FDI in Space Revisited: The Role of Spillovers on Foreign Direct Investment within the European Union

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ABSTRACT We estimate a spatial econometric interaction model for bilateral aggregate FDI stock data between 25 European Union member countries in 2010. We find evidence for spatial spillovers of foreign direct investment for three different types of spatial dependence. Our results document FDI spillovers between neighboring countries of FDI origin countries, neighboring countries of FDI destination countries as well as between neighboring countries of both FDI origin and destination countries. Relying on recently developed methods, we provide the first model-consistent interpretation of marginal effects of market size (measured by GDP) as well as GDP per capita on bilateral FDI activity. Our research highlights the importance of taking into account spatial lags when estimating bilateral FDI gravity models.

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Introduction

This paper contributes to the literature on the determinants of foreign direct investment (FDI) that empirically analyzes the existence and magnitude of spillovers (indirect or network effects) of FDI activity on third countries' FDI. We study the effect of FDI spillovers for the case of the European Union (EU). The EU is the best example of deeply integrated countries and one of the world's largest trading blocs. The high level of economic integration between EU member countries makes the existence of FDI spillovers especially likely, providing an ideal testing ground. Our main hypothesis is that the attractiveness of an EU country for FDI increases the attractiveness of neighboring countries for EU investors, fostering economic activity. Therefore, FDI spillovers are expected to present a positive impact on neighboring countries' foreign investments. In terms of methodology, we use a spatial econometric interaction model following LeSage and Thomas-Agnan (2015). This model allows to detect the existence of FDI spillovers between neighbors of FDI origin countries, neighbors of FDI destination countries, as well as spillovers between neighbors of both the origin and destination countries of FDI. Our spatial matrices are based on both first-order contiguity and nearest neighbors of EU countries. We estimate our model by a Bayesian Markov Chain Monte Carlo (MCMC) procedure. We find that origin-dependence, destination-dependence and origin-destination (O-D) dependence matter for FDI. Finally, we quantify the EU-wide long-run network effects using the scalar summary measures recently proposed by LeSage and Thomas-Agnan (2015). This method also allows us to make statements about the statistical significance of spatial spillover effects.

The previous literature considers two different ways to analyze the existence and magnitude of FDI spillovers between countries using spatial approaches. Firstly, FDI spillovers are measured through weighting matrices that determine the effect of characteristics of neighboring third countries on FDI, i.e., using spatial lags of the regressors. Hence, bilateral flows or stocks of FDI do not only depend on characteristics of the specific two countries in question but also on third countries. For example, Baltagi et al. (2007) study bilateral US outward FDI stocks and foreign affiliate sales at the industry level in a model which includes spatially weighted averages of third-country characteristics as determinants of FDI as well as spatial interactions in the error term. Their results support the importance of third-country effects. Similarly, Badinger and Egger (2013) estimate a gravity model of bilateral FDI stocks for 22 European OECD countries and include spatially weighted averages of market-sizes in neighboring origin and destination countries as additional regressors to allow for market-size related interactions while also allowing for spatial interactions in the error term.

Secondly, FDI spillovers to third countries can be modeled by including spatial lags of FDI itself, i.e., of the dependent variable, to measure spatial origin or destination dependence. This is done by, e.g., Coughlin and Segev (2000), Blonigen et al. (2007) and Leibrecht and Riedl (2014).

To the best of our knowledge, Coughlin and Segev (2000) were the first authors to consider spatial interactions for modeling FDI determinants. They use provincial data from China to analyze whether neighboring provinces can affect one another in terms of FDI, as an agglomeration effect might lead to higher FDI levels in neighboring provinces. Also, FDI in one province might negatively affect FDI in neighboring provinces if province-specific advantages attract FDI to a particular province rather than to its neighbors. Their study highlights the importance of taking into account spatial dependence for consistent parameter estimates and inference. Blonigen et al. (2007) focus on US outbound FDI and show that the traditional determinants of FDI and the estimated spatial interdependence are sensitive to the countries under study. They estimate a gravity-type model that considers spatially-dependent FDI by introducing a spatial autoregressive term which is found to be positive and statistically significant, pointing towards the agglomeration effect stated by Coughlin and Segev (2000). The importance of considering indirect effects when analyzing the determinants of FDI is illustrated in the following quotation: *"MNE [multinational enterprises] motivations may generate important spatial relationships in the data that may not be adequately controlled for using standard econometric techniques on bilateral-country pairs. The remaining analysis below provides evidence for the degree of bias from ignor-*

ing spatial interdependence of FDI decisions" (See Blonigen et al., 2007:1308).

In this line, Leibrecht and Riedl (2014) study the presence of spatial interdependencies in FDI between origin and destination countries. They model FDI flows from advanced OECD countries to Central and Eastern European Countries (CEECs) using a spatial autoregressive model with two spatial lags, one for FDI origin countries and one for FDI destination countries. They find that a CEEC receives more FDI the more FDI a neighboring CEEC is able to attract and that agglomeration forces are becoming increasingly important for FDI in the CEECs.

The remainder of the paper is structured as follows: Section 2 describes how to measure FDI spillovers in an O-D interaction framework. The estimation strategy and data are presented in Section 3. The estimation results of the coefficients and the construction of scalar summary measures to quantify FDI spillovers are presented in Sections 4 and 5, respectively. Section 6 concludes.

Measuring FDI Spillovers Using A Spatial Econometric Interaction Model

Equation (1) shows a non-spatial gravity model to estimate the determinants of bilateral FDI stocks (or flows) from origin country o invested in destination country d typically used in the literature:

$$\begin{aligned} \ln FDI_{do} &= \beta_0 + \beta_1 \ln GDP_d + \beta_2 \ln(GDP/POP)_d + \\ &\quad \beta_3 \ln GDP_o + \beta_4 \ln(GDP/POP)_o + \beta_5 \ln DIST_{do} + e_{do}, \end{aligned} \tag{1}$$

where ln denotes the natural logarithm, GDP_o and GDP_d are the GDP in the origin and destination country, and POP_o and POP_d are the populations in the respective countries, i.e., GDP_o/POP_o denotes GDP per capita of the origin country. $DIST_{do}$ measures the distance between countries d and o and e_{do} is the error term.

Destination and origin GDPs are typically included to proxy the size of the respective economies. The larger an economy, the higher its potential for outward and inward FDI. Hence, we expect the coefficients of GDP to be positive, consistent with Coughlin and Segev (2000). As wealthier countries tend to invest in poorer countries, we expect the coefficients of origin GDP per capita to have a positive sign and destination GDP per capita to have a negative sign, similar to results found in Blonigen et al. (2007) and Márquez-Ramos (2011).[1] As GDP per capita proxies real wages, this argument is in line with vertical FDI motives, i.e., investors seek to take advantage of wage differences. However, horizontal FDI, i.e., market-seeking FDI, would imply a positive impact of destination GDP per capita. Hence, the effect of GDP per capita is ambiguous, see Bénassy-Quéré et al. (2007). In the end, it is an empirical question which of these two factors is more important for EU countries. Finally, we expect distance to have a negative impact on bilateral FDI, in line with, e.g., Blonigen and Davies (2004), Blonigen et al. (2007) and Badinger and Egger (2013).

FDI stocks are georeferenced data, i.e., they can be linked to specific countries on the world map. Therefore, it seems natural to investigate whether FDI values are spatially correlated. There are three possible types of spatial correlation between countries when analyzing bilateral FDI activity: origin, destination and origin-destination dependence. To get an intuition for these three possible types, consider Figure 1. It presents four countries, I, J, K and L. I and K are neighbors, and so are J and L. Let us focus on the determinants of the investment of country I in J.

Non-spatial bilateral models such as Equation (1) only consider the red, dashed arrow, i.e., only take into account determinants located in both I and J. Spatial interaction models also take into account the three additional blue, undashed arrows. Investments of I in J also depend on investments of K in J (origin dependence). In addition, investments of I in J also depend on investments of I in L (destination dependence). Finally, investments of I in J also depend on investments of K in L (origin-destination dependence), possibly due to complex FDI motives or general equilibrium effects.

Spatial interaction models focus on dyads of countries rather than on individual countries. They aim to explain the variation of spatial interaction across geographic space and draw attention to the three types of neighborhood effects introduced above: those related to properties of neighbors of origin countries, those related to properties of neighbors of destination countries and those related to

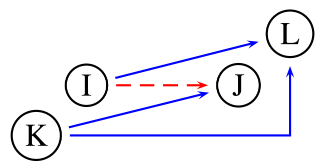

FIGURE 1: ILLUSTRATION OF POTENTIAL ORIGIN-DESTINATION INTERACTIONS

the spatial interactions between neighbors of origin and neighbors of destination countries.

For spatial econometric interaction models, it is useful to switch from an observation based notation as in Equation (1) to a data matrix notation. Following LeSage and Pace (2008) and LeSage and Thomas-Agnan (2015), let us define $\mathbf{Y}$, a $n \times n$ matrix, with typical element Y_{ij} in row i and column j which represents the (log of) the FDI stock of country j invested in country i (origin-centric flow matrix). We can reshape $\mathbf{Y}$ into a $n^2 \times 1$ vector $\ln \mathbf{FDI} = vec(\mathbf{Y})$, i.e., we obtain an origin-centric ordering of our dependent variable. $\ln \mathbf{FDI}$ contains the vertically concatenated columns of $\mathbf{Y}$, i.e., in the first n observations, $\ln \mathbf{FDI}$ contains the FDI stocks from origin country 1 in all n destinations, and so on.

We construct three matrices that specify destination-dependence, origin-dependence and origin-destination dependence which allow us to include three types of spatial lags to consider spatial FDI spillovers in the following model:

$$\begin{aligned} \ln \mathbf{FDI} &= \beta_0 + \beta_1 \ln \mathbf{GDP}_d + \beta_2 \ln (\mathbf{GDP}/\mathbf{POP})_d + \\ & \beta_3 \ln \mathbf{GDP}_o + \beta_4 \ln (\mathbf{GDP}/\mathbf{POP})_o + \\ & \beta_5 \ln \mathbf{DIST} + \rho_1 \mathbf{B}_d \ln \mathbf{FDI} + \rho_2 \mathbf{B}_o \ln \mathbf{FDI} + \\ & \rho_3 \mathbf{B}_w \ln \mathbf{FDI} + \mathbf{e}, \end{aligned} \tag{2}$$

where variables in bold are the stacked matrix equivalents (origin-centric ordering) from Equation (1).[2] The difference to Equation (1) comes from the inclusion of three spatial lag terms: $\rho_1 \mathbf{B}_d \ln \mathbf{FDI}$, $\rho_2 \mathbf{B}_o \ln \mathbf{FDI}$ and $\rho_3 \mathbf{B}_w \ln \mathbf{FDI}$. The spatial lag vector $\mathbf{B}_d \ln \mathbf{FDI}$ is constructed by averaging FDI stocks in neighbors of the destination country (destination dependence) and parameter ρ_1 would measure the impact of FDI stocks from origin to all neighbors of the destination country. The spatial lag vector $\mathbf{B}_o \ln \mathbf{FDI}$ is constructed by averaging FDI stocks from neighbors to the origin country (origin dependence) and parameter ρ_2 would capture the impact of these neighbors on the dependent variable. The third spatial lag in the model, $\mathbf{B}_w \ln \mathbf{FDI}$, is constructed by using an average of all neighbors to both the origin and destination countries (origin-destination dependence) and parameter ρ_3 measures the impact of this type of interaction on FDI stocks. The spatial weight matrices $\mathbf{B}_d$, $\mathbf{B}_o$ and $\mathbf{B}_w$ specify the neighborhood definitions for the calculation of the aforementioned averages. Estimating parameters ρ_1, ρ_2 and ρ_3 allows to infer the relative importance of the three types of spatial dependence between the origin and destination countries.

We will use two neighborhood definitions in this paper: one based on sharing a common border and one which defines the k nearest countries to be neighbors. We will use these definitions to specify the spatial weight matrices $\mathbf{B}_d$, $\mathbf{B}_o$ and $\mathbf{B}_w$ for the contiguity criterion and $\mathbf{D}_d$, $\mathbf{D}_o$ and $\mathbf{D}_w$ for the nearest neighbor criterion.

For this, we introduce a spatial contiguity matrix $\tilde{\mathbf{B}}$ with dimensions $n \times n$, where n is the number of countries. We define its typical entry in row i and column j, $\tilde{b}_{ij}$, as follows:

$$\tilde{b}_{ij} = \begin{cases} 1 & \text{if } i \text{ and } j \text{ share a common border} \\ 0 & \text{if } i \text{ and } j \text{ do not share a common border or } i = j. \end{cases} \tag{3}$$

As $\mathbf{B}$ will be used to measure the spatial spillovers across neighboring observations, the main diagonal of $\tilde{\mathbf{B}}$ is set to 0, i.e., a country does not exert an influence on itself. Dividing each row of $\tilde{\mathbf{B}}$ by the respective row sum yields $\mathbf{B}$, a row-normalized contiguity matrix, as is common in spatial econometrics, see, e.g., LeSage and Pace (2009).

We use a four country example to illustrate. Table 1 shows the 4×4 matrix $\tilde{\mathbf{B}}$ for the four countries Austria, Spain, France and Italy. The corresponding element of the matrix takes the value of 1 when countries are neighbors, and zero otherwise. The diagonal elements of the matrix $\tilde{\mathbf{B}}$ are set to zero.

TABLE 1: ILLUSTRATION OF MATRIX $\tilde{\mathbf{B}}$

	Austria	Spain	France	Italy
Austria	0	0	0	1
Spain	0	0	1	0
France	0	1	0	1
Italy	1	0	1	0

Similarly, we define a second measure of neighborhood by using a k nearest neighbors matrix. Specifically, for country i, we will rank all distances of i to all other countries and declare the k nearest countries to be a neighbor of i. Let us denote the distance of the k nearest neighbor to country i as $d_i^{(k)}$. Repeating this for all countries, we can collect this information in a matrix $\tilde{\mathbf{D}}$ with dimensions $n \times n$, where n is the number of countries. Its typical entry in row i and column j, $\tilde{d}_{ij}$, is given by:

$$\tilde{d}_{ij} = \begin{cases} 1 & \text{if the distance between } i \text{ and } j \text{ is} \leq d_i^{(k)} \\ 0 & \text{if the distance between } i \text{ and } j \text{ is} > d_i^{(k)} \text{ or } i = j. \end{cases} \tag{4}$$

Again, we set the main diagonal of $\tilde{\mathbf{D}}$ to 0, i.e., a country does not exert an influence on itself. Dividing each row of $\tilde{\mathbf{D}}$ by the respective row sum yields $\mathbf{D}$, a row-normalized matrix.

The following steps apply to both $\mathbf{B}$ and $\mathbf{D}$. For expositional reasons, we will continue to refer to $\mathbf{B}$ only.

Destination-based dependence captures the effect that FDI stocks from one origin country in a destination country may be correlated with the FDI stocks from the origin country in countries which are neighbors to the destination country. Denoting the first column of our origin-centric flow matrix by $\ln \mathbf{FDI}_1$, i.e., the FDI stocks from origin country 1, we can construct the spatial lag $\mathbf{B} \ln \mathbf{FDI}_1$, which is a spatial average of the FDI stocks from country 1 in all neighboring destinations. Similarly, we can construct the same spatial lag for origin country

2, $\mathbf{B}\ln\mathbf{FDI}_2$. We can do this for all n origin countries. In matrix notation, this operation can be represented by the $n^2 \times n^2$ matrix $\mathbf{B}_d$:

$$\mathbf{B}_d = \mathbf{I}_n \otimes \mathbf{B} = \begin{pmatrix} \mathbf{B} & \mathbf{0}_n & \dots & & \mathbf{0}_n \\ \mathbf{0}_n & \mathbf{B} & & & \vdots \\ \vdots & & \mathbf{B} & & \\ & & & \ddots & \\ \mathbf{0}_n & & \dots & & \mathbf{B} \end{pmatrix}. \tag{5}$$

where $\otimes$ denotes the Kronecker product, $\mathbf{I}_n$ is a $n \times n$ identity matrix and $\mathbf{0}_n$ is a $n \times n$ matrix of zeros.

In a similar fashion, we can define $\mathbf{B}_o$, a $n^2 \times n^2$ matrix, to construct a spatial lag of the dependent variable for all FDI stocks invested by neighboring countries of the origin country, thus capturing origin-based dependence. $\mathbf{B}_o$ is calculated as:

$$\mathbf{B}_o = \mathbf{B} \otimes \mathbf{I}_n. \tag{6}$$

Finally, we can construct a measure of spatial origin-to-destination dependence. It measures the spatial correlation between FDI stocks from countries which are neighbors to the origin country to countries which are neighbors of the destination country. We measure this dependence by $\mathbf{B}_w$ in the following way:

$$\mathbf{B}_w = \mathbf{B}_o\mathbf{B}_d = \mathbf{B} \otimes \mathbf{B}. \tag{7}$$

We show these amplified weight matrices $\mathbf{B}_d$, $\mathbf{B}_o$ and $\mathbf{B}_w$ for our four-country example in Figures 2 to 4. The interpretation of Figure 2 is that, for example, destination-based dependence measures whether foreign direct investment from Spain to Austria is related to foreign direct investment from Spain to the countries that have a common border with Austria, i.e., Italy. The value of the spatially lagged dependent variable for FDI from Spain to Austria is given by:

$$[\mathbf{B}_d \ln\mathbf{FDI}]_{\textit{Spain, Austria}} = 1 \times \ln\mathbf{FDI}_{\textit{Spain, Italy}}, \tag{8}$$

which is a weighted average over the values of foreign direct investment from Spain for all neighboring countries of the destination country Austria. Note that

origin	destination	spatial flow matrix ($\mathbf{B}_d$)																ln $FDI_{origin, destination}$
Austria	Austria	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	$Y_{Austria, Austria}$
Austria	Spain	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	$Y_{Austria, Spain}$
Austria	France	0	0.5	0	0.5	0	0	0	0	0	0	0	0	0	0	0	0	$Y_{Austria, France}$
Austria	Italy	0.5	0	0.5	0	0	0	0	0	0	0	0	0	0	0	0	0	$Y_{Austria, Italy}$
Spain	**Austria**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**1**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	$\mathbf{Y_{Spain, Austria}}$
Spain	Spain	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	$Y_{Spain, Spain}$
Spain	France	0	0	0	0	0	0.5	0	0.5	0	0	0	0	0	0	0	0	$Y_{Spain, France}$
Spain	Italy	0	0	0	0	0.5	0	0.5	0	0	0	0	0	0	0	0	0	$Y_{Spain, Italy}$
France	Austria	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	$Y_{France, Austria}$
France	Spain	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	$Y_{France, Spain}$
France	France	0	0	0	0	0	0	0	0	0	0.5	0	0.5	0	0	0	0	$Y_{France, France}$
France	Italy	0	0	0	0	0	0	0	0	0.5	0	0.5	0	0	0	0	0	$Y_{France, Italy}$
Italy	Austria	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	$Y_{Italy Austria}$
Italy	Spain	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	$Y_{Italy, Spain}$
Italy	France	0	0	0	0	0	0	0	0	0	0	0	0	0	0.5	0	0.5	$Y_{Italy, France}$
Italy	Italy	0	0	0	0	0	0	0	0	0	0	0	0	0.5	0	0.5	0	$Y_{Italy, Italy}$

FIGURE 2: AMPLIFIED WEIGHT MATRIX TIMES THE DEPENDENT VARIABLE, $\mathbf{B}_d \ln \mathbf{FDI}$.

origin	destination	spatial flow matrix ($\mathbf{B}_o$)																ln $FDI_{origin, destination}$
Austria	Austria	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	$Y_{Austria, Austria}$
Austria	Spain	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	$Y_{Austria, Spain}$
Austria	France	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	$Y_{Austria, France}$
Austria	Italy	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	$Y_{Austria, Italy}$
Spain	**Austria**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**1**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	$\mathbf{Y_{Spain, Austria}}$
Spain	Spain	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	$Y_{Spain, Spain}$
Spain	France	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	$Y_{Spain, France}$
Spain	Italy	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	$Y_{Spain, Italy}$
France	Austria	0	0	0	0	0.5	0	0	0	0	0	0	0	0.5	0	0	0	$Y_{France, Austria}$
France	Spain	0	0	0	0	0	0.5	0	0	0	0	0	0	0	0.5	0	0	$Y_{France, Spain}$
France	France	0	0	0	0	0	0	0.5	0	0	0	0	0	0	0	0.5	0	$Y_{France, France}$
France	Italy	0	0	0	0	0	0	0	0.5	0	0	0	0	0	0	0	0.5	$Y_{France, Italy}$
Italy	Austria	0.5	0	0	0	0	0	0	0	0.5	0	0	0	0	0	0	0	$Y_{Italy, Austria}$
Italy	Spain	0	0.5	0	0	0	0	0	0	0	0.5	0	0	0	0	0	0	$Y_{Italy, Spain}$
Italy	France	0	0	0.5	0	0	0	0	0	0	0	0.5	0	0	0	0	0	$Y_{Italy, France}$
Italy	Italy	0	0	0	0.5	0	0	0	0	0	0	0	0.5	0	0	0	0	$Y_{Italy, Italy}$

FIGURE 3: AMPLIFIED WEIGHT MATRIX TIMES THE DEPENDENT VARIABLE, $\mathbf{B}_o \ln \mathbf{FDI}$.

the spatial weight of the lagged dependent variable is equal to one because, in our example, Italy is the only neighbor of Austria.

According to Figure 3, origin-based dependence measures whether foreign direct investment from Spain in Austria is related to the foreign direct investment in Austria from countries that have a common border with Spain (i.e., France). Hence, the value of the spatially lagged dependent variable, $\mathbf{B}_o \ln \mathbf{FDI}$, for FDI from Spain to Austria is given by:

$$[\mathbf{B}_o \ln \mathbf{FDI}]_{\textit{Spain, Austria}} = 1 \times \ln \mathbf{FDI}_{\textit{France, Austria}}, \tag{9}$$

which is a weighted average over the values of foreign direct investment into Austria from all neighboring countries of the origin country Spain. Note that the spatial weight of the lagged dependent variable is again equal to one because, in our example, France is the only neighbor of Spain.

According to Figure 4, the foreign direct investment from Spain to Austria is related to foreign direct investment from countries that have a common border with Spain to countries that have a common border with Austria, i.e., investments from France to Italy. Hence, the value of the spatially lagged dependent variable, $\mathbf{B}_w \ln \mathbf{FDI}$, for FDI from Spain to Austria is given by:

$$[\mathbf{B}_w \ln \mathbf{FDI}]_{\textit{Spain, Austria}} = 1 \times \ln \mathbf{FDI}_{\textit{France, Italy}}, \tag{10}$$

which is a weighted average over the values of foreign direct investment into neighboring countries of Austria from all neighboring countries of Spain. Note that the spatial weight of the lagged dependent variable is again equal to one because, in our example, France is the only neighbor of Spain and Italy is the only neighbor of Austria.

Estimation Strategy and Data

We use a Bayesian MCMC approach following LeSage and Thomas-Agnan (2015) to estimate the spatial interaction model given in Equation (2).[3] We generate 6,000 draws where we throw away the first 3,000 to get rid of the dependence

origin	destination	spatial flow matrix ($\mathbf{B}_w$)																ln $FDI_{origin, destination}$
Austria	Austria	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	$Y_{Austria, Austria}$
Austria	Spain	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	$Y_{Austria, Spain}$
Austria	France	0	0	0	0	0	0	0	0	0	0	0	0	0	0.5	0	0.5	$Y_{Austria, France}$
Austria	Italy	0	0	0	0	0	0	0	0	0	0	0	0	0.5	0	0.5	0	$Y_{Austria, Italy}$
Spain	**Austria**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**1**	**0**	**0**	**0**	**0**	$\mathbf{Y_{Spain, Austria}}$
Spain	Spain	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	$Y_{Spain, Spain}$
Spain	France	0	0	0	0	0	0	0	0	0	0.5	0	0.5	0	0	0	0	$Y_{Spain, France}$
Spain	Italy	0	0	0	0	0	0	0	0	0.5	0	0.5	0	0	0	0	0	$Y_{Spain, Italy}$
France	Austria	0	0	0	0	0	0	0	0.5	0	0	0	0	0	0	0	0.5	$Y_{France, Austria}$
France	Spain	0	0	0	0	0	0	0.5	0	0	0	0	0	0	0	0.5	0	$Y_{France, Spain}$
France	France	0	0	0	0	0	0.25	0	0.25	0	0	0	0	0	0.25	0	0.25	$Y_{France, France}$
France	Italy	0	0	0	0	0.25	0	0.25	0	0	0	0	0	0.25	0	0.25	0	$Y_{France, Italy}$
Italy	Austria	0	0	0	0.5	0	0	0	0	0	0	0	0.5	0	0	0	0	$Y_{Italy, Austria}$
Italy	Spain	0	0	0.5	0	0	0	0	0	0	0	0.5	0	0	0	0	0	$Y_{Italy, Spain}$
Italy	France	0	0.25	0	0.25	0	0	0	0	0	0.25	0	0.25	0	0	0	0	$Y_{Italy, France}$
Italy	Italy	0.25	0	0.25	0	0	0	0	0	0.25	0	0.25	0	0	0	0	0	$Y_{Italy, Italy}$

FIGURE 4: AMPLIFIED WEIGHT MATRIX TIMES THE DEPENDENT VARIABLE, $\mathbf{B}_w \ln \mathbf{FDI}$.

of the Markov chain on the starting values. For comparison, we also estimate the non-spatial model given in Equation (1) using ordinary least squares.

We use data on bilateral stocks of FDI from UNCTAD for 25 EU member countries for the year 2010.[4] FDI stock data have the advantage that they are less volatile than FDI flow data, see Bénassy-Quéré et al. (2007). Bilateral FDI data are characterized by differences in reporting standards across countries as well as discrepancies between FDI statistics for inward and outward FDI activity, see, e.g., Weigl and Fujita (2003). We use bilateral inward FDI stock data from UNCTAD's bilateral FDI statistics. For 25 countries, we should observe $25 \times 24 =$ 600 observations of bilateral FDI stocks. Of these, 103 observations are missing. We therefore follow the strategy used by Barthel et al. (2010) and Badinger and Egger (2013) who use both data on inward and outward FDI stocks (so-called "mirror statistics") to fill up missing values. This allows us to fill up 88 missing values. In total, of the non-missing observations, 24 are negative. If we observe positive outward FDI stocks, we replace 0 or negative inward FDI stocks with their corresponding outward FDI stocks. After this, we end up with 14 negative inward FDI stocks, 45 FDI stocks which are zero as well as 15 genuinely missing values. As we use a log-linear model, we replace these 14+45+15 = 74 observations with the value 1.

Another reason for missing observations is the fact that even though the spatial econometric model also applies to the FDI stock from i in i, i.e., the direct investment of country i in itself, UNCTAD's data base on FDI stocks by definition only includes *foreign* direct investment. To the best of our knowledge, the ii observations for spatial FDI models have not been used previously in the spatial FDI literature. However, it is common in other spatial econometric studies. For example, in their study of commuter flows in Toulouse, France, LeSage and Thomas-Agnan (2015) also include flows of commuters who work in the same district where they live.[5] This raises the question of how to measure domestic investments. We propose the following measure. We use data on national capital stocks, $CAPITAL_i$, from the Penn World Tables 8.1.[6] We then construct our measure of domestically sourced capital, FDI_{ii}, by subtracting the sum of foreign direct investment stocks from all source countries different than i, i.e., $FDI_{ii} = CAPITAL_i - \sum_{j,j \neq i} FDI_{ij}$. Obviously, this measure is not without difficulties. As our sample only includes 25 countries from the European Union, we count as domestic capital stock also FDI stocks which come from countries outside the EU. Hence, we overstate the level of FDI_{ii}. If anything, this will probably overestimate the negative impact of distance on bilateral FDI stocks as well as the intranational effects calculations. Still, we think that including a measure for FDI_{ii} is at least an improvement over simply filling up the dependent variable for the ii observations with 1s or dropping them altogether. By using our constructed measure of FDI_{ii} we get 25 additional observations for our data set.[7]

For our regressors, we use GDP (current US$) and population data from the World Development Indicators from the World Bank. Our distance and contiguity measures are from Centre d'études prospectives et d'informations internationales (CEPII).

Coefficient Estimates

Column (1) of Table 2 displays the results of estimating the baseline FDI regression by ordinary least squares, i.e., Equation (1). The estimated coefficients obtained for destination and origin GDP are positive and significant. The effect of GDP per capita of the FDI origin country is positive and significant, whereas the coefficient of GDP per capita of the destination country is negative and not significant, as well as smaller in absolute magnitude than its source country counterpart. Distance has a negative effect on FDI stocks. Columns (2) and (3) show the results of estimating Equation (2) by the Bayesian MCMC algorithm, where column (2) presents the results for the weight matrices using the contiguity criterion ($\mathbf{B}_d$, $\mathbf{B}_o$, $\mathbf{B}_w$) and column (3) for the weight matrices using the four nearest neighbors matrix ($\mathbf{D}_d$, $\mathbf{D}_o$, $\mathbf{D}_w$). Beginning with column (2), the estimated coefficients obtained for destination and origin GDP are positive and significant, as obtained in the baseline model, but smaller in magnitude. Interestingly, when controlling for spatial FDI spillovers, the negative effect of GDP per capita of the destination country turns significant. The coefficient of GDP per capita of the origin country, in contrast, now turns negative and not significant. This highlights the potential bias when neglecting spatial spillover effects, which we detect by the significant estimates of the spatial lags. Destination and origin dependence have a positive effect on FDI stocks among EU member states, and also the coefficient for origin-destination dependence is found to be positive and significant. The coefficient for the distance variable is negative and closer to zero than when estimating by ordinary least squares. This result is in line with LeSage and Thomas-Agnan (2015) who also find that the importance of geographical distance diminishes after taking spatial dependence into account. It suggests that distance may be acting as a proxy for spatial dependence, or that spatial dependence plays a role similar to that of distance in non-spatial models.

Turning to column (3), i.e., the spatial interaction model where we use the four nearest neighbor countries to define neighborhood, results change only slightly. The coefficients of GDP in the destination and origin country remain quite similar, both in terms of magnitude and significance. GDP per capita in the destination country also exerts a significant and negative effect on bilateral FDI stocks, while the effect of GDP per capita in the origin country turns positive but is still not significant. The coefficient of distance has an intermediate value between the least squares estimate from column (1) and the estimate from column (2). Turning to the spatial dependence measures, we find larger coefficients for destination and origin dependence but now origin-destination dependence is no longer significant.[8]

Summing up, our results are consistent with origin-, destination- and, at least in one specification, origin-destination-dependence for FDI stocks. Until now, we have only described the estimated coefficients of the spatial interaction model. Policy makers or researchers, however, are mostly interested in the interpretation of marginal effects, i.e., how do FDI stocks change if a regressor changes? As stressed by LeSage and Thomas-Agnan (2015), the coefficients of a spatial model are not identical to the marginal effects of interest, as the coefficients do not take into account the changes in neighboring observations in the sample.[9] Instead, marginal effects vary across all country pairs. Therefore, we turn to the calculation of scalar summary measures of the marginal effects in the following section.

Scalar Summary Effects Estimates for GDP and GDP per capita

In the non-spatial model given in Equation (1), the parameter β_1 is interpreted as a partial derivative reflecting the impact of changes in GDP at the destination and β_3 is associated to a change in GDP at the origin of the FDI stocks. A similar interpretation for GDP per capita holds for β_2 and β_4. As LeSage and Thomas-Agnan (2015) point out, although the conventional approach of interpreting the coefficient sum $\beta_1 + \beta_3$ as a measure of the total effect on FDI arising from changes in origin and destination GDP is correct ($\beta_2 + \beta_4$ for the case of GDP per capita), the approach of LeSage and Thomas-Agnan (2015) allows us to decompose the total effect into origin, destination and intracountry effects.

In the case of spatial interaction models, the change in the characteristics of a single country can impact foreign direct investment into and out of this country to its partners, but also FDI into and out of its neighbors and neighbors of its destination country that are not part of the dyad. Then, four different effects can be distinguished: origin effect (OE), destination effect (DE), intracountry effect (IE) and network effect (NE). Spatial models differ from non-spatial models by the inclusion of network effects. For example, a change in GDP of country i may not only affect FDI from and into country i but may also affect neighboring countries within the sample of n countries in the long-run; the strength of this effect is measured by the network effects.

Let us now explain how to calculate the four different effects. First, the OE represents the effect in the dependent variable of a change in the rth explanatory variable of the origin country in the O-D dyad. Second, the DE refers to the change in the dependent variable as a consequence of a change in the rth explanatory variable of the destination country. The IE measures how changes in the rth explanatory variable of country i affect investments from i in i (i.e., domestic investments). The OE, DE and IE can be interpreted as short-run effects. In the long-run, a change in the rth explanatory variable in i will ripple through the whole sample through the neighborhood interactions, not only for those dyads where i

TABLE 2: COEFFICIENT ESTIMATES

	(1)	(2)	(3)
	non-spatial	**B**	**D**
	Least Squares	Bayesian MCMC	Bayesian MCMC
CONSTANT	-40.446***	-14.444***	-17.151***
	(3.099)	(2.979)	(3.526)
$\ln GDP_d$	0.776***	0.436***	0.440***
	(0.075)	(0.090)	(0.095)
$\ln(GDP/POP)_d$	-0.312	-0.651***	-0.537***
	(0.195)	(0.188)	(0.197)
$\ln GDP_o$	0.936***	0.420***	0.348***
	(0.071)	(0.087)	(0.095)
$\ln(GDP/POP)_o$	2.049***	-0.155	0.179
	(0.181)	(0.180)	(0.193)
$\ln(DIST)_{do}$	-2.343***	-0.691***	-0.925***
	(0.229)	(0.153)	(0.165)
$\mathbf{B}_d \ln \mathbf{FDI}$		0.368***	
		(0.039)	
$\mathbf{B}_o \ln \mathbf{FDI}$		0.313***	
		(0.055)	
$\mathbf{B}_w \ln \mathbf{FDI}$		0.288***	
		(0.056)	
$\mathbf{D}_d \ln \mathbf{FDI}$			0.518***
			(0.053)
$\mathbf{D}_o \ln \mathbf{FDI}$			0.326***
			(0.065)
$\mathbf{D}_w \ln \mathbf{FDI}$			0.142
			(0.106)

Notes: Table reports coefficient estimates for the (non-)spatial regression model given in Equations (1) and (2). All models are estimated using 625 observations. Column (1) is estimated by least squares and reports robust standard errors in parenthesis. Columns (2) and (3) are estimated using a Bayesian MCMC estimator following LeSage and Thomas-Agnan (2015) and using 6,000 draws of which we throw away the first 3,000 for burn-in. In parenthesis, we report the standard deviation of the parameter draws. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. We calculate p-values for columns (2) and (3) by calculating an equivalent t-statistic and compare it to the according quantiles of the standard normal distribution.

is directly involved. These interactions not only occur between direct (first-order) neighbors, but also between neighbors of neighbors, etc. If the spatial model is stable, i.e., $\rho_1+\rho_2+\rho_3<1$, these effects will eventually peter out and the system will reach a new equilibrium in the long-run. The NE measures how FDI stocks would change across the whole sample due to these indirect spatial spillovers in the long-run if a regressor in a typical country changes, i.e., excluding the direct effects which are measured by OE, DE and IE.[10]

But what is the combined effect of these four components, i.e., how do all FDI stocks across all observations change with a change in the value of the regressor r of country i, x_i^r, in the long-run? The total effect (TE) answers this question. We can express TE for the non-spatial gravity model as the following partial derivative:

$$\begin{aligned}
\mathbf{TE}^{Non-spatial} &= \begin{pmatrix} \partial\mathbf{Y}/\partial\mathbf{X}_1^r \\ \vdots \\ \partial\mathbf{Y}/\partial\mathbf{X}_n^r \end{pmatrix} = \begin{pmatrix} \partial y_{11}/\partial x_1^r & \partial y_{12}/\partial x_1^r & \dots & \partial y_{1n}/\partial x_1^r \\ \partial y_{21}/\partial x_1^r & \partial y_{22}/\partial x_1^r & \dots & \vdots \\ \vdots & \ddots & & \vdots \\ \partial y_{n1}/\partial x_1^r & \dots & \dots & \partial y_{nn}/\partial x_1^r \\ \partial y_{11}/\partial x_2^r & \dots & \dots & \partial y_{1n}/\partial x_2^r \\ \partial y_{21}/\partial x_2^r & \ddots & & \vdots \\ \vdots & & \ddots & \vdots \\ \partial y_{n1}/\partial x_n^r & \dots & \dots & \partial y_{nn}/\partial x_n^r \end{pmatrix} \\
&= \begin{pmatrix} Jd_1\beta_d^r + Jo_1\beta_o^r \\ \vdots \\ Jd_n\beta_d^r + Jo_n\beta_o^r \end{pmatrix} \qquad (11)
\end{aligned}$$

In Equation (11), $\mathbf{Y}$ is the $n\times n$ matrix of bilateral (log) FDI stocks as defined above with typical entry y_{ij}, the foreign direct investment from country j in country i. $\mathbf{X}_i^r$ is given by $x_i^r\times\iota_n$, where x_i^r is the value of the rth regressor of country i, and ι_n is a $n\times 1$ vector of ones. Jd_i is a $n\times n$ matrix of zeros with the ith row equal to $\iota_n'\beta_d^r$, and Jo_i is an $n\times n$ matrix of zeros with the ith column equal to $\iota_n\beta_o^r$ (see LeSage and Thomas-Agnan, 2015).[11] There are n sets of $n\times n$ outcomes resulting in the $n^2\times n$ matrix $\mathbf{TE}^{Non-spatial}$ which contains the partial derivatives reflecting the total effect on FDI stocks from changing the rth explanatory variable of all n countries.

When we add spatial lags to the O-D model, LeSage and Thomas-Agnan (2015) show that the spatial total effects are calculated as:

$$\mathbf{TE} = \begin{pmatrix} \partial \mathbf{Y}/\partial \mathbf{X}_1^r \\ \vdots \\ \partial \mathbf{Y}/\partial \mathbf{X}_n^r \end{pmatrix} = \mathbf{A}^{-1} \begin{pmatrix} Jd_1\beta_d^r + Jo_1\beta_o^r \\ \vdots \\ Jd_n\beta_d^r + Jo_n\beta_o^r \end{pmatrix}, \tag{12}$$

where, in the case of the contiguity matrix defined above, $\mathbf{A} \equiv \mathbf{I}_{n^2} - \rho_1\mathbf{B}_d - \rho_2\mathbf{B}_o - \rho_3\mathbf{B}_w$. As can be seen, in the spatial model, the spatial dependence parameters and weight matrices now affect the total effect calculation. Hence, ignoring spatial dependence at the estimation stage leads to erroneous marginal effects interpretations and inferences.

The $n^2 \times n$ matrix of total effects can be condensed into a scalar summary measure. It takes the following form:

$$te = \frac{1}{n^2}\iota_{n^2}'\mathbf{TE}\iota_n. \tag{13}$$

This scalar summary measure can be interpreted in the same way as a marginal effect in a standard regression model. Specifically, it can be interpreted as the change in the dependent variable across the whole sample for a change in a regressor of a typical country in the long-run. In our application, it indicates how FDI stocks would change across the whole European Union (i.e., across *all* country-pairs) in the long-run if a regressor in a typical EU member country changes. When we replace $\mathbf{TE}$ by $\mathbf{TE}^{Non-spatial}$, we can calculate a similar scalar summary measure for the non-spatial model.

LeSage and Thomas-Agnan (2015) and LeSage (2014) show that the total effects can be decomposed into OE, DE, IE and, in the case of the spatial model, NE.[12] For every of these components, one can calculate similar scalar summary measures as for TE. We denote these by lower case letters. The effects are given by the following formulae:

$$\text{Origin effects:}\quad \mathbf{OE} = \mathbf{A}^{-1}\begin{pmatrix} \widetilde{Jo}_1\beta_o^r \\ \widetilde{Jo}_2\beta_o^r \\ \vdots \\ \widetilde{Jo}_n\beta_o^r \end{pmatrix}, \quad oe = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{1}{n}\sum_{k\neq i}\frac{\partial y_{ki}}{\partial x_i^r}\right),$$

$$\text{Destination effects:}\quad \mathbf{DE} = \mathbf{A}^{-1}\begin{pmatrix} \widetilde{Jd}_1\beta_d^r \\ \widetilde{Jd}_2\beta_d^r \\ \vdots \\ \widetilde{Jd}_n\beta_d^r \end{pmatrix}, \quad de = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{1}{n}\sum_{k\neq i}\frac{\partial y_{ik}}{\partial x_i^r}\right),$$

$$\text{Intracountry effects:}\quad \mathbf{IE} = \mathbf{A}^{-1}\begin{pmatrix} Ji_1(\beta_d^r+\beta_o^r) \\ Ji_2(\beta_d^r+\beta_o^r) \\ \vdots \\ Ji_n(\beta_d^r+\beta_o^r) \end{pmatrix}, \quad ie = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{1}{n}\sum_{k=i}\frac{\partial y_{kk}}{\partial x_i^r}\right),$$

$$\text{Network effects:}\quad \mathbf{NE} = \mathbf{TE} - \mathbf{OE} - \mathbf{DE} - \mathbf{IE}, \quad ne = te - oe - de - ie,$$

where $\widetilde{Jo}_i$ is the $n \times n$ matrix Jo_i but where we replace its ii element by 0, so that we exclude the intracountry effect, which we calculate separately. We adjust Jd_i in a similar way to get $\widetilde{Jd}_i$. From this it follows that Ji_i is a matrix of zeros but ones for the ii element.[13]

We cannot simply interpret the obtained coefficients of the origin and destination characteristics as marginal effects. Instead, we have to rely on the effects calculations laid out above, even though the model does not contain a spatial component. The reason is that the *ceteris paribus* condition needed for this interpretation does not hold: for example, when we change the origin GDP of a specific country by one percent, we simultaneously change GDP for all observations where this country acts as a destination. Hence, we cannot simply change one regressor in isolation. The calculations above take these simultaneous changes into account.

We can now calculate these effects for our estimated model of FDI stocks. Effects estimates are shown in Table 3 for the non-spatial model and in Table 4

TABLE 3: EFFECTS ESTIMATES FOR THE NON-SPATIAL AUTOREGRESSIVE INTERACTION MODEL

	Least-Squares				
	lower 0.05	mean	median	std. dev.	upper 0.95
Origin GDP	0.788	0.898	0.898	0.067	1.007
Destination GDP	0.622	0.746	0.747	0.072	0.860
Domestic (Intra) GDP	0.061	0.069	0.069	0.005	0.076
Network GDP	-0.000	-0.000	0.000	0.000	0.000
Total GDP	1.518	1.713	1.714	0.116	1.902
Origin GDP p.c.	1.686	1.973	1.972	0.176	2.263
Destination GDP p.c.	-0.611	-0.300	-0.298	0.188	0.014
Domestic (Intra) GDP p.c.	0.049	0.070	0.070	0.012	0.090
Network GDP p.c.	-0.000	-0.000	-0.000	0.000	0.000
Total GDP p.c.	1.224	1.743	1.748	0.311	2.253

Notes: Effects are calculated using the method by LeSage and Thomas-Agnan (2015) based on parameter estimates from column (1) of Table 2. Dispersion measures are calculated by a parametric bootstrap generating 3,000 draws from a multivariate normal distribution using as parameters the estimated coefficients and variance covariance matrix from column (1) of Table 2. "lower 0.05" denotes the 5 percent quantile of the effects calculated using the bootstrap parameter draws and "upper 0.95" the 95 percent quantile. "mean" denotes the mean of the draws, "median" their median and "std. dev." their standard deviation.

TABLE 4: EFFECTS ESTIMATES FOR THE SPATIAL AUTOREGRESSIVE INTERACTION MODEL USING A CONTIGUITY WEIGHTING MATRIX

	Spatial Autoregressive				
	lower 0.05	mean	median	std. dev.	upper 0.95
Origin GDP	1.942	3.100	3.024	0.792	4.499
Destination GDP	1.842	2.899	2.802	0.753	4.295
Domestic (Intra) GDP	0.138	0.206	0.201	0.047	0.289
Network GDP	15.319	25.359	24.332	7.318	38.492
Total GDP	19.488	31.563	30.364	8.792	47.301
Origin GDP p.c.	-3.680	-1.787	-1.781	1.148	0.105
Destination GDP p.c.	-5.678	-3.777	-3.688	1.134	-2.042
Domestic (Intra) GDP p.c.	-0.296	-0.188	-0.186	0.065	-0.085
Network GDP p.c.	-40.450	-25.320	-24.469	8.797	-12.258
Total GDP p.c.	-49.317	-31.072	-30.186	10.744	-15.026

Notes: Effects are calculated using the method by LeSage and Thomas-Agnan (2015) based on parameter estimates from column (2) of Table 2. "lower 0.05" denotes the 5 percent quantile of the effects calculated using the MCMC parameter draws and "upper 0.95" the 95 percent quantile. "mean" denotes the mean of the draws, "median" their median and "std. dev." their standard deviation.

Table 5: Comparison of Mean Effects

	GDP				
	oe	*de*	*ie*	*ne*	*te*
Non-spatial model	0.898	0.746	0.069	0.000	1.713
Spatial model using **B**	3.100	2.899	0.206	25.359	31.563
Spatial model using **D**	4.485	4.193	0.225	78.778	87.680
	GDP p. c.				
	oe	*de*	*ie*	*ne*	*te*
Non-spatial model	1.973	-0.300$^{n.s.}$	0.070	0.000	1.743
Spatial model using **B**	-1.787$^{n.s.}$	-3.777	-0.188	-25.320	-31.072
Spatial model using **D**	-1.717$^{n.s.}$	-3.438	-0.118$^{n.s.}$	-55.822	-61.094

Notes: Mean effects are calculated using the method by LeSage and Thomas-Agnan (2015) for the three estimated models from Table 2. *oe* denotes the origin-dependence scalar summary measure, *de* the destination-dependence scalar summary measure, *ie* the intracountry effect, *ne* the network effect scalar summary measure and *te* the total effect scalar summary measure. *n.s.* denotes an effect which is not statistically different from 0 when judged by the according 90 percent credible interval.

for the spatial model using the contiguity weight matrix.[14] The non-spatial results show that a one percent increase in GDP at the typical origin country of investments would lead to a 0.898 percent increase in outward FDI stocks, while a one percent increase in GDP per capita at the typical origin would increase outward FDI stocks by 1.973 percent.[15] The effect of increasing GDP per capita at the destination is not significant, while a one percent increase in GDP at destination increases inward FDI stocks by 0.746 percent. These results are close to the coefficient estimates presented in column (1) of Table 2. It is worth mentioning that there is a small difference due to the fact that our effects decomposition explicitly takes into account intracountry effects. For example, the marginal effect of GDP at origin is 0.898 percent in the decomposition that considers intracountry effects, while it is 0.936 percent when simply using the estimated coefficient. Intracountry effects of increasing GDP or GDP per capita are positive and significant, although small in magnitude (0.069 and 0.07, respectively). This implies that increasing GDP or GDP per capita in a country leads to higher investment stocks within the same country. Finally, total effects reflect the sum of origin, destination and intracountry effects, which equal 1.713 percent for GDP and 1.743 percent for GDP per capita.

In the spatial model, the effects also show how FDI stocks would change if GDP and GDP per capita of a country change by one percent, but in this case the non-zero estimates of the endogenous interaction parameters ρ_d, ρ_o, ρ_w have to be taken into account. Regarding the spatial contiguity model (Table 4), if GDP at origin increases by one percent, outward FDI stocks increase by 3.1 percent, but origin GDP per capita is not statistically significant, based on the 0.05 and 0.95 credible interval. Additionally, if GDP at destination increases by one percent, inward FDI stocks increase by 2.899 percent, while destination GDP per capita decreases inward FDI stocks by 3.777 percent. The intracountry impact of increasing GDP is relatively small, although larger than the one found for the non-spatial model. The relatively small effect can be explained by the fact that the domestic capital stock, $\ln FDI_{ii}$, is typically several times the current GDP of a country. Hence, a one percent increase in GDP will lead to a smaller percent increase in the domestic capital stock, even if all of GDP were to be invested. The effect of GDP per capita is negative and statistically significant, in contrast to the positive intracountry effect found for the non-spatial model. Intuitively, though, the negative effect makes sense: the richer the country, the less it invests into itself but spreads its investments to other countries. In the case of Europe, this reflects the fact that richer countries like, e.g., Germany invest more into other, poorer countries such as the Eastern European transition economies. This could be interpreted as evidence that vertical FDI motives are more prevalent between EU countries than market-seeking FDI. This also highlights the potential for bias, not only in terms of coefficient estimates but also in terms of policy conclusions when neglecting spatial dependence in FDI data. Finally, the network effect equals 25.359 and -25.32 percent for GDP and GDP per capita, respectively. This means that a one percent increase in GDP in the typical EU country leads to a 25.359 percent increase in FDI stocks across all 25 EU countries in the sample in the long-run, while a one percent increase in GDP per capita leads to a decrease of 25.32 percent of FDI stocks across the whole EU in the long-run. Even though these effects seem large, it has to be noted that the majority of the increase of FDI stocks within the EU due to the increase of GDP in a typical EU country would fall predominantly on the direct neighbors of the respective country, as spatial dependence decreases with the increasing order of neighborhood, see LeSage and Thomas-Agnan (2015).

Using the contiguity matrix, the results provide evidence in line with the importance of the network effect on the FDI activity between EU countries. In fact, it seems that the most important variation of FDI stocks among EU countries is due to the indirect effects (spillovers or NE) that arise between countries.

Let us now compare calculated effects for the different weighting matrices we used. To ease the comparison of the calculated effects, we present mean scalar summary measures for all three estimated models in Table 5. The upper panel compares the effects for GDP, whereas the lower panel shows the effects for GDP per capita.

Mean effects for GDP calculated using the nearest neighbors matrix are similar in sign and more or less in magnitude. Effect sizes are also fairly similar for both spatial weight matrices for GDP per capita. However, the statistical significance of the intracountry GDP per capita effects vanishes when using the four nearest neighbors matrix.[16]

To sum up, we find evidence for spatial spillovers of foreign direct investment decisions for our sample of 25 EU member countries, which highlights the importance of taking into account spatial dependence structures when estimating bilateral FDI models.

Conclusions

This paper presents evidence for spatial spillovers of bilateral foreign direct investment decisions in a sample of 25 European Union member countries in 2010. To do so, we rely on a spatial gravity equation that considers spatial lags using the spatial interaction model framework by LeSage and Pace (2008). This framework allows us to take into account that foreign direct investment decisions may be correlated across neighboring countries of the origin of FDI (origin-based dependence), across neighboring countries of the destination of FDI (destination-based dependence), as well as across neighboring countries of both origin and destination countries of FDI (origin-destination-based dependence).

To correctly interpret the estimates from this type of spatial bilateral model, we follow the methodology by LeSage and Thomas-Agnan (2015). This allows us to present scalar summary measures that are easily interpreted and are similar to standard marginal effects in non-spatial unilateral regression models.

We find that larger economies invest more and attract more investments. Crucially, our findings provide evidence that non-spatial gravity models of FDI underestimate the total impact of increasing market size (measured as GDP) on investments across European countries, as spatial spillover effects are not considered. In fact, spatial spillover effects are the single most important component of the total effect of the increase in market size. In addition, we find evidence that wealthier economies (measured by GDP per capita) invest less at home and more abroad, contrary to results from a model without spatial spillovers. The significance of the reduction in domestic investment (i.e., the intracountry effect) due to an increase in GDP per capita, however, depends on the specific way of modeling the spatial neighborhood relations between countries.

The main conclusion is that spatial lags are significant in a gravity-type model for FDI between EU member countries and should therefore be included in further regression analyses to prevent an omitted variable bias.

NOTES

[1]Note that interpreting the coefficients for GDP per capita in a *ceteris paribus* fashion is identical to assume that a country's population *de*creases for a given level of GDP.

[2]For a detailed exposition of the construction of the matrices, see LeSage and Pace (2008).

[3]We thank James P. LeSage for cordially sharing his code with us.

[4]We leave out Cyprus and Malta even though they were EU member states in 2010, as both are island countries and hence do not have any contiguous border with another country.

[5]In the literature on structural trade gravity models, Yotov (2012), Bergstrand et al. (2015) and Heid et al. (2015) use both intranational and international trade flows.

[6]We use *ck*, the capital stock in current million US$ (PPP). For a detailed description of the Penn World Tables as well as the included capital stock measures, see Feenstra et al. (2013), Feenstra et al. (2015a), Feenstra et al. (2015b) and Inklaar and Timmer (2013).

[7]Some authors deal with zero or negative values in the dependent variable by using an inverse hyperbolic sine transformation, i.e., $\sinh^{-1}(y) \equiv \ln[y+(y^2+1)^{1/2}]$. For example, Kristjánsdóttir (2012) and Rotunno et al. (2013) use it to model trade flows; Kristjánsdóttir (2005) uses it to model FDI flows. The advantage of this transformation is that for large positive values, $\ln(y) \approx \sinh^{-1}(y)$. Hence, for this range of the data, the inverse hyperbolic sine transformation behaves as a constant-elasticity model if the regressors are also in logs. Therefore, when estimating a regression model with only positive values of the dependent variable, choosing $\ln(y)$ or $\sinh^{-1}(y)$ yields very similar coefficients, see e.g., Kristjánsdóttir (2012). When estimating the model including many zeros and negative values, the estimated model coefficients at least for these values cannot be interpreted as elasticities. In sum, the inverse hyperbolic transformation imposes a non-linearity in the implied marginal effects for which there is no clear intuition in terms of its economic implications. We therefore abstain from using this transformation.

[8]In unreported results, we also estimated our model with a six nearest neighbors weight matrix. As expected, see LeSage and Pace (2014), effect calculations presented in the following section are very similar for different values of k.

[9]Similar arguments are used in the structural trade gravity literature, see, e.g., Heid and Larch (2016).

[10] For a detailed explanation, see LeSage and Thomas-Agnan (2015). Note that the authors refer to "cumulative" effects instead of effects in the long-run.

[11] β_o^r and β_d^r denote the parameters associated with the explanatory variables for origins and destinations.

[12] Note that while LeSage and Thomas-Agnan (2015) use an origin-centric ordering of the dependent variable, LeSage (2014) uses a destination-centric ordering. We adjusted the notation accordingly.

[13] Note that for the non-spatial model, **OE**, **DE** and **IE** can be calculated by setting $\rho_1 = \rho_2 = \rho_3 = 0$, i.e., $\mathbf{A} = \mathbf{I}_{n^2}$, and $\mathbf{NE} = 0$ by construction.

[14] We present effect calculations for the nearest neighbors matrix in Table A.1 in the Appendix.

[15] As we estimate a log-log model, the parameters represent elasticities.

[16] We experimented also with a six nearest neighbors matrix. As expected by LeSage and Pace (2014), results hardly change for varying k.

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Appendix Effects Estimates for Four Nearest Neighbor Matrix

Table A.1 shows the effects calculations using the spatial weighting matrix **D** as explained in the main text. The table is organized in the same way as Table 4.

TABLE A.1: EFFECTS ESTIMATES FOR THE SPATIAL AUTOREGRESSIVE INTERACTION MODEL USING A FOUR NEAREST NEIGHBORS WEIGHTING MATRIX

	Spatial Autoregressive				
	lower 0.05	mean	median	std. dev.	upper 0.95
Origin GDP	2.446	4.485	4.207	1.651	7.440
Destination GDP	2.255	4.193	3.893	1.601	7.118
Domestic (Intra) GDP	0.131	0.225	0.214	0.073	0.357
Network GDP	37.532	78.778	71.586	35.547	144.425
Total GDP	42.489	87.680	79.932	38.835	159.159
Origin GDP p.c.	-4.777	-1.717	-1.603	1.816	1.009
Destination GDP p.c.	-6.586	-3.438	-3.258	1.804	-0.820
Domestic (Intra) GDP p.c.	-0.266	-0.118	-0.114	0.087	0.015
Network GDP p.c.	-119.874	-55.822	-51.115	35.439	-7.914
Total GDP p.c.	-131.871	-61.094	-56.058	38.993	-7.849

Notes: Effects are calculated using the method by LeSage and Thomas-Agnan (2015) based on parameter estimates from column (3) of Table 2. "lower 0.05" denotes the 5 percent quantile of the effects calculated using the MCMC parameter draws and "upper 0.95" the 95 percent quantile. "mean" denotes the mean of the draws, "median" their median and "std. dev." their standard deviation.