes of trade flows within trading blocs. Thus, including the notion of trade-creating effects evoked by the similarity S_{ij} of two trading partners i and j

yields (4).

$$\ln X_{ijt} = \beta_0 + \beta_1 \ln GDP_{it} + \beta_2 \ln GDP_{jt} + \beta_3 \ln D_{ijt} + \beta_4 S_{ijt} + \varepsilon_{ijt} \tag{4}$$

Recent advances in international trade theory, however, suggest that trade volumes between two countries are not only influenced by trade-generating factors and *bilateral* resistance to cross-border economic interactions – as implied in (4) – but by *multilateral* resistance as well (Anderson & van Wincoop, 2003). Put simply, the concept of multilateral trade resistance posits that flows between two trading partners depend on the relative size of their bilateral trade resistance compared to the average trade resistance among trading partners and third countries.

Augmenting the empirical gravity equation in (4) by allowing for multilateral trade resistance as proposed by Anderson & van Wincoop (2003) and, subsequently, Baier & Bergstrand (2007), yields an adapted version of the theoretically grounded gravity equation

$$ln \frac{X_{ijt}}{GDP_{it} \times GDP_{jt}} = \beta_0 + \beta_3 \ln D_{ijt} + \beta_4 S_{ijt} - \ln P_{it}^{1-\sigma} - \ln P_{jt}^{1-\sigma} + \varepsilon_{ijt} \tag{5}$$

with

$$P_{Nt}^{1-\sigma} = \sum_{i=1}^{Nt} P_i^{1-\sigma} \left(\frac{GDP_{Nt}}{GWP_t} \right) e^{\beta_3 \ln D_{iNt} + \beta_4 S_{iNt}} \tag{6}$$

where GWP_t denotes the gross world product at time t and $P_{it}^{1-\sigma}$ and $P_{jt}^{1-\sigma}$, respectively, denote price indices capturing multilateral resistance among countries.

2.2 Spatial gravity equations for international trade flows[4]

As can be seen in (5) and (6), multilateral resistance implies that international trade patterns exhibit spatial dependence structures linking both trading partners to third countries. Consequently, bilateral trade flows cannot be explained by means of two countries' factor endowments and political or cultural (dis-)similarities only without explicitly accounting for these spatial

[4] In line with the state-of-the-art literature, this section adopts the conventional spatial econometrics notation while maintaining the standard gravity notation introduced in the preceding section.

structures.

In a similar manner, Behrens et al. (2012) argue that dyadic trade flows are affected by third country pairs' trading levels due to spatial competition effects. The theoretical rationale is that spatial competition evokes patterns of dependence across space because of larger externalities among geographically proximate countries (cf., e.g., Krugman, 1991; Porojan, 2001; Anselin, 2003).

Taking the traditional gravity equation as a point of departure, (4) can be rewritten as

$$X_{ijt} = \alpha \iota_N + Y_t \beta + \varepsilon_{ijt} \tag{7}$$

with Y_t being a vector of all (log-transformed) explanatory factors introduced in the preceding section, i.e., $Y_t = (GDP_i, GDP_j, D_{ij}, S_{ij})$, at time t. For brevity, the subscript t is omitted hereinafter. Accounting for multilateral spatial dependence structures among countries resulting from spatial competition then yields (8)

$$X_{ij} = \alpha \iota_N + \rho W X_{ij} + Y\beta + \varepsilon_{ij} \tag{8}$$

where W denotes an $N \times N$ spatial weights matrix capturing spatially defined connectivities among country pairs. As Neumayer & Plümper (2013) point out, W reflects the underlying causal mechanism evoking multilateral dependence between trading partners and third countries. Thus, the scalar parameter ρ serves as a proxy for the hypothesized spatial competition mechanism.

Given the dyadic nature of trade flows, however, both competing markets located close to the country of origin (A) and markets nearby the country of destination (B) cause patterns of spatial dependence. This theoretical reasoning is in line with LeSage & Pace (2008) who argue that increased trade flows between any origin A to any destination B are associated with three types of spatial effects, namely, (1) *origin-dependence*, i.e., increased trade flows from countries C located nearby country A to B, (2) *destination-dependence*, i.e., increased trade flows from A to countries D located nearby country B and, (3) *origin-destination dependence*, i.e., increased trade flows from neighboring countries C to neighboring countries D. Including the notion of

LeSage & Pace's origin-, destination- and origin-destination-based spatial dependence in (8), (9) is obtained.

$$X_{ij} = \alpha \iota_N + \rho_o W_o X_{ij} + \rho_d W_d X_{ij} + \rho_{od} W_{od} X_{ij} + Y\beta + \varepsilon_{ij} \tag{9}$$

Put less formally, (9) states that determinants causing trade flows from country A to country B evoke similar levels of trade from third countries C located nearby country A to country B (W_o), determinants causing trade flows from A to B evoke similar levels of trade to third countries D located nearby B (W_d) as well as similar levels of trade flows among third countries C and D themselves (W_{od}).

Substantively, the spatial lag vectors $W_o X_{ij}$, $W_d X_{ij}$ and $W_{od} X_{ij}$ then measure (1) the average of aggregate trade flows from countries C (neighbors to A) to each destination B ($W_o X_{ij}$), (2) the average of trade flows from each origin A to countries D (neighbors to B) ($W_d X_{ij}$) and (3) the average of trade flows from countries C (neighbors to A) to countries D (neighbors to B) ($W_{od} X_{ij}$). In other words, $W_o X_{ij}$ captures dependence structures between each origin's neighbors and each destination, $W_d X_{ij}$ the dependence structures between each origin and each destination's neighbors and $W_{od} X_{ij}$, in turn, describes dependence structures among each origin's and each destination's neighbors.

Bringing together the main theoretical arguments of sections 2.1 and 2.2, the working hypotheses adopted in this paper are as follows:

Hypothesis 1. Trade-generating potentials (proxied by each country's GDP) as well as cultural and political similarities between trading partners increase bilateral trade volumes, whereas geographic distance exerts a negative effect on cross-border trade flows.

Hypothesis 2. Spatial competition mechanisms affect trade flows among geographically proximate countries which, as a result, evoke complex pattern of origin, destination and origin-destination spatial dependence.

3 Methods

3.1 Data and sample selection

The spatial analysis in this paper originally relies on a balanced panel dataset consisting of 63.585 dyadic observations from $n = 161$ countries for the years 2002-2006.[5] Given the directional nature of bilateral trade flows, each pair of countries (N) yields two observations, that is, $i \to j$ and $j \to i$.[6] The comparatively short time period of only five consecutive years was chosen to prevent biased estimates resulting from serial correlation in the data. Consequently, extending the time period would require controlling for temporal dynamics by, e.g., including a temporally lagged dependent variable.[7]

For computational reasons, however, the subsequent analyses need to be restricted to a smaller subset of $n = 42$ countries. While drawing a random sample of units from the population under scrutiny is a promising approach in many empirical applications, it is not advisable for spatial analyses relying on connectivity specifications as randomizing will lead to arbitrary and, thus, substantively meaningless connections among countries (cf., section 3.2). Therefore, and in line with traditional spatial research, the subset of countries was chosen based on the countries' geographical locations.

Taking the seminal work of Baier & Bergstrand (2007) as a point of departure, the spatial analyses in section 4 build on a subsample of Baier & Bergstrand's sample restricted to countries located in the Americas and Europe. Figure 1 depicts both the full set of countries for which balanced dyadic trade and gravity data is available (grey) as well as the subset for the spatial analyses conducted in this paper (red). Countries coloured in black are excluded due to missing data for the years 2002-2006.

Data on trade-generating factors come from the CEPII *Gravity* dataset which covers all country pairs in the world for the years 1948-2006 (Head, Mayer, & Ries, 2010; Head & Mayer,

[5] The full (unbalanced) dyadic dataset including directed aggregate trade flows, gravity variables and geographic information consists of 2.960.384 observations for all country pairs for the years 1948-2006.

[6] Working with directed data yields, among other reasons, the advantage that asymmetric observations with missing data on either direction, i.e., $i \to j$ or its reverse counterpart $j \to i$, are still included in the sample as is the case in this paper.

[7] Unfortunately, estimating dynamic spatial panel models is not implemented in R yet.

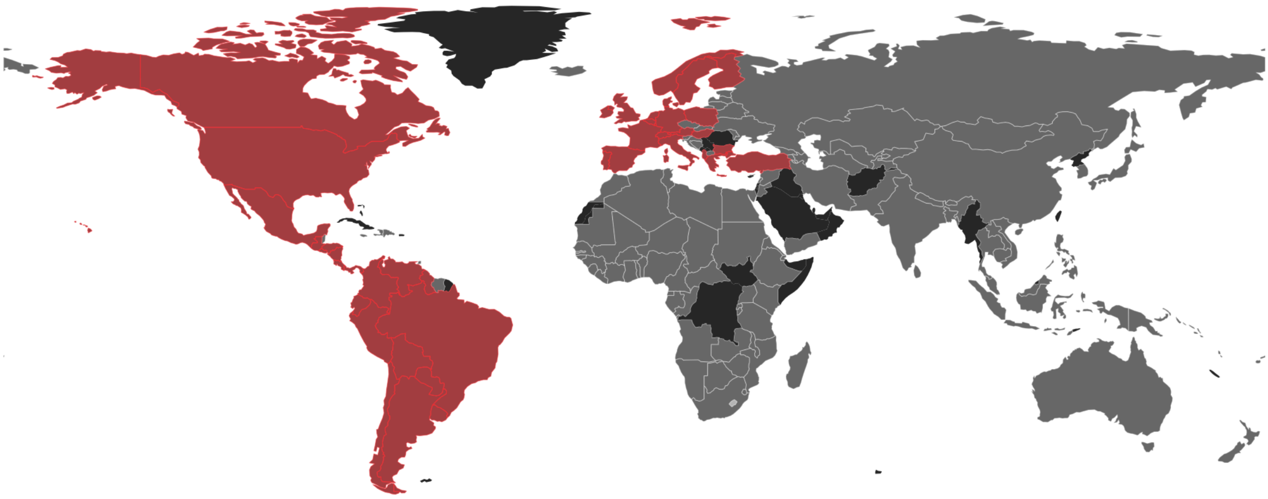

Figure 1: Unprojected map of countries in sample

2013).[8] The CEPII, short for *Centre d'études prospectives et d'informations internationales*, provides an extensive dataset with data on common borders, official languages, nominal GDP in current millions of USD compiled from the World Bank's *World Development Indicators* as well as information on RTAs in force obtained from Baier & Bergstrand (2007) and supplemented with information from the WTO, Frankel (1997) and Glick & Rose (2002). Geodesic distances between capital cities were retrieved from the CEPII *GeoDist* dataset as the *Gravity* dataset only contains population-weighted distances between countries.[9]

Aggregate trade data in millions of USD were obtained from the *Correlates of War* dataset by Barbieri, Keskh, & Pollins (2009) and Barbieri & Keshk (2012) which contains data on both bilateral trade flows and total national imports and exports for the years 1870-2009, compiled from the International Monetary Fund's *Direction of Trade Statistics*.[10]

Lastly, cartographic boundary shapefiles for creating the spatial connectivity matrices and information on geographical locations were extracted from the R **rworldmap** package (South, 2011) which contains a vector map of state boundaries for 244 countries. Geographic locations obtained from **rworldmap** are, by default, described by latitude and longitude coordinates

[8] The *Gravity* dataset provided by CEPII can be accessed online at `http://www.cepii.fr/cepii/en/bdd_modele/presentation.asp?id=8` (last accessed on 04-07-2016).

[9] The *GeoDist* dataset can be accessed online at `http://www.cepii.fr/CEPII/en/bdd_modele/presentation.asp?id=6` (last accessed on 04-07-2016).

[10] The *Correlates of War* trade data can be accessed online at `http://correlatesofwar.org/data-sets/bilateral-trade` (last accessed on 04-07-2016). Note that all *Correlates of War* datasets use COW codes as country identifiers instead of conventional ISO codes.

in WGS84 datum format as commonly used for global GIS data. All data contained in the **rworldmap** package were originally derived from version 1.4.0 of the *Natural Earth* data.[11]

3.2 Modeling dyadic spatial dependence structures[12]

The biggest challenge when dealing with spatial dependence structures for either monadic or, even more complex, dyadic data is how to operationalize and, subsequently, model connectivity among spatial units.

The point of departure for capturing spatial relationships between two countries i and j is a $n \times n$ connectivity matrix C with elements $i = \{1, 2..., n\}$ and $j = \{1, 2..., n\}$ representing the countries in the sample. If two countries are connected, $C_{ij} = 1$ and $C_{ij} = 0$ otherwise. As discussed in section 2.2, the resulting binary connectivity matrix C approximates the hypothesized causal mechanism. Thus, the definition of when two countries are considered neighbors of each other is not an arbitrary choice but should rather be guided by theoretical considerations.

While the notion of connectivity is not necessarily limited to *geographic* proximity *per se* (see, e.g., Beck et al., 2006 or Neumayer & Plümper, 2013 for further information), resorting to geographical characteristics such as areal contiguity or great-circle distances between countries exploits the advantage of geography being exogenous to economic or social interaction flows. On this account, spatial competition is subsequently captured through geographic connectivities among neighboring countries.

Broadly speaking, three distinct measures of geographic connectivity are commonly applied in spatial analyses: (1) areal contiguity, (2) distance-based and (3) graph-based connectivity. Areal contiguity, in its simplest form, states that $C_{ij} = 1$ if countries i and j share a common border and $C_{ij} = 0$ otherwise. Distance-based connectivity, on the other hand, comes in two forms. One option is to define countries as *minimum distance* neighbors if the interpoint distance between two points representing each country's polygon centroid (i.e., the center of a polygon) or capital lies within a specificed distance band. Another approach, which is more commonly applied in spatial econometrics, is to consider two countries as *k nearest neighbors*

[11] The original dataset can be accessed online at `http://www.naturalearthdata.com/downloads/110m-cultural-vectors/110m-admin-0-countries/` (last accessed on 04-07-2016).

[12] For brevity, the subscript t is omitted in this section as both the connectivity matrix and the resulting spatial weights matrices are time-invariant.

of each other with k being a user-defined parameter.[13]

Contrary to most empirical applications in spatial econometrics or political economy, however, this paper operationalizes spatial dependence among countries as graph-based connectivities building on Euclidean instead of great-circle distances (as is the case when computing minimum distances or k nearest neighbors). While this so-called *sphere of influence* approach to modeling geographic connectivity is less intuitive than areal contiguity or distance bands, it yields the advantage of minimizing the number of substantively irrelevant connections (as is the weak point of minimum distance relationships) and is less arbitrary than specifying adjacency based on a user-defined number of k nearest neighbors (cf., Stewart & Zhukov, 2010).[14]

Adapted from Avis & Horton (1985), the rationale behind the *sphere of influence* graph can be expressed as follows. As a starting point, let S be a finite set of points in a plane representing each country's polygon centroid. For each $x \in S$, let r_x be the minimum (Euclidean) distance to any other point in the set and let D_x be a circle of radius r_x, centered at x. Two points x_i and x_j are considered *sphere of influence* neighbors when D_i and D_j intersect in two points. In other words, two points representing geographically proximate countries are considered graph-based neighbors if the respective circles centered around the two points – with the size of the radii determined by the points' nearest neighbor distances – overlap twice.[15] Implementing this *sphere of influence* connectivity specification then yields an $n \times n$ square connectivity matrix with the n columns (rows) corresponding to each country i (j). By convention, countries are not considered neighbors of themselves (i.e., $C_{ii} = C_{jj} = 0$).

The resulting connectivity matrix, which describes the spatial relations among all countries in the sample, can then be visualized as a simple map-based network graph with the centroids representing the nodes (figure 2).

[13] Bivand, Pebesma, & Gómez-Rubin, 2008 or Stewart & Zhukov, 2010 provide further information on this topic.

[14] Another, and often overlooked, specification issue concerns the representation of spatial units in the study area, that is, how to choose the respective points – informally defined as spatial objects located at specified coordinates within each country – for computing interpoint relationships between these points. By construction, graph-based connectivity measures compute Euclidean distances between two points representing each country's polygon centroid. However, when using interpoint distances based on great-circle distances, points can represent specific locations such as capitals reflecting political power for traditional political analyses or cities with large airports when analyzing transportation flows.

[15] See the appendix for a visualization and Bivand et al. (2008) or Stewart & Zhukov (2010) for further information.

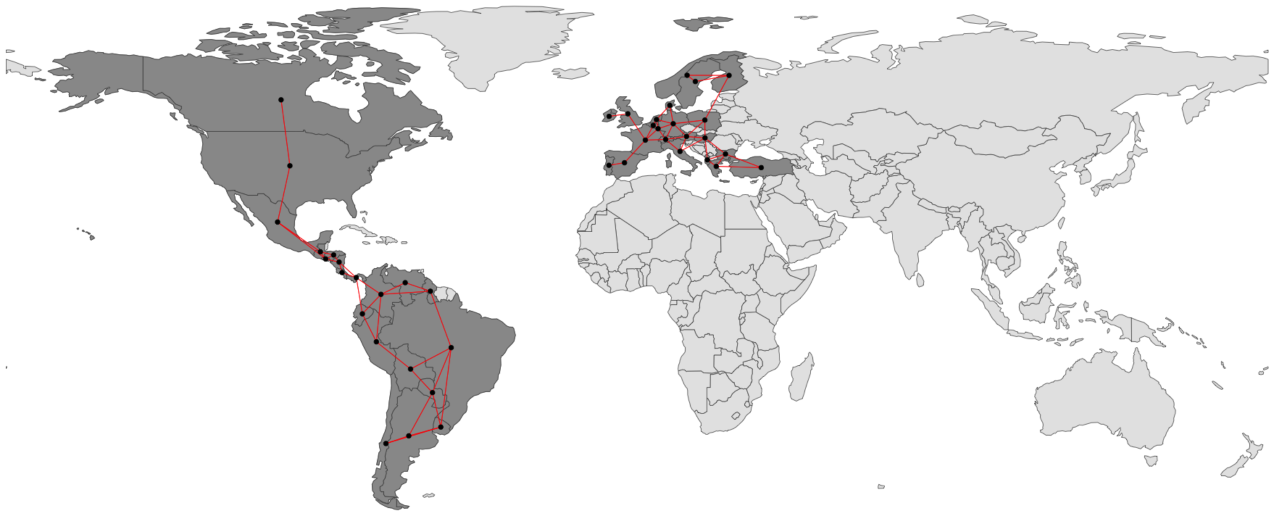

Figure 2: Network graph of centroidal *sphere of influence* connectivities

When working with dyadic data, however, the $n \times n$ connectivity matrix needs to be transformed into two distinct $N \times N$ country pair spatial weights matrices W_o and W_d, capturing both origin- (W_o) and destination-specific (W_d) dependence structures.

In order to better illustrate the construction of the two spatial weights matrices, (11) provides an oversimplified example for obtaining W_o from a binary $n \times n$ connectivity matrix C and its corresponding identity matrix I_n.

Consider the case of $n = 2$ countries A and B with

$$C = \begin{matrix} & A & B \\ A & 0 & 1 \\ B & 1 & 0 \end{matrix} \quad \text{and} \quad I_n = \begin{matrix} & A & B \\ A & 1 & 0 \\ B & 0 & 1 \end{matrix} \tag{10}$$

Following the approach of LeSage & Pace (2008, 2009) for spatial interaction models introduced in section 2.2, W_o can be obtained via $W_o = C \otimes I_n$ with $\otimes$ denoting the Kronecker product and I_n denoting the $n \times n$ identity matrix, that is,

$$W_o = \begin{array}{c} \\ A \\ B \end{array}\!\!\begin{array}{c} \begin{array}{cc} A & B \end{array} \\ \begin{pmatrix} 0 & 1 \\ 1 & 0 \end{pmatrix} \end{array} \otimes \begin{array}{c} \\ A \\ B \end{array}\!\!\begin{array}{c} \begin{array}{cc} A & B \end{array} \\ \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix} \end{array} =$$

$$\begin{array}{c|cccc} & A:A & A:B & B:A & B:B \\ \hline A:A & 0\cdot 1 & 0\cdot 0 & 1\cdot 1 & 1\cdot 0 \\ A:B & 0\cdot 0 & 0\cdot 1 & 1\cdot 0 & 1\cdot 1 \\ B:A & 1\cdot 1 & 1\cdot 0 & 0\cdot 1 & 0\cdot 0 \\ B:B & 1\cdot 0 & 1\cdot 1 & 0\cdot 0 & 0\cdot 1 \end{array} = \begin{array}{c|cccc} & A:A & A:B & B:A & B:B \\ \hline A:A & 0 & 0 & 1 & 0 \\ A:B & 0 & 0 & 0 & 1 \\ B:A & 1 & 0 & 0 & 0 \\ B:B & 0 & 1 & 0 & 0 \end{array} \quad (11)$$

Correspondingly, W_d can be obtained via $W_d = I_n \otimes C$ as exemplified below (12).

$$W_d = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix} \otimes \begin{pmatrix} 0 & 1 \\ 1 & 0 \end{pmatrix} = \begin{pmatrix} 1\cdot 0 & 1\cdot 1 & 0\cdot 0 & 0\cdot 1 \\ 1\cdot 1 & 1\cdot 0 & 0\cdot 1 & 0\cdot 0 \\ 0\cdot 0 & 0\cdot 1 & 1\cdot 0 & 1\cdot 1 \\ 0\cdot 1 & 0\cdot 0 & 1\cdot 1 & 1\cdot 0 \end{pmatrix} = \begin{pmatrix} 0 & 1 & 0 & 0 \\ 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & 1 & 0 \end{pmatrix} \quad (12)$$

After obtaining the required $N \times N$ connectivity matrices W_o and W_d, a third matrix W_{od} – reflecting origin-destination dependence structures – can be created via $C \otimes C$. Subsequently, all matrices are standardized by dividing the elements of each row of the respective matrix by its row sum so that the weights in each row sum to unity. As a result, all weights range from 0 to 1 and the point estimates for the spatial lags can be interpreted as an average of the lagged dependent variables of neighboring countries (cf., Elhorst, 2014, p. 12; Ward & Gleditsch, 2008, p. 80).[16]

[16] While row-standardizing spatial weight matrices is common practice in spatial econometrics, this standardizing procedure is accompanied by (rarely discussed) theoretical implications. Plümper & Neumayer (2010) and Neumayer & Plümper (2013) point out that row-standardizing any spatial weights matrix W yields substantively different conceptualizations of the underlying spatial mechanism compared to non-standardized weight matrices as row-standardizing implies that, for instance, connections from any country A to any neighboring

3.3 Analytical procedure and model specifications

The spatial analysis in this paper is conducted in two steps. In the first step, it is tested whether spatial autocorrelation is present in dyadic trade flows by calculating Moran's autocorrelation coefficient, denoted by I, which gauges the extent to which the phenomenon under scrutiny is correlated to itself in space (Moran, 1950). Thus, when testing for global spatial autocorrelation in trade flows, it is examined whether observed values of directed trade flows between two trading partners at one location are independent from values of trade flows observed at neighboring locations with neighbors being defined by the respective connectivity matrix. In a second step, spatial autoregressive panel models (SAR) containing a spatially lagged dependent variable are employed to explicitly account for the hypothesized spatial competition mechanism.

As discussed by Elhorst (2014, pp. 53-57), longitudinal spatial regression analyses often rely on random effects models (RE) rather than fixed effects specifications (FE) due to known reasons such as the loss of degrees of freedom when N is large or the omission of time-invariant variables in FE models.

In this paper, however, there are two main objections against relying solely on RE specifications. First and foremost, spatial RE models do – anagolous to non-spatial panel models – not account for spatial heterogeneity which is critical given that spatial units will most likely differ in terms of geographic characteristics resulting from the units' respective locations. Consequently, the omission of these spatial effects will lead to biased estimates. Second, the theoretical framework as outlined in section 2 calls for a FE specification. Feenstra (2002, 2004) and Anderson & van Wincoop (2003, p. 180) argue that when estimating the theoretically grounded gravity equation with FE specifications, consistent parameter estimates are obtained (cf., De Benedictis & Taglioni, 2011 for a discussion). In other words, an RE model specification reflects the empirical gravity equation, whereas FE models approximate – at least to a certain degree – the notion of multilateral resistance as formally modeled by Anderson & van Wincoop (2003).

Accounting for these time-invariant unit-specific factors implied by the theoretical framework, FE model specifications with dyadic fixed effects for each country pair ij are employed (μ_{ij}) to capture time-invariant spatial effects (e.g., common borders or great-circle distances between

country B receive greater weight if A has fewer connections to other countries C.

trading partners).

Moreover, all models control for unit-invariant time-varying effects (λ_t) affecting all country pairs likewise. Prominent examples for time period effects in international trade are, for instance, common shocks or decreasing transportation costs.

In sum, the aforementioned specifications result in the following baseline models for the subsequent spatial regression analyses

$$\ln TRADE_{ijt} = \alpha_{ij} + \rho_o W_o \ln TRADE_{ijt} + \rho_d W_d \ln TRADE_{ijt} + \rho_{od} W_{od} \ln TRADE_{ijt} + \beta_1 \ln GDP_{it} + \beta_2 \ln GDP_{jt} + \beta_3 \ln DIST_{ijt} + \beta_4 ADJ_{ijt} + \beta_5 LANG_{ijt} + \beta_6 RTA_{ijt} + \lambda_t + \varepsilon_{ijt} \tag{13.1}$$

$$\ln TRADE_{ijt} = \alpha_{ij} + \rho_o W_o \ln TRADE_{ijt} + \rho_d W_d \ln TRADE_{ijt} + \rho_{od} W_{od} \ln TRADE_{ijt} + \beta_1 \ln GDP_{it} + \beta_2 \ln GDP_{jt} + \beta_3 \ln DIST_{ijt} + \beta_4 ADJ_{ijt} + \beta_5 LANG_{ijt} + \beta_6 RTA_{ijt} + \mu_{ij} + \lambda_t + \varepsilon_{ijt} \tag{13.2}$$

with (13.1) being the baseline RE specification and (13.2) being the baseline FE specification, respectively. In line with the spatially augmented gravity equation discussed in section 2, $TRADE_{ijt}$, denoting aggregate bilateral trade flows, serves as the dependent variable, while the proxies for the two countries' market potentials ($GDP_{i,j}$) and great-circle distances ($DIST_{ijt}$) – the latter reflecting bilateral trading costs – serve as explanatory variables. Furthermore, the three binary dummy variables accounting for the similarity between trading partners are included, which take the value of 1 if two countries i and j share either a common border (ADJ_{ijt}), a common official language ($LANG_{ijt}$) or membership in a regional trade agreement (RTA_{ijt}).

Adapted from LeSage & Pace (2008), the following restrictions are then imposed which yields four distinct model specifications, depending on the included spatial weights matrix:[17]

[17] Note that all model specifications assume $\lambda_o = \lambda_d = \lambda_{od} = 0$ with λ conventionally denoting spatial dependence in the disturbance terms (not to be confused with the standard econometric notation for time period effects λ_t). In other words, all spatial regression models in section 4.2 build on the assumption that the

Model (1). $\rho_d = \rho_{od} = 0$ obtains the spatial gravity model with a single weights matrix W_o for capturing origin-based spatial dependence.

Model (2). $\rho_o = \rho_{od} = 0$, in turn, obtains the spatial gravity model with a single weights matrix W_d for capturing destination-based spatial dependence.

Model (3). $\rho_o = \rho_d$ and $\rho_{od} = 0$ yields a spatial gravity model with a single weights matrix W_{o+d}, constructed via $\frac{1}{2}(W_o + W_d)$, which captures the cumulative effect of origin- and destination-based spatial dependence.

Model (4). $\rho_o = \rho_d = 0$ yields a spatial gravity model with a single weights matrix W_{od} capturing spatial dependence structures resulting from interactions between neighboring countries of both the country of origin and destination.

In conformity with models (1)-(4), $\rho_o = \rho_d = \rho_{od} = 0$ reflects the conventional non-spatial gravity model assuming independence of observations, i.e., no spatial autoregressive dependence is controlled for.

Contrary to empirical applications of spatial autoregressive models in spatial econometrics (e.g., Behrens et al., 2012; LeSage & Llano-Verduras, 2014), however, this paper departs from the common practice of reporting misleading non-spatial 'benchmark' models. This is due to the reason that estimation results obtained from spatial autoregressive models do not conform to their non-spatial counterparts since parameter estimates reflect spatial feedback structures among dyadic observations. Section 4.2 discusses the empirical implications in detail.

Given the endogenous spatial lag resulting from these multilateral dependence structures, maximum likelihood estimation (ML) is employed as OLS estimates will be biased due to the violation of the independence assumption (see, e.g., Anselin, 1988 and Anselin, Le Gallo & Jayet, 2008), assuming normality of ε_{ijt} and μ_{ij}.

Since unit fixed effects μ_{ij} are included in (13.2), one crucial issue – known as the *incidental parameters problem* leading to inconsistent ML estimators in models where the number of estimated parameters increases with N – needs to be discussed briefly. Without going into further detail, Elhorst (2014, chapter 3.2.1) points out that despite the inconsistency of the unit fixed effects, spatial FE models can be estimated consistently after demeaning the regression

respective error terms exhibit no patterns of spatial dependence.

equation beforehand since the estimated β coefficients of interest are not a function of the estimated μ_{ij}.[18]

Data management, mapping and all statistical analyses were carried out in the R *software environment for statistical computing and graphics* (R Core Team, 2016). All packages used are available from the *Comprehensive R Archive Network* (CRAN) at `http://CRAN.R-project.org/` and are listed in the references.[19]

4 Preliminary results

4.1 Testing for global spatial autocorrelation

As mentioned in the preceding section, the empirical analysis in this paper begins with examining if the (log-transformed) bilateral trade flows in the subsample show patterns of spatial dependence.

By computing Moran's I, it can be tested whether the observed spatial pattern is the result of a random spatial process. Accordingly, the null hypothesis posits that no spatial autocorrelation is present in the data. It is important to note, however, that Moran's I is sensitive to the specification of spatial connectivity among countries. Thus, if the corresponding spatial weights matrices do not approximate the underlying spatial mechanism, I will be biased. Another important issue to consider is that Moran's I is only reliable for examining spatial autocorrelation in cross-sectional settings for a univariate series, although the latter is often ignored in practice (cf., Ward & Gleditsch, 2008, p. 34).

Generally speaking, I ranges from -1 to $+1$ with significant positive values indicating that spatial clustering occurs, whereas negative values indicate dispersed spatial patterns. Put differently, positive (negative) values suggest that neighboring units exhibit similar (dissimilar) observed values of directed trade flows.

[18] See Elhorst (2014, pp. 43-46) for more detailed information on the estimation procedure.

[19] Instead of using the **splm** package for spatial panel models from the CRAN package repository, the regression analyses in this paper were carried out with a patched version compiled in collaboration with Sebastian Schutte. Modifications were needed as two internal functions for estimating fixed effects models with spatial lags (*splm:::splaglm*) and spatial errors (*splm:::sperrorlm*), respectively, did not return the log likelihood as desired. Moreover, the *sphtest()* function for conducting spatial Hausman tests for comparing random and fixed effects model specifications needed adjustments as well to run properly.

Table 1: Testing for global spatial autocorrelation

Year	Moran's I_{W_o}	Moran's I_{W_d}	Moran's $I_{W_{o+d}}$	Moran's $I_{W_{od}}$
2002	0.627***	0.639***	0.619***	0.440***
	(29.416)	(29.923)	(41.714)	(34.508)
2003	0.625***	0.637***	0.616***	0.434***
	(29.355)	(29.839)	(41.494)	(34.047)
2004	0.632***	0.624***	0.613***	0.432***
	(29.669)	(29.236)	(41.277)	(33.845)
2005	0.635***	0.625***	0.612***	0.428***
	(29.809)	(29.252)	(41.429)	(33.541)
2006	0.623***	0.632***	0.614***	0.425***
	(29.257)	(29.615)	(41.396)	(33.353)

Notes: Standard deviates in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

The empirical results in table 1 indicate that the null hypothesis of no (global) spatial autocorrelation must be rejected. For all years under scrutiny and all connectivity specifications, I is highly significant and positive, ranging approximately from 0.4 ($I_{W_{od}}$) to 0.6 (I_{W_o}, I_{W_d} and $I_{W_{o+d}}$). Therefore, it can be concluded that the observed spatial pattern is not the outcome of a random spatial process but rather shows patterns of spatial clustering. In other words, spatial dependence is present in directed trade flows between two trading partners.[20]

4.2 Spatial autoregressive panel models

Building on the empirical findings of the preceding section, which indicate that trade flows in the subsample are indeed spatially clustered, this section further examines these spatial dependence structures by reporting and briefly discussing the preliminary results for both the random and fixed effects spatial autoregressive panel models in (13.1) and (13.2).[21][22]

[20] Additionally, Baltagi, Song, & Koh's (2003) marginal Lagrange multiplier test for spatial autocorrelation was carried out, testing the null hypothesis of no spatial autocorrelation, i.e., H_0: $\rho_o = \rho_d = \rho_{od} = 0$, while assuming no random effects. In line with Moran's autocorrelation coefficients, the results confirm that spatial autocorrelation is present in the data. However, the results obtained from **splm**'s *bsktest()* should be treated with a degree of caution (cf., footnote 21).

[21] Pooled model specifications were not employed since the marginal Lagrange multiplier test for random spatial effects by Baltagi et al. (2003), which tests for H_0: $\sigma^2_\mu = 0$ while assuming no spatial autocorrelation, indicated the presence of random effects. Irrespective of this result, it is important to note that *bsktest()* apparently tests for a reverse direction of H_0 and the corresponding alternative hypothesis H_a: $\sigma^2_\mu > 0$ (cf., Millo & Piras, 2012, p. 23).

[22] Lee & Yu (2010) demonstrate that ML estimation can lead to inconsistent parameter estimates in spatial autoregressive models with fixed effects specifications where the number of time periods T is small as is the case in this paper. To ensure the consistency of the parameter estimates, the results for the bias correction proposed by Lee & Yu are reported in the appendix, showing no substantial differences compared to the

Table 2: Regression estimates

	Dependent variable: Directed trade flows (ln)							
	Random effects				*Fixed effects*			
Determinants	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
$\ln GDP_i$	0.938***	0.868***	0.848***	0.966***	0.524***	0.499***	0.483***	0.526***
	(0.012)	(0.017)	(0.016)	(0.017)	(0.074)	(0.074)	(0.074)	(0.074)
$\ln GDP_j$	0.793***	0.877***	0.788***	0.897***	0.528***	0.591***	0.536***	0.595***
	(0.016)	(0.016)	(0.016)	(0.017)	(0.074)	(0.074)	(0.074)	(0.074)
RTA_{ij}	0.189***	0.165***	0.162***	0.184***	−0.009	−0.035	−0.023	−0.028
	(0.057)	(0.057)	(0.056)	(0.058)	(0.062)	(0.062)	(0.062)	(0.062)
$\ln DIST_{ij}$	−0.777***	−0.808***	−0.656***	−0.919***				
	(0.040)	(0.039)	(0.039)	(0.041)				
ADJ_{ij}	0.919***	0.885***	0.995***	0.801***				
	(0.137)	(0.135)	(0.133)	(0.141)				
$LANG_{ij}$	0.827***	0.819***	0.835***	0.829***				
	(0.087)	(0.086)	(0.085)	(0.090)				
$\rho_o W_o$	0.191***				0.158***			
	(0.015)				(0.017)			
$\rho_d W_d$		0.175***				0.090***		
		(0.015)				(0.18)		
$\rho_{o+d} W_{o+d}$			0.320***				0.218***	
			(0.020)				(0.024)	
$\rho_{od} W_{od}$				0.039***				0.043**
				(0.018)				(0.025)

Notes: Standard errors in parentheses. Time dummies and intercept not reported.
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 2 lists the regression results obtained with the four different model specifications (1)-(4) described in section 3.3. In all models, the coefficients for GDP_i and GDP_j, reflecting the two countries' trade potentials, show the expected positive sign and, thus, suggest that bilateral trade-generating factors lead to increased volumes of trade. Furthermore, in all four RE models the two binary similarity measures ADJ_{ij} and $LANG_{ij}$ – which are omitted in the FE specifications as they are constant over time – indicate a positive effect of having a common border or sharing an official language on trade flows. Geodesic distance ($DIST_{ij}$) between capitals serving as a proxy for bilateral transaction costs, in turn, decreases trade flows as expected theoretically. All coefficients are highly significant.

By contrast, the policy-based covariate of interest, namely, regional trade agreements being in force between two trading partners, yields mixed results. While all RE models suggest that co-membership in regional trading blocs increases bilateral trade flows, the effects of RTAs are no longer different from zero when controlling for time-invariant fixed effects in the FE models.[23]

Since both the dependent and explanatory variables are log-transformed in all models, the coefficients can, at least in theory (cf., below), be interpreted as elasticities. For binary similarity variables in log-log-transformed models, the percentage effects can be calculated via (14)

$$p = 100 \times (exp(\beta) - 1) \tag{14}$$

as suggested by Halvorsen & Palmquist (1980) and Wooldridge (2009, p. 190) with p reflecting the difference in trade flows of the binary variable taking the value of 1 compared to the binary variable taking the value of 0, *ceteris paribus*.

Table 3 reports the corresponding percentage effects of the binary RTA variables accounting for similarity between trading partners.[24] For the sake of completeness, the effects for the fixed effects models are reported alongside its random effects counterparts, although they are insignificant.

results for the FE specifications listed in table 2.

[23] This empirical finding, however, could – at least potentially – be caused by a lack of spatio-temporal variation in the data on regional trade agreements covered in the subsample.

[24] The percentage effects of sharing a common border or an official language can be calculated analogously.

Table 3: Effects of regional trade agreements in %

Model specifications	(1)	(2)	(3)	(4)
Random effects	20.784%***	17.978%***	17.618%***	17.618%***
Fixed effects	−0.854%	−3.340%	−2.310%	−2.752%

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

When turning to the parameter estimates of main interest, i.e., $\rho_o W_o$, $\rho_d W_d$, $\rho_{o+d} W_{o+d}$ and $\rho_{od} W_{od}$ measuring the hypothesized spatial dependence structures, it is evident that spatial mechanisms are at work. All estimated dependence parameters ρ in the random and fixed effects model specifications (1)-(3) are highly significant and show substantial levels of origin- ($\rho_o W_o$), destination- ($\rho_d W_d$) and cumulative origin- and destination-based dependence ($\rho_{o+d} W_{o+d}$).

Substantively, these results suggest (albeit with reservation as is shown below) that, first, determinants causing trade flows from the country of origin to each destination evoke similar levels of trade from countries nearby the origin to the same destination ($\rho_o W_o$) and, second, determinants causing trade flows from each origin to the same destination evoke similar levels of trade from the origin to countries located nearby the destination country ($\rho_d W_d$). However, as indicated by the comparatively smaller estimated values for $\rho_{od} W_{od}$ in models (4), these determinants do not evoke trade flows between third countries C and D in a similar magnitude.

While it appears promising to interpret the aforementioned parameter estimates in the same fashion as if they were obtained by non-spatial regression models, this reasoning is invalid and will bias causal inferences drawn from the empirical findings.[25] As indicated in section 3.3 and demonstrated in detail by, e.g., Kelejian, Tavlas, & Hondroyiannis (2006), LeSage & Pace (2009) or Elhorst (2014), the interpretation of parameter estimates in spatial and non-spatial regression models differs substantively.

The (simplified) reason for this is easy to grasp. Recall that in non-spatial regression models, parameter estimates can be interpreted as the effects of a change in any of the explanatory variables on the dependent variable. Following the terminology of LeSage & Pace (2009), these effects are called *direct effects*, that is, changes in any of the explanatory variables only affect bilateral trade flows between two trading partners i and j and do not (indirectly) affect trade

[25] Moreover, reporting spatial and non-spatial point estimates alongside each other – as is common practice even in spatial econometrics – reinforces the (false) impression of comparability.

flows among third countries since dyadic observations are assumed to be independent from each other. In turn, parameter estimates in spatial autoregressive models reflect dependence structures and thus, by construction, multilateral feedback effects among observations arise. Consequently, changes in any of the explanatory variables not only affect bilateral trade flows between two trading countries i and j directly but trade flows of third country pairs as well. The latter is what LeSage & Pace term *indirect effects*. In other words, since bilateral trade flows are modeled as a function of trading volumes of neighboring countries (cf., equations 13.1 and 13.2 in section 3.3), these multilateral spatial dependence structures must be considered when interpreting the parameter estimates for models (1)-(4).

Interpreting the resulting parameter estimates, however, is more challenging.[26] On this account, LeSage & Pace (2009; cf., LeSage & Thomas-Agnan, 2015 for dyadic data) propose summarized scalar measures for ease of interpretation. Put briefly, the basic intuition behind these scalar measures is to calculate the average of impacts arising from changes in the explanatory variables to allow for a partial derivative interpretation similar to the interpretation of coefficients in non-spatial models.

For brevity, table 4 only lists the impact estimates for the theoretically grounded fixed effects model specifications (1)-(4), while the corresponding results for the random effects models are reported in the appendix.[27] For all models, the z-values and significance levels were calculated from a set of 10.000 simulated parameter values.

Recall that indirect effects measure the impacts of changes in any of the explanatory variables on bilateral trade flows among third country pairs. Thus, as implied in the explanation on differing parameter estimates above and explicitly pointed out by Elhorst (2014, p. 24), indirect effects rather than estimates for ρ should be used to assess spatial (spillover) effects. The indirect effects listed in the middle section of table 4, however, indicate that the spatial effects of two countries' trade-generating potentials $GDP_{i,j}$ are – compared to the estimates reported in table 2 – rather small for either origin, destination, or dyadic connectivity specifications

[26] LeSage & Pace (2009, chapter 2.7) and Elhorst (2014, chapter 2.7) provide technical details on this topic.

[27] In line with the theoretical arguments pointing towards FE specifications, a spatial Hausman test for assessing the consistency of random vs. fixed effects spatial models using W_{o+d} was conducted. The obtained results ($\chi^2 = 133.57$, $df = 7$, $p < 0.01$) indicate that the spatial RE model must be rejected as the differences between the two specifications are, at least from a statistical perspective, systematic.

Table 4: Impact estimates for fixed effects models

	Direct effects				*Indirect effects*				*Total effects*			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
$\ln GDP_i$	0.527***	0.500***	0.485***	0.526***	0.098***	0.048***	0.133***	0.023***	0.623***	0.548***	0.618***	0.550***
	(6.989)	(6.597)	(6.374)	(6.918)	(5.332)	(3.951)	(4.796)	(1.726)	(6.931)	(6.554)	(6.272)	(6.833)
$\ln GDP_j$	0.5304***	0.592***	0.539***	0.595***	0.096***	0.057***	0.147***	0.027	0.627***	0.649***	0.686***	0.621***
	(7.247)	(8.091)	(7.225)	(7.980)	(5.375)	(4.174)	(5.497)	(1.795)	(7.159)	(7.987)	(7.257)	(8.037)
RTA_{ij}	−0.009	−0.035	−0.023	−0.028	−0.002	−0.003	−0.006	−0.001	−0.010	−0.038	−0.030	−0.029
	(0.029)	(−0.398)	(−0.207)	(−0.280)	(0.030)	(−0.387)	(−0.216)	(−0.275)	(0.029)	(−0.398)	(−0.210)	(−0.281)

Notes: Simulated z-values in parentheses. Simulated $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.
Models (1) $\rho_d = \rho_{od} = 0$, (2) $\rho_o = \rho_{od} = 0$, (3) $\rho_o = \rho_d$ and $\rho_{od} = 0$, (4) $\rho_o = \rho_d = 0$.

when simultaneously controlling for unit fixed effects. The reason for this is, again, given by Elhorst (2014, p. 58) who points out that fixed effects partly absorb interaction effects since most variables tend to decrease or increase synchronously over time among nearby spatial units (cf., table 6 in the appendix). Irrespective of this decrease in the magnitude of the presumed spatial effects, the empirical findings, in sum, strongly suggest that hypothesis 2 is valid.

Without going into further detail, the direct effects of $GDP_{i,j}$ are positive and highly significant in all fixed effects model specifications (1)-(4), supporting hypothesis 1 in part. The effects of regional trade agreements (RTA_{ij}), in turn, remain insignificant.

5 Concluding remarks, discussion and limitations

The main objective of this paper was to model the effects of multilateral spatial dependence structures in policy-based gravity equations for dyadic trade flows. In doing so, origin-, destination- and origin-destination-specific dependence structures among countries, resulting from the underlying spatial competition mechanisms, were operationalized as graph-based connectivities using Euclidean distances. Empirically, the spatial analysis drew on a subsample of $n = 42$ countries covering the years 2002-2006. In a nutshell, the preliminary empirical findings support the main arguments of this paper, namely, that spatial autocorrelation is, first, present in bilateral trade flows and, second, the hypothesized spatial competition mechanism evoking patterns of spatial dependence among neighboring countries is at work. Hence, one can draw the (preliminary) conclusion that the bulk of econometric articles relying on either the empirical or the theoretical non-spatial gravity equation yield biased point estimates resulting from the omission of variables controlling for these spatial competition effects.

Despite these initial findings, the spatial analyses in this paper still face several challenges. Methodologically, given the limited sample size due to computational limitations, generalizations of the preliminary results are restricted since randomization is not feasible for geographical analyses. On a positive note, however, the required data are available in the full dataset. Additionally, further computational restrictions are imposed as the spatially lagged dependent variables W_oX_{ij} and W_dX_{ij} should, ideally, enter the respective spatial panel model simultaneously. To date, functions for including two distinct connectivity matrices in the substantive part of the model are only implemented in the *Spatial Econometrics* toolbox for MATLAB by James P. LeSage. Both R and Stata do not support the inclusion of more than one spatial weights matrix for modeling spatially lagged dependent variables.

Moreover, recall that from a theoretical perspective, the choice of an appropriate connectivity specification should – contrary to common practice in spatial econometrics – be theory-driven as it reflects the notion of (and, thus, proxies) the hypothesized spatial mechanism. While the operationalization of dyadic spatial dependence structures and the baseline specifications of the spatial models in this paper build on the theoretical arguments laid out in section 2, they do not constitute a full-fledged theory. Therefore, an increased consistency between formal gravity models in international trade theory and the corresponding spatial econometric model is required in future analyses – particularly with regard to both the lack of (implemention of) goodness-of-fit measures for spatial panel models and the comparability between spatial autoregressive models and non-spatial benchmark models, respectively.

Given these aforementioned methodological and theoretical limitations, one solution-oriented middle ground between computational limitations on the one hand and valid causal inferences derived from the longitudinal spatial models employed in this paper one the other hand are robustness checks to assess whether different subsamples and connectivity specifications (e.g., for connectivity defined by great-circle distances with and without distance decay) yield similar empirical results. Additionally, controlling for selection bias due to zero trade flows, which are omitted when log-transforming the dependent variable, as well as accounting for heterogenous treatment effects regarding the trade-creating and trade-diverting effects of RTAs are fruitful directions for future research.

References

Anderson, J. E. (1979). A theoretical foundation for the gravity equation. *American Economic Review*, 75(1), 178-190.

Anderson, J. E., & van Wincoop, E. (2003). Gravity with Gravitas: A Solution to the Border Puzzle. *American Economic Review*, 93(1), 170-192.

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

Anselin, L. (2003). Spatial externalities, spatial multipliers, and spatial econometrics. *International Regional Science Review*, 26(2), 153-166.

Anselin, L., Le Gallo, J., & Jayet, H. (2008). Spatial panel econometrics. In L. Mátyás & P. Sevestre (Eds.), T*he Econometrics of Panel Data. Fundamentals and Recent Developments in Theory and Practice* (pp. 625-660). Berlin: Springer.

Avis, D., & Horton, J. (1985). Remarks on the sphere of influence graph. *Annals of the New York Academy of Sciences*, 440(1), 323-327.

Baier, S. L., & Bergstrand, J. H. (2007). Do free trade agreements actually increase members' international trade? *Journal of International Economics*, 71(1), 72-95.

Baltagi, B. H., Egger, P., & Pfaffermayr, M. (2007). Estimating models of complex FDI: Are there third-country effects? *Journal of Econometrics*, 140(1), 260-281.

Baltagi, B. H., Song, S. H., & Koh, W. (2003). Testing panel data regression models with spatial error correlation. *Journal of Econometrics*, 117(1), 123-150.

Barbieri, K., & Keshk, O. (2012). *Correlates of War Project Trade Data Set Codebook*, Version 3.0. Available online: http://correlatesofwar.org [last accessed on 04-07-2016].

Barbieri, K., Keshk, O., & Pollins, B. (2009). Trading Data: Evaluating our Assumptions and Coding Rules. *Conflict Management and Peace Science*, 26(5), 471-491.

Beck, N., Gleditsch, K. S., & Beardsley, K. (2006). Space is more than geography: Using spatial econometrics in the study of political economy. *International Studies Quarterly*, 50(1), 27-44.

Behrens, K., Ertur, C., & Koch, W. (2012). 'Dual' gravity: Using spatial econometrics to control for multilateral resistance. *Journal of Applied Econometrics*, 27(5), 773-794.

Bivand, R. S., Pebesma, E., & Gómez-Rubio, V. (2008). *Applied Spatial Data Analysis with R.* 2^{nd} edition. New York: Springer.

Curry, L. (1972). A spatial analysis of gravity flows. *Regional Studies*, 6(2), 131-147.

De Benedictis, L., & Taglioni, D. (2011). The gravity model in international trade. In L. De Benedictis & L. Salvatici (Eds.), *The Trade Impact of European Union Preferential Policies* (pp. 55-89). New York: Springer.

Elhorst, J. P. (2014). *Spatial econometrics: from cross-sectional data to spatial panels.* New York: Springer.

Feenstra, R. C. (2002). Border effects and the gravity equation: consistent methods for estimation. *Scottish Journal of Political Economy*, 49(5), 491-506.

Feenstra, R. C. (2004). *Advanced international trade: theory and evidence.* Princeton: Princeton University Press.

Fotheringham, A. S. (1981). Spatial structure and distance-decay parameters. *Annals of the Association of American Geographers*, 71(3), 425-436.

Frankel, J. (1997). *Regional Trading Blocks in the World Economic System.* Washington, DC: Institute for International Economics.

Glick, R., & Rose, A. K. (2002). Does a currency union affect trade? The time-series evidence. *European Economic Review*, 46(6), 1125-1151.

Griffith, D. A., & Jones, K. G. (1980). Explorations into the relationship between spatial structure and spatial interaction. *Environment and Planning A*, 12(2), 187-201.

Halvorsen, R. & Palmquist, R. (1980). The Interpretation of Dummy Variables in Semilogarithmic Equations. *The American Economic Review*, 70(3), 474-475.

Head, K., Mayer, T., & Ries, J. (2010). The erosion of colonial trade linkages after independence. *Journal of International Economics*, 81(1), 1-14.

Head, K., & Mayer, T. (2013). Gravity Equations: Toolkit, Cookbook, Workhorse. In G. Gopinath, E. Helpman, & K. Rogoff (Eds.), *Handbook of International Economics*, Vol. 4 (pp. 131-195).

Kelejian, H. H., Tavlas, G. S., & Hondroyiannis, G. (2006). A spatial modelling approach to contagion among emerging economies. *Open Economies Review*, 17(4-5), 423-441.

Krisztin, T., & Fischer, M. (2015). The gravity model for international trade: Specification and estimation issues. *Spatial Economic Analysis*, 10(4), 451-470.

Krugman, P. (1991). Increasing Returns and Economic Geography. *The Journal of Political Economy*, 99(3), 483-499.

Lee, L. F., & Yu, J. (2010). Estimation of spatial autoregressive panel data models with fixed effects. *Journal of Econometrics*, 154(2), 165-185.

LeSage, J. P., & Llano-Verduras, C. (2014). Forecasting spatially dependent origin and destination commodity flows. *Empirical Economics*, 47(4), 1543-1562.

LeSage, J. P., & Pace, R. K. (2008). Spatial econometric modeling of origin-destination flows. *Journal of Regional Science*, 48(5), 941-967.

LeSage, J. P., & Pace, R. K. (2009). *Introduction to spatial econometrics.* Boca Raton: Chapman & Hall/CRC.

LeSage, J. P., & Thomas-Agnan, C. (2015). Interpreting Spatial Econometric Origin-Destination Flow Models. *Journal of Regional Science*, 55(2), 188-208.

Moran, P. A. (1950). Notes on continuous stochastic phenomena. *Biometrika*, 37(1/2), 17-23.

Neumayer, E., & Plümper, T. (2010). Spatial effects in dyadic data. *International Organization*, 64(1), 145-166.

Neumayer, E., & Plümper, T. (2013). W. *Political Science Research and Methods*, 4(1), 175-193.

Newton, I. ([1713] 1999). *Philosophiae Naturalis Principia Mathematica, General Scholium.* 2^{nd} edition. Translation by I. Cohen, Bernard & Anne Withman. California: University of California Press.

Plümper, T., & Neumayer, E. (2010). Model specification in the analysis of spatial dependence. *European Journal of Political Research*, 49, 418?442.

Porojan, A. (2001). Trade flows and spatial effects: the gravity model revisited. *Open Economies Review*, 12(3), 265-280.

Pöyhönen, P. (1963). A tentative model for the volume of trade between countries. *Weltwirtschaftliches Archiv*, 90, 93-99.

Stewart, B. M., & Zhukov, Y. (2010). Choosing Your Neighbors: The Sensitivity of Geographical Diffusion in International Relations. *APSA 2010 Annual Meeting Paper.*

Tinbergen, J. (1962). *Shaping the World Economy – Suggestions for an International Economic Policy.* Twentieth Century Fund.

Tobler, W. R. (1970). A computer movie simulating urban growth in the Detroit region. *Economic Geography*, 46, 234-240.

Viner, J. (1950). *The customs union issue.* New York: Carnegie Endowment for International Peace.

Ward, M. D., & Gleditsch, K. S. (2008). *Spatial regression models.* Los Angeles: Sage.

Wooldridge, J. M. (2009). *Introductory Econometrics.* 4^{th} edition. London: Cengage Learning.

Data analysis

Arel-Bundock, V. (2014). **countrycode**: Convert Country Names and Country Codes. R package version 0.18. https://CRAN.R-project.org/package=countrycode.

Arya, S., Mount, D., Kemp, S. E., & Jefferis, G. (2015). **RANN**: Fast Nearest Neighbour Search (Wraps Arya and Mount's ANN Library). R package version 2.5. https://CRAN.R-project.org/package=RANN.

Bates, D., & Maechler, M. (2016). **Matrix**: Sparse and Dense Matrix Classes and Methods. R package version 1.2-4. https://CRAN.R-project.org/package=Matrix.

Bivand, R. S., Hauke, J., & Kossowski, T. (2013). Computing the Jacobian in Gaussian spatial autoregressive models: An illustrated comparison of available methods. Geographical Analysis, 45(2), 150-179.

Bivand, R. S., Keitt, T., & Rowlingson, B. (2015). **rgdal**: Bindings for the Geospatial Data Abstraction Library. R package version 0.9-3. https://CRAN.R-project.org/package=rgdal.

Bivand, R. S., & Lewin-Koh, N. (2015). **maptools**: Tools for Reading and Handling Spatial Objects. R package version 0.8-36. https://CRAN.R-project.org/package=maptools.

Bivand, R. S., Pebesma, E., & Gómez-Rubio, V. (2013). Applied spatial data analysis with R. 2^{nd} edition. New York: Springer. http://www.asdar-book.org/.

Bivand, R. S., & Piras, G. (2015). Comparing Implementations of Estimation Methods for Spatial Econometrics. Journal of Statistical Software, 63(18), 1-36. URL http://www.jstatsoft.org/v63/i18/.

Bivand, R. S., & Rundel, C. (2016). **rgeos**: Interface to Geometry Engine – Open Source (GEOS). R package version 0.3-17. https://CRAN.R-project.org/package=rgeos.

Hijmans, R. J. (2015). **raster**: Geographic Data Analysis and Modeling. R package version 2.5-2. https://CRAN.R-project.org/package=raster.

Millo, G., & Piras, G. (2012). **splm**: Spatial Panel Data Models in R. Journal of Statistical Software, 47(1), 1-38. URL http://www.jstatsoft.org/v47/i01/.

Pebesma, E. J., & Bivand, R. S. (2005). Classes and methods for spatial data in R. *R News*, 5(2), `http://cran.r-project.org/doc/Rnews/`.

R Core Team (2015). **foreign**: Read Data Stored by Minitab, S, SAS, SPSS, Stata, Systat, Weka, dBase. R package version 0.8-66. `https://CRAN.R-project.org/package=foreign`.

R Core Team (2016). **R**: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. URL `https://www.R-project.org/`.

South, A. (2011). **rworldmap**: A New R package for Mapping Global Data. The R Journal, 3/1, 35-43.

Warnes, G. R., Bolker, B., Gorjanc, G., & Grothendieck, G. [et al.] (2015). **gdata**: Various R Programming Tools for Data Manipulation. R package version 2.17.0. `https://CRAN.R-project.org/package=gdata`.

Wickham, H. (2007). Reshaping Data with the reshape Package. Journal of Statistical Software, 21(12), 1-20. URL `http://www.jstatsoft.org/v21/i12/`.

Wickham, H. (2009). **ggplot2**: Elegant Graphics for Data Analysis. Springer-Verlag New York.

Wuertz, D., Setz, T., & Chalabi, Y. (2014). **fBasics**: Rmetrics – Markets and Basic Statistics. R package version 3011.87. `https://CRAN.R-project.org/package=fBasics`.

Zuyev, S.,& White, D. (2015). **tripack**: Triangulation of Irregularly Spaced Data. R package version 1.3-7. `https://CRAN.R-project.org/package=tripack`.

Appendix

A *Sphere of influence* (SOI) graph

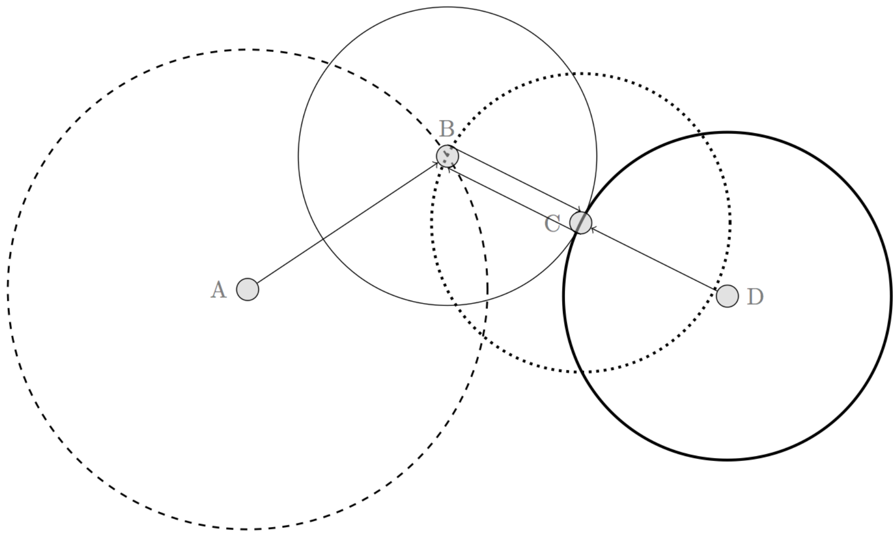

Figure 3: *Sphere of influence* graph (source: Stewart & Zhukov, 2010, p. 7)

Adapted from Stewart & Zhukov (2010), countries are considered *sphere of influence* neighbors whenever the circles around each country's polygon centroid (i.e., the nodes in the graph) overlap in two points. In this simplified example, country A is considered a neighbor of countries B and C, B is a neighbor of countries A and C, C is a neighbor of countries A, B and D, while D is a neighbor of C.

B Spatial regression results for Lee & Yu (2010) correction

Table 5: Regression estimates

	Dependent variable: Directed trade flows (ln)			
	Fixed effects: Lee &Yu (2010)			
Determinants	(1)	(2)	(3)	(4)
$\ln GDP_i$	0.524***	0.499***	0.483***	0.526***
	(0.082)	(0.083)	(0.083)	(0.083)
$\ln GDP_j$	0.528***	0.591***	0.536***	0.595***
	(0.083)	(0.083)	(0.082)	(0.083)
RTA_{ij}	−0.009	−0.035	−0.023	−0.028
	(0.069)	(0.069)	(0.069)	(0.070)
$\rho_o W_o$	0.158***			
	(0.020)			
$\rho_d W_d$		0.090***		
		(0.020)		
$\rho_{o+d} W_{o+d}$			0.218***	
			(0.027)	
$\rho_{od} W_{od}$				0.043
				(0.027)

Notes: Standard errors in parentheses.
Time dummies and intercept not reported.
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

C Impact estimates for random effects models (1)-(4)

Table 6: Impact estimates for random effects models

	Direct effects				*Indirect effects*				*Total effects*			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
$\ln GDP_i$	0.944***	0.873***	0.857***	0.966***	0.215***	0.179***	0.391***	0.039***	1.160***	1.053***	1.248***	1.006***
	(56.526)	(53.012)	(52.705)	(56.979)	(10.365)	(9.554)	(10.632)	(2.177)	(39.121)	(37.888)	(28.240)	(39.288)
$\ln GDP_j$	0.799***	0.883***	0.796***	0.897***	0.182***	0.181***	0.364***	0.037***	0.981***	1.064***	1.160***	0.934***
	(49.350)	(54.800)	(50.026)	(53.994)	(10.390)	(9.607)	(10.665)	(2.181)	(36.903)	(38.870)	(28.056)	(38.609)
RTA_{ij}	0.190***	0.166***	0.164***	0.185**	0.043***	0.034***	0.075***	0.008*	0.233***	0.200***	0.239***	0.193***
	(3.398)	(3.078)	(2.951)	(3.279)	(3.226)	(2.856)	(2.762)	(1.654)	(3.392)	(3.061)	(2.914)	(3.255)
$\ln GDP_{ij}$	−0.783***	−0.813***	−0.663***	−0.920***	−0.178***	−0.167***	−0.303***	−0.038***	−0.961***	−0.980***	−0.965***	−0.957***
	(−21.072)	(−22.167)	(−18.257)	(−24.367)	(−9.420)	(−8.767)	(−9.179)	(−2.158)	(−19.567)	(−20.293)	(−15.820)	(−21.989)
ADJ_{ij}	0.925***	0.891***	1.005***	0.801***	0.211***	0.183***	0.459***	0.033***	1.136***	1.073***	1.464***	0.834***
	(6.651)	(6.387)	(7.418)	(5.624)	(5.646)	(5.390)	(6.234)	(2.034)	(6.609)	(6.361)	(7.300)	(5.612)
$LANG_{ij}$	0.832***	0.824***	0.844***	0.830***	0.1902***	0.169***	0.385***	0.034***	1.022***	0.993***	1.229***	0.863***
	(9.878)	(9.344)	(10.280)	(9.626)	(6.978)	(6.571)	(7.596)	(2.133)	(9.609)	(9.141)	(9.923)	(9.538)

Notes: Simulated z-values in parentheses. Simulated $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.
Models (1) $\rho_d = \rho_{od} = 0$, (2) $\rho_o = \rho_{od} = 0$, (3) $\rho_o = \rho_d$ and $\rho_{od} = 0$, (4) $\rho_o = \rho_d = 0$.