

FDI in Space: Spatial Autoregressive Relationships in Foreign Direct Investment

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Abstract

There are a number of theoretical reasons why FDI into a host country may depend on the FDI in proximate countries. Such spatial interdependence has been largely ignored by the empirical FDI literature with only a couple recent papers accounting for such issues in their estimation. This paper conducts a general examination of spatial interactions in empirical FDI models using data on US outbound FDI activity. We find that estimated relationships of traditional determinants of FDI are surprisingly robust to inclusion of terms to capture spatial interdependence, even though such interdependence is estimated to be significant. However, we find that both the traditional determinants of FDI and the estimated spatial interdependence are quite sensitive to the sample of countries one examines.

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1. Introduction

Since 1980, worldwide foreign direct investment (FDI) has grown at a remarkable rate. According to Markusen (2002), in the latter half of the 1990s FDI flows grew annually by nearly 32 percent. When compared to the 1.5 percent annual growth in exports and the 0.6 percent annual increase in world GDP, it comes as no surprise that this same period has seen the development of formal economic models of multinational enterprises (MNEs) and increased empirical investigation of factors driving FDI patterns.

Development of formal MNE theory stems from Markusen (1984) and Helpman (1984). Markusen (1984) provides a general-equilibrium model where MNEs arise due to a market-access motive to substitute for export flows, or what is termed “horizontal” FDI. In contrast, Helpman (1984) develops a general-equilibrium model where MNEs arise due to the desire to access cheaper factor inputs abroad, or what is termed “vertical” FDI. Both are developed in a two-country framework and have spawned significant theoretical work on MNEs. Empirical work on the determinants of FDI over recent decades has mainly relied on a gravity-type framework, where market size and distance provide explanatory power, and have primarily used data on bilateral country-level FDI activity.¹

A potential weakness of the standard theoretical and empirical work on MNEs and FDI is this reliance on the two-country (or bilateral) framework. Recent theoretical work has begun to relax the two-country assumption, leading to the development of alternative motivations for FDI. For example, recent work by Ekholm, Forslid, and Markusen (2003), Yeaple (2003), and Bergstrand and Egger (2004) develop models of export-platform FDI where a parent country invests in a particular host country with the intention of serving “third” markets with exports

¹ Recent work by Carr, Markusen and Maskus (2001) introduces a modified gravity framework, where endowments are also part of the regressor matrix. This regression specification is based on a “knowledge-capital” MNE model that displays both horizontal and vertical motivations for FDI (see Markusen, 2002, for a treatment). However, for our purposes, this innovation is still similar to previous work in that the modeling is within a two-country framework and the empirical work is based on bilateral country-level data.

from the affiliate in the host country.² Alternatively, an MNE may set up its vertical chain of production across multiple countries to exploit the comparative advantages of various locales. This motivation has been developed in a model by Baltagi, Egger and Pfaffermayr (2004) and termed “complex vertical.” Both export-platform and complex vertical motivations imply that FDI decisions are multilateral in nature and, therefore, cannot be captured by a two-country framework. Other factors may also create interdependent FDI decisions across host destinations, including agglomeration externalities and imperfect capital markets that limit the funds an MNE has to invest abroad.³

The existence of multilateral decision-making has significant implications for empirical work on FDI, as multilateral decision-making means that FDI decisions across various host countries are not independent. Yet, estimating models of FDI where each observation measures activity between a separate bilateral country-pair does not allow for the potential interdependence between FDI decisions across host destinations.

Empirical work allowing for the impact of third-country effects – much less, general interdependence across multiple host markets – is sparse. Head and Mayer (2004) examine Japanese FDI patterns into regions of developed Europe with a particular focus on the measurement of market potential that extends beyond the host region. In addition to the standard inclusion of host GDP, they include a distance-weighted measure of the GDP of adjacent regions in an empirical specification of Japanese plant locations. They find that both regions with high GDPs and/or regions surrounded by larger markets tend to attract more FDI. Head, Ries, and Swenson (1995) look for evidence of agglomeration externalities by examining patterns of related producers in states adjacent to the US state chosen by a Japanese affiliate. Their

² Consistent with this, anecdotal evidence suggests that as much as 94 percent of U.S. affiliate production in Ireland is intended for export, 76 percent of which is bound for the European Union (IDA, 2004).

³ See Blomström and Kokko (1998), for example, for a general discussion of how agglomeration economies may arise in the context of FDI.

conditional-logit specification explicitly models an interdependence of the location decisions across all possible locales and their estimates provide evidence of agglomeration effects between bordering states for the Japanese automobile industry's FDI into the US. While conditional-logit specifications can and do speak to the potential interdependence of FDI decisions, such models impose significant restrictions on the data, including the assumption of the independence of irrelevant alternatives and a discrete measure of FDI choice. A more flexible alternative is offered by standard spatial econometric techniques, which directly model spatial interdependence in a linear regression framework.

The first paper to use spatial econometric techniques to examine FDI behavior is Coughlin and Segev (2000), which considers US FDI across Chinese provinces. The paper finds a positive spatial-lag coefficient, which is attributed to agglomeration economies. That is, FDI into one location within China is found to be increasing in the FDI into other proximate Chinese locations. The only other paper to use spatial econometric techniques to examine FDI patterns is Baltagi, Egger and Pfaffermayr (2004) whose approach is more closely related to ours.⁴ The paper first develops a model of MNE activity that allows for a variety of MNE motivations and then maps these into the implied spatial interactions that should be associated with each type of MNE motivation. The resulting econometric specification is then estimated using US outbound FDI for seven manufacturing industries across both developed and less-developed destinations. Their results find substantial evidence of spatial interactions, though they cannot definitively conclude whether export-platform or complex vertical FDI is more prevalent.

In this paper we take a more general look at empirically modeling spatial interactions in FDI and ask some fundamental questions not yet addressed by the previous literature. First, to

⁴ In fact, we are aware of only one other paper applying spatial methods to trade issues. Keller and Shiue (forthcoming) analyze 18th-century trade patterns within China. Given the considerable interest in issues of trade and distance in the international economics (e.g., Anderson and van Wincoop, 2003; Redding and Venables, 2004) and the usefulness of spatial econometrics in their study, we hope that our paper fosters additional use of spatial techniques.

what extent does omission of spatial interactions bias the coefficients on the traditional regressor matrix in empirical FDI studies? Significant bias would call into question much of the existing empirical work and inference. Second, how robust are estimated spatial relationships in FDI patterns across specifications and samples? Given the existing literature, an obvious issue to examine in this regard is differences across samples of developed and less-developed countries. In addition, because of the nature of space and how this influences the interpretation of estimated coefficients, it is necessary to examine differences across geographic sub-samples. Finally, we ask, to what extent can we uncover evidence of various theories of FDI using these techniques and available data?

To explore these issues, we use various samples of US outbound FDI from 1983 through 1998. We find that the estimated relationships of traditional determinants of FDI are surprisingly robust to the inclusion of terms to capture spatial interdependence, even though empirical patterns in the data suggest that such interdependence can itself be significant. However, our analysis also reveals that both the traditional determinants of FDI and the estimated spatial interdependence are quite sensitive to the sample of countries examined. The fragility of estimated spatial interdependence in the country-level data suggests, generally, that tying such results back to motivations of FDI is a difficult task and depends crucially on the sample chosen. Nevertheless, our estimates are broadly suggestive of vertical-specialization motives for FDI for non-OECD (less-developed) countries and export-platform FDI in the developed European countries.

The remainder of the paper proceeds as follows. In the next section we discuss hypotheses concerning the implications of various models of multinational firm behavior for spatial relationships between FDI into various regions. Section 3 provides a brief overview of spatial econometric methods and discusses our data. Section 4 reports our estimates and

highlights the importance of including both market potential and a spatially-weighted dependent variable. Section 5 concludes.

2. Sources of Spatial Interdependence

There are a variety of FDI motivations that have been illustrated in the literature, each with distinct implications for the spatial relationships one might anticipate observing through our estimation procedure. The type of spatial relationship we focus on is what is referred to in the spatial econometrics literature as spatial autoregression. Somewhat analogous to a lagged dependent variable in time series analysis, the estimated “spatial lag” coefficient characterizes the *contemporaneous* correlation between one region’s FDI and other geographically-proximate regions’ FDIs. While we provide econometric details of our empirical specification and estimation procedure below, our intent here is to briefly discuss the expected sign of the estimated spatial lag for various models of FDI. Before doing so, however, recall that these predictions are based on a model of a particular type of MNE firm. Thus, predictions hold in aggregate data only to the extent that all (or a significant share) of the firms are of this particular type. We come back to this point below.

One of the most basic forms of FDI is horizontal FDI in which investment is motivated by market access and avoidance of trade frictions such as transport costs and import protection in the host country. In its simplest form, such a model would be consistent with no spatial relationship between FDI into neighboring markets as the MNE makes independent decisions about the extent to which it will serve that market through exports or affiliate sales. A sufficient condition for such a theoretical prediction is that the destination markets have sufficiently high trade protection against imports from other destination markets, thereby making exports from third countries an unattractive option.

If trade protection between destination markets (or at least a group of destination markets) is low enough relative to trade frictions between the parent and destination countries,

then export-platform FDI is a plausible outcome. In this scenario, the multinational firm will choose the most preferred destination market and use it as a platform to serve other markets through exports. This implies a negative spatial lag in observed FDI, as FDI to the platform substitutes for FDI to other destination markets. In addition, the amount of FDI going into the export-platform region will depend on the size of the proximate markets it will be serving through exports. Thus, if export-platform FDI is occurring we would expect to find both a negative spatial lag *and* positive correlation between FDI and the market size of neighboring regions. This market potential effect is important in distinguishing this form of FDI from the next form – vertical FDI.

The purest form of vertical FDI is a model in which a multinational firm evaluates all potential destination markets to find the one that is the lowest-cost provider of the activity it wishes to relocate. This clearly predicts a negative spatial lag coefficient, as the FDI going into the preferred region is at the expense of that going into other regions. However, the market potential of neighboring regions should be insignificant in this form of FDI since the output of the subsidiary is shipped back to the parent country.

A more complicated variation of a vertical model is complex vertical (or fragmentation) FDI, where multinational firms separate out a number of production activities, each of which may be in a separate geographic region (e.g., Baltagi, Egger and Pfaffermayr, 2004, and Davies, 2005). In this form of FDI and production, having suppliers (related or unrelated) in neighboring regions is likely to increase FDI to a particular market. In addition, there may be other cross-region forces that generate agglomeration incentives besides supplier networks. To the extent that these agglomerative forces are operating amongst US firms, we should expect to see a positive spatial lag coefficient in our estimates of US outbound FDI determinants. In these scenarios, market potential *per se* should not matter. However, the level of industrial production in neighboring countries should be correlated with increasing potential for vertical suppliers,

including non-US suppliers. Since industrial production and market potential measures will be highly correlated, our market potential variable likely proxies for both and we may therefore expect a positive coefficient on market potential if this model generally describes that data best. Thus, agglomeration externalities arising among US firms across regional borders would be evidenced by a positive spatial lag coefficient, whereas such agglomeration effects with non-US forces could potentially be captured by our market potential variable to the extent it is a close proxy for related industrial production in neighboring countries.

Table 1 summarizes our expected signs for various forms of FDI behavior at the firm level. Of course, there may be a mixture of these motivations behind the country- and industry-level data we observe. Thus, our empirical work below will identify only net effects. To the extent that one form dominates the others, however, confirmatory evidence of one dominant form of MNE activity in the data is possible.

3. Empirical Methods and Data

In this section, we begin with an overview of spatial econometric techniques and then discuss our initial econometric specification for FDI and characterize the sample of countries on which we test the above models.

3.1. Spatially-Dependent FDI

In general, one would be interested in fitting data with a spatial model for one of two reasons.⁵ First, a spatial autocorrelation or “spatial error” model places additional structure on the unobserved determinants of FDI that would otherwise be captured by the traditional error term.⁶ Second, and of particular interest in examining connections to the theories of FDI discussed above, the estimation of a spatial autoregressive or “spatial lag” model accounts

⁵ See Anselin (1988) for detailed discussion.

⁶ Spatially-correlated errors can be thought of as analogous to the better-known practice of clustering error terms where the econometrician is relaxing the OLS assumption of independence between all errors and assuming, instead, that while the errors are independent across groups they need not be independent within groups. If the researcher

directly for relationships between dependent variables that are believed to be related in some spatial way. As such, these methods allow the data to reveal patterns of substitution or complementarity, as well as the strength of any such patterns, through the estimated spatial lag coefficient. For our purposes, the spatially-treated error structure is of secondary interest because although it may improve standard errors where estimation errors are spatially dependent, it does not affect point estimates. In addition, it is silent with respect to evidence of the substitution or complementarity of FDI across countries and therefore does not inform theory. In any case, we find little evidence of spatial errors in our data.⁷

3.2. *A Modified Gravity Model*

To examine the impact of spatial correlations on statistical inference, we begin with a specification that generally encompasses those used in prior work by researchers considering determinants of cross-country FDI activity. To this end, we begin with a “gravity” specification, which is arguably the most widely used empirical specification of FDI (e.g., Eaton and Tamura, 1994; Brainard, 1997; Blonigen and Davies, 2004), and modify it based on the recent literature to include variables measuring skill endowments and the market potential of countries proximate to the host. In particular, where all non-discrete variables are measured in natural logs, our specification is:

$$[1] \quad FDI = \alpha_0 + \alpha_1 Host Variables + \varepsilon ,$$

where FDI is an $n \times 1$ vector with row j equal to FDI from the US (the parent country) to host country j . Despite the fact that [1] is estimated on a panel of countries, we ignore time subscripts for notational purposes. We specify our model in log-linear form because, as documented by Blonigen and Davies (2004), such a model more likely leads to well-behaved residuals given the

believes that “groups” are not so much defined by specifically observable characteristics but, rather, by “likeness” in a way that is best captured by geographic proximity, a spatial error model would correct for such relationships.
⁷ Moreover, the primary explanatory variables do not differ from OLS estimates in terms of either their point estimates or their significance. Therefore, we omit these results here and instead make them available on request.

skewness of most FDI data samples. Such a log-linear model also allows for interactions of the underlying linear forms of the variables, as found in Carr, Markusen and Maskus (2001) and Markusen and Maskus (2002).

“*Host Variables*” captures standard gravity-model variables for the host countries (GDP, population, distance between the parent and host countries, and trade/investment friction variables), as well as a measure of skilled-labor endowments. Given the existing literature, our priors are that the higher is host GDP, the higher will be FDI. Holding GDP constant, increasing a country’s population reduces its per capita GDP and therefore FDI as well. Populations are therefore included to control for the known tendency for FDI to move between wealthy markets. We anticipate negative coefficients on population. With regard to trade costs, if FDI is undertaken to exploit vertical linkages, then higher host trade costs reduce the value to FDI. Alternatively, if FDI is primarily horizontal and intended to replace US exports, then higher host trade costs should induce tariff-jumping FDI. Thus, we remain agnostic on the effect of trade costs. Following Carr, Markusen, and Maskus (2001), we include information on skill endowments to proxy for the abundance of skilled laborers who are required for skilled-labor intensive production by MNEs and expect that greater skill levels (particularly for the typically skill-deficient host) will be positively correlated with FDI. As a measure of investment risk we adopt a composite index that includes measures of political risk, financial risk, and other economic indicators. Our expectation is that higher risk is correlated with higher investment costs, implying lower FDI. As in the traditional gravity model, distance between the parent and host is also included, which may proxy for both higher management costs (which reduce FDI) and higher trade costs (with an ambiguous effect).

While the standard specification would include characteristics of the parent country (e.g., real GDP, population and measures of trade costs, etc.), we discard such correlates since in our data the parent country is always the US and these variables only have time-series variation. We

instead capture such time-series variation in US FDI into our sample of countries by allowing for a quadratic trend in FDI. In unreported results, such parent country-variable controls are statistically insignificant and do not affect our results in any notable manner. We include host-skill variables as previous studies find such characteristics significant in explaining observed variation in FDI. Thus, to this point, our framework can be seen as a reduced form model that informally nests these previous specifications.

In subsequent sections of the paper, the estimation of Eq. [1] will form our baseline results, against which one might compare. We then modify our baseline specification with the inclusion of two further variants – *Market Potential* and the spatially lagged dependent variable, $W \cdot FDI$. In particular, we estimate:

$$[2] \quad FDI = \alpha_0 + \alpha_1 \text{Host Variables} + \alpha_2 \text{Market Potential} + \rho \cdot W \cdot FDI + \varepsilon .$$

The *Market Potential* variable for a country j is defined as the sum of inverse-distance-weighted GDPs of all other $k \neq j$ host countries in the sample, by year. This is similar to the Harris (1954) measure of market potential of neighboring regions which Head and Mayer (2004) find has the best explanatory power out of a number of market potential measures for their analysis of Japanese investment in the European Union. We use the same set of weights for construction of this variable as we will use for our construction of the spatial lag term which we discuss next.⁸

The addition of $\rho \cdot W \cdot FDI$ in Eq. [2] reflects the spatial autoregression term, where W is the spatial lag weighting matrix and ρ is a parameter to be estimated, which will indicate the strength and sign of any spatial relationship in *FDI*. It is important to recognize that $\rho \cdot W \cdot FDI$ captures the proximity of the observed host to other host countries; $W \cdot FDI$ should therefore not be confused with the standard gravity distance that measures the distance between the parent and

⁸ In unreported results, we experimented with several alternative weighting schemes. These yielded broadly similar results to those reported and are available on request.

host countries. W itself is a block-diagonal matrix of dimension $n \times n$, with each block capturing a single year's observations. Specifically, for any year, $y \in [1983, 1998]$, we define W_y as:

$$[3] \quad W_y = \begin{bmatrix} 0 & w_y(d_{i,j}) & w_y(d_{i,k}) \\ w_y(d_{j,i}) & 0 & w_y(d_{j,k}) \\ w_y(d_{k,i}) & w_y(d_{k,j}) & 0 \end{bmatrix},$$

where $w_y(d_{i,j})$ defines the functional form of the weights, declining in the distance, $d_{i,j}$, between any two host countries i and j . As distances are time-invariant, it will generally be the case that $W_{1983} = W_{1984} = \dots = W_{1998}$.^{9, 10} With our sample of FDI over years 1983 through 1998, the full weight matrix, W , is given by:

$$[4] \quad W = \begin{bmatrix} W_{1983} & 0 & 0 \\ 0 & . & 0 \\ 0 & 0 & W_{1998} \end{bmatrix}.$$

In the construction of the weights themselves, the theoretical foundation for $w_y(d_{i,j})$ is quite general and the particular functional form of any single element in W_y is therefore not prescribed. In our baseline results, we calculate weights using a simple inverse distance function where the shortest bilateral distance within the sample (i.e., the 173 kilometers separating Brussels and Amsterdam) receives a weight of unity and all other distances within the sample receive a weight that declines according to:

$$[5] \quad w_y(d_{i,j}) = \frac{173}{d_{i,j}} \quad \forall i \neq j,$$

where $d_{i,j}$ is the distance between hosts i and j , measured between capital cities. According to the above rule, a non-zero entry in the k th column of row j indicates that the k th observation will be

⁹ The exceptions to this in our sample are due to missing observations in 1991, 1995, 1997, and 1998. Thus, W_{1991} is of dimension 33×33 , W_{1995} and W_{1997} are of dimension 34×34 , and W_{1998} is of dimension 30×30 , while all other years are of dimension 35×35 . Denmark and Singapore are missing two observations, while Austria, Columbia, Greece, Portugal, and Sweden each have one missing observation.

¹⁰ Since distance is time invariant, it is not surprising that in unreported results, after controlling for host-country fixed effects, we do not find a significant spatial lag. A similar result is found in Baltagi, Egger, and Pfaffermayr's (2004) fixed effects estimates.

used to adjust the prediction of the j th observation ($j \neq k$).¹¹ The diagonal elements of W_y are set equal to zero in order that no observation of FDI predicts itself. As is common, we use a row-standardized weighting matrix where W is normalized so that each row sums to unity. Multiplied by the vector of dependent variables, the spatially-weighted variable, $W \cdot FDI$, then has the simple interpretation of row-sums being a proximity-weighted average of FDI into alternative countries.

Before continuing, note that the linear combination of the FDI 's appearing on the right-hand side of Eq. [2] is clearly endogenous and correlated with the error term. To see this point more formally, note that the random component of FDI_k is equal to the inner product of the k^{th} row of the matrix $(I - \rho W)^{-1}$ and the vector of errors, ε . Each element of FDI thus depends on all of the error terms. As a result, each of the FDI_i on the right-hand side depends on the equation's error term. Thus, OLS estimates of [2] are inconsistent. As such, we follow the literature by estimating the model Eq. [2] using maximum likelihood (ML) methods. Such methods are described in more detail in Appendix A.

3.3. Sample Data

We begin our estimations with a panel of annual data on US outbound FDI activity into the top forty host country destinations (as measured by affiliate sales) for the period 1983 through 1998.¹² Then, as mentioned above, we explore alternative sub-samples such as ones only including developed countries or only including less-developed countries. At the end of our analysis we also explore data disaggregated by both country and industry classifications.

¹¹ For example, the distance between France and Germany will weight the US-outbound FDI to France in predicting the US-outbound FDI to Germany. Likewise, the distance between Great Britain and Germany will weight the US-outbound FDI to Great Britain in predicting the US-outbound FDI to Germany, and so on.

¹² Limiting to the top forty FDI destinations is primarily due to electronic processing constraints of estimating these spatial lag models. However, we note that these top forty destinations accounted for more than 96% of all US FDI activity in 1992.

In choosing our data, we specifically restrict ourselves to publicly available datasets as these are among the most used in FDI studies. This is done to provide insights into how the results from earlier studies may be sensitive to the inclusion of third-country effects. Our data begin in 1983, as this is when US data for our measure of FDI (i.e., affiliate sales) were first reported on a consistent basis. Given our interest in disaggregating to the industry level, we end the sample in 1998, as the US Bureau of Economic Analysis began reporting FDI activity by very different industry classifications in subsequent years. We examine only outbound FDI activity since there is little theory to inform expectations of spatial correlations for inbound FDI. In addition, as demonstrated by Markusen and Maskus (2001) and Blonigen, Davies, and Head (2003), standard specifications of FDI determinants yield quite different coefficient estimates across separate samples of inbound and outbound FDI, suggestive that pooling inbound and outbound data is inappropriate.¹³

Our measure of outbound FDI is sales of US affiliates in the host country as reported by the Bureau of Economic Analysis, which we convert into billions of real dollars using the chain-type price index for gross domestic investment from the Economic Report of the President.¹⁴ In some specifications, rather than using country-level affiliate sales, we use annual affiliate sales disaggregated by country and industry. These were obtained from the same sources and converted into real values using the same method as the country-level data. Host country real gross domestic product (GDP) and population data come from Penn World Tables (PWT), which reports such data for 1950 through 2000.¹⁵ Our trade-cost measure is the inverse of the openness measure reported by the PWT, which itself is equal to exports plus imports divided by GDP.

¹³ Blonigen, Davies, Naughton, and Waddell (2005) provide an initial set of theoretical and empirical results regarding spatial interactions in US inbound FDI.

¹⁴ The BEA's FDI data can be found at <http://www.bea.doc.gov/bea/di/di1usdbal.htm>. The price deflator can be found at <http://www.gpoaccess.gov/usbudget/fy05/sheets/b7.xls>.

¹⁵ The PWT Version 6.1 data are available online at http://pwt.econ.upenn.edu/php_site/pwt_index.php.

Host country skill is measured by average years of schooling for those over age 25, reported every five years for 1960-2000.¹⁶ Linear interpolation was used for other years. Host country investment costs are measured as the inverse of a composite index comprising operations risk index, political risk index and remittance and repatriation factor index. These indices are developed by Business Environment Risk Intelligence S.A. and are available from 1980 to 2003.¹⁷ Missing data from this source forces us to exclude Iceland and New Zealand. As such, our final sample spans from 1983 to 1998 for thirty-five countries, twenty of which we designate as OECD countries. To control for transport costs and other distance-related costs, we follow the literature in using great circle distances between capital cities, measured in kilometers.¹⁸ Table 2 provides a list of the 35 included countries, as well as summary statistics of the variables in our model from 1983 through 1998.

4. Empirical Results

In this section, we present our initial results followed by some discussion of issues related to the specification of our baseline estimation. We then explore alternative specifications and sub-samples to deal with the issues raised by these initial estimates.

4.1. Base Results

Table 3 presents our initial results using our full sample of country-level data. Our initial objective is to examine whether the data reveal any spatial relationships to FDI patterns and whether inclusion of such spatial terms significantly affects the coefficient estimates on the standard determinants of FDI used in many previous studies. In order to examine this, we present four different specifications side-by-side. Column (1) presents OLS results of Eq. [1] without the two variables that capture the potential spatial patterns in the data. Columns (2) and

¹⁶ Acquired from Barro and Lee (2000), International Data on Educational Attainment.

¹⁷ For more information see <http://www.beri.com>.

¹⁸ With the exception of Belgium, these data were provided by Raymond Robertson at his website. Belgian distances were acquired from <http://www.indo.com>.

(3) present ML estimates that separately include the market potential and the spatial lag variables, and Column (4) provides the full specification of Eq. [2], which includes both the market potential and spatial lag variables.¹⁹

A number of interesting observations can be made from results in Table 3. First, the traditional determinants of FDI – GDP, population, trade frictions, etc. – each have their predicted signs, are generally statistically significant, and are remarkably unaffected by the omission of the market potential or spatial lag variable. The one exception is the host skill variable, which is a recent addition to the “traditional” FDI specification. The significance of this variable disappears when market potential is included although it continues to have a positive coefficient. In general, this is reassuring evidence of the validity of previous empirical studies of cross-country FDI that have not considered spatial patterns.

The second important observation regarding results in Table 3 is that, although inclusion of the spatial terms does not generally affect the other coefficients, the estimated parameters relating to the spatial patterns in the data are both statistically and economically important. Looking at column (4), the market potential variable is significantly negative, with an elasticity of FDI into a given host country of -0.451 with respect to the distance-weighted GDP of markets around the host. In other words, a 10 percent increase in markets around the host decreases FDI by 4.5 percent. In contrast, the spatial lag is statistically positive with a point estimate of 0.511, suggesting that a 10 percent increase in FDI into other proximity-weighted countries increases FDI into a host country by a little over 5 percent. The estimation of statistically significant spatial relationships suggests that FDI activity for this full sample goes beyond simple horizontal

¹⁹ Columns (2) and (3) that include the spatial lag and market potential variable separately are important since they allow us to examine the potential for omitted variable bias on the spatial lag from not including the market potential variable. If country- k GDP correlates with FDI into country k and country- k GDP also correlates with FDI into country j , then including country- k FDI in the prediction of j 's FDI (e.g., through $\rho \cdot W \cdot FDI$) while not directly including country- k 's GDP leaves the estimation of ρ prone to bias.

FDI motivations. The positive spatial lag is evidence for the prevalence of vertical specialization motivations with agglomeration effects between US FDI in neighboring host countries and against export-platform FDI. The negative coefficient on the market potential variable is unexpected and opposite in sign to that of Head and Mayer (2003) using Japanese FDI into Europe. We will come back to this issue below when we focus on a European sample.

A third general observation of note is that the spatial lag parameter and the coefficient on the market potential variable are strongly affected by whether the other variable is included. This suggests that we should interpret results from previous studies that only include one or the other with caution. In particular, given the positive coefficient on host GDP, it comes as no surprise that the market potential and the spatial lag are positively correlated. Since the coefficients on these variables in Column (4) have opposite signs, omission of either of these two variables would bias the other towards zero. Comparing columns (2) and (3) to (4) we see that this is indeed the case. This suggests that the results of Coughlin and Segev (2000), who do not include a market potential variable in their estimation of US FDI into China, may suffer from omitted variable bias.

4.2. Alternative Samples

An important, but often ignored, issue for any empirical FDI study is the issue of the appropriateness of pooling observations from diverse countries into one sample. For example, Blonigen and Davies (2004) and Blonigen and Wang (2005) find substantial differences in traditional FDI determinants across samples of developed versus less-developed countries. Spatial considerations may add an entirely new dimension to this as many developed countries are geographically located north of the equator (and primarily clustered in Europe), while less-developed countries are geographically more spread out across a number of continents. As Figure 1 illustrates, this has important implications for the spatial distribution of US outbound FDI. We therefore investigate the stability of our estimates across alternative samples in Table

4. The first column simply replicates our results for the full sample to ease comparison. The next two columns of results provide estimates for the developed (OECD) countries in our sample and the less-developed (non-OECD) countries.²⁰ Splitting the sample this way is motivated by the expectation that horizontal (and perhaps export-platform) motivations for FDI are more likely in the OECD sample, while vertical motivations are more likely in the non-OECD sample. The last column then reports on the estimation of Eq. [2] for a sample of European OECD countries.

Comparison of results for the OECD and non-OECD samples provides a number of interesting results. First, the estimated spatial relationships vary significantly across these two samples. The OECD results mirror the full sample results with a statistically significant and negative market potential coefficient and a statistically significant and positive spatial lag. This is unexpected, as pure horizontal motivations would yield no spatial correlations and export-platform would suggest exactly opposite signs on the market potential variable and spatial lag. In contrast, the market potential variable is significantly positive in the non-OECD sample and the spatial lag is positive, though statistically insignificant. This sign pattern is consistent with vertical specialization motivations for FDI with agglomeration effects, as one may expect with a sample of less-developed countries.

Comparison of coefficients on the traditional determinants of FDI across OECD and non-OECD samples reveals significant differences, consistent with previous studies mentioned above. The magnitudes of the coefficients are substantially different across samples and the host skill variable has opposite signs. Higher skill in the host country is associated with greater US FDI in the OECD sample, whereas lower skill is associated with greater US FDI in the non-OECD sample. This too is consistent with vertical motivations for FDI prevailing in the non-OECD sample.

²⁰ The list of countries in the OECD group is found in Table 2 and in Figure 2. Figure 2 also provides the US outbound FDI patterns to OECD countries.

We do not show results for the OECD and non-OECD samples when not including the market potential variable and spatial lag for the sake of brevity. However, we note that, as in the full sample, the traditional determinants of FDI are very similar regardless of including these spatial terms or not.²¹ This is an important and surprising result. While our inference on the factors that affect FDI patterns is quite sensitive to the sample of countries one chooses to examine, there is no evidence of significant bias for the coefficients on the traditional regressors from omitting the market potential variable or spatial lag.

A remaining issue is the unusual coefficient pattern on the market potential variable and spatial lag for the OECD sample. Examination of the spatial distribution of OECD countries and the intensity of US FDI into those countries provides a potential answer. As can be seen in Figure 2, Australia, Canada, and Japan are spatial outliers from the primary OECD markets for the US in Europe. Considering this, “continental agglomeration” may in fact be a more likely story and a more appropriate conclusion from the results reported for our OECD sample. As an alternative, then, we exclude these three most-remote countries and re-estimate the empirical model for the sub-sample of European OECD countries illustrated in Figure 3. These results are reported in Column (4) of Table 4.

Results from this sub-sample of European countries are quite different from those of our full sample of OECD countries. First, while the host variables are generally of the same sign as previous results, their magnitudes can differ considerably. The effect of host GDP is less than half the size we estimated for the full sample, potentially reflecting the fact that FDI in the remote OECD hosts is more geared towards servicing only the market in which it locates. In addition, the elasticity of FDI to distance from the US is almost an order of magnitude larger in

²¹ One item worth noting is that when excluding the market potential variable in the non-OECD sample, we find a significantly positive spatial lag. Similarly, when omitting the spatial lag, we find a greater positive coefficient on market potential. Therefore once again this demonstrates the importance of including both of these spatially-related variables in order to avoid omitted variable bias between them.

the European sample, suggesting that after restricting attention to a given continent, that distance from the US becomes a more important consideration for MNEs. Another notable difference is that the sign of host population for the European sample is positive (though statistically insignificant), whereas it was negative for the full sample. Again, this highlights how sensitive determinants of FDI can be for various sub-samples of countries even before taking into account spatial considerations.

Second, the spatial terms also change substantially when we turn to the European OECD sample. The market potential variable is now significantly positive, rather than negative, in sign, while the spatial lag becomes statistically insignificant. The market potential variable is now consistent with export-platform motivations for FDI, though an insignificant spatial lag is not. In other words, the results indicate that affiliate sales are larger when closer to bigger markets, suggesting they are exporting to these neighboring markets, but this activity is not associated with lower affiliate presence in the neighboring markets (i.e., there is no clustering of activity in a few select markets).

In summary, our country-level data analysis shows that the sample of countries chosen has substantial impacts on the coefficients on the traditional determinants of FDI. Spatial relationships do matter and also vary significantly across various samples of countries, but surprisingly the traditional determinants of FDI are not significantly affected by whether these spatial terms are included or not. Importantly, it seems that the sensitivity of the spatial variables hinges on the stage of a country's development and the geographic scope of the countries in the sample.

4.3. Examination of Disaggregated Country-Industry Level Data

Country-level data aggregates FDI decisions across firms and industries that might be quite heterogeneous in their FDI motivations. For example, micro-level evidence by Feinberg and Keene (2001) and Hanson, Mataloni, and Slaughter (forthcoming) find substantial vertical

activity going on only for certain manufacturing sectors (such as electronics) and host countries. Because of this, country-level data will only uncover statistically significant spatial interdependence to the extent that there is a prevailing form of FDI that generates a particular pattern of such spatial interdependence. Disaggregating by sector may therefore lead to additional insights because whereas export-platform motivations may dominate in some industries, vertical motivations may dominate in others. Publicly available data on FDI activity has limitations in how disaggregated such data can be reported. However, the US BEA does report data for a number of sectors by host country. In this section, we explore such data for our sample of European OECD countries.

Table 5 present results when we estimate our FDI specification for each individual sector. Our time period, sample countries, and control variables match those for the European OECD regression above. The number of observations for each of the sector estimations varies due to missing data when the BEA suppresses the data point out of confidentiality concerns. There is substantial heterogeneity in estimates across sectors as one may expect, though these differences are mainly in the magnitude of estimated parameters, not their sign. Importantly, we find much stronger evidence of export-platform activity in the European-OECD sample when adopting these more disaggregated sector-level data. Nine of the eleven sectors show a sign pattern that is consistent with export-platform motivations for FDI – a positive coefficient on the market potential variable and a negative spatial lag. The coefficient on market potential is statistically significant in seven of these nine sectors, while the spatial lag is likewise statistically significant in seven of these nine sectors. The two exceptions to this export-platform sign pattern are the “Chemicals and Allied Products” and “Electric and Electronic Equipment” sectors, both of which display a positive and significant spatial lag. This may suggest that vertical specialization and agglomeration effects are much more prevalent for these sectors, a result consistent with the findings of Hanson, Mataloni, and Slaughter (forthcoming).

In summary, by disaggregating the data (as much as public data allow) and focusing on a fairly homogeneous group of countries distributed evenly across space, we get stronger evidence for an FDI motivation that we would expect in the European sub-sample – export-platform FDI. This highlights how important sample selection is in estimating empirical FDI models, particularly those with spatial terms, if one wants to be able to relate such results back to FDI theory.

5. Conclusion

There are a number of theoretical reasons why FDI into a host country may depend on the FDI in proximate countries. Such spatial interdependence has been largely ignored by the empirical FDI literature with only a couple recent papers accounting for such issues in their estimation. This paper conducts a more general examination of spatial interactions in empirical FDI models using data on US outbound FDI activity. We find that estimated relationships of traditional determinants of FDI are surprisingly robust to inclusion of terms to capture spatial interdependence, even though such interdependence is estimated to be substantial in the data. However, we find that both the traditional determinants of FDI and the estimated spatial interdependence are quite sensitive to the sample of countries one examines. In particular, the geographic scope of the sample can be important in trying to separate evidence supporting different motivations for FDI from simple “continental agglomeration”.

These general results are quite important for the extensive previous work on FDI. Omitted variable bias from not modeling spatial interdependence is apparently quite small in these cross-country FDI estimations across the variety of samples we explore. This is good news for the statistical inference drawn by previous empirical studies regarding determinants of FDI. On the other hand, it is worth noting that we find significant omitted variable bias for the market potential measure or spatial lag, when not including both in the specification.

This point is particularly applicable to the few previous studies of spatial effects in empirical FDI patterns, as ours is the first to include both spatial effects. Furthermore, our results highlight that estimates of cross-country determinants of FDI are not very robust to changing the sample of countries. In a related vein, the fragility of estimated spatial interdependence in the country-level data suggests that tying such results back to motivations of FDI is a difficult task and depends crucially on the sample chosen. This is a potential explanation for why the Baltagi, Egger, and Pfaffermayr (2004) study that pools data across a wide variety of countries and industries does not reach unambiguous conclusions. However, once we pursue estimation of sub-samples of our data we find evidence suggestive of vertical specialization motives for FDI with agglomeration effects for non-OECD (less-developed) countries and export-platform FDI for most industries within the developed European countries.

Table 1: Summary of Hypothesized Spatial Lag Coefficient and Market Potential Effect for Various Forms of FDI.

| FDI Motivation | Sign of Spatial Lag | Sign of Market Potential Variable |
|--|---------------------|-----------------------------------|
| Pure Horizontal | 0 | 0 |
| Export-platform | - | + |
| Pure Vertical | - | 0 |
| Vertical Specialization with Agglomeration | + | + |

Table 2: Descriptive Statistics

Sample of OECD countries for the years 1983-1998. FDI is measured by the affiliate sales as reported by the Bureau of Economic Analysis. Host real gross domestic product (GDP) and population data come from Penn World Tables (PWT). Host trade costs are the inverse of the openness measure reported by the PWT, which itself is equal to exports plus imports divided by GDP. Host skill is measured by average years of schooling for those over age 25. Host investment costs are measured as the inverse of a composite index comprising operations risk index, political risk index and remittance and repatriation factor index, developed by Business Environment Risk Intelligence S.A.. Great circle distances between capital cities are used in all specifications, measured in kilometers. Market Potential is measured as the distance-weighted average real gross domestic product of other host countries in the sample, with weights ascribed according to Eq. [5]. For purposes of clarity, below we report market potential in billions of dollars.

| Variable | Mean | Standard Deviation | Minimum | Maximum |
|-------------------------------|--------|--------------------|---------|---------|
| FDI | 41,686 | 61,604 | 964 | 35,0173 |
| Host GDP (\$billions) | 392 | 490 | 24 | 3,120 |
| Host Population (thousands) | 40,259 | 41,921 | 2,681 | 203,678 |
| Host Trade Costs | 0.025 | 0.018 | 0.003 | 0.110 |
| Host Skill | 7.334 | 2.239 | 2.642 | 11.844 |
| Host Investment Costs | 55.320 | 12.238 | 33.000 | 82.667 |
| Host Distance from US in km | 8,327 | 3,855 | 734 | 16,371 |
| Market Potential (\$billions) | 811 | 667 | 116 | 3,360 |

Sample countries included: Argentina, Australia*, Austria*, Belgium*, Brazil, Canada*, Chile, Columbia, Denmark*, Egypt, Finland*, France*, Germany*, Greece*, Indonesia, Ireland*, Italy*, Israel, Japan*, Korea, Malaysia, Mexico, Netherlands*, Norway*, Philippines, Portugal*, Singapore, South Africa, Spain*, Sweden*, Switzerland*, Thailand, Turkey*, United Kingdom*, Venezuela. * denotes OECD country.

Table 3: Spatial Analysis of US Outbound FDI – Full Sample

Sample of countries for the years 1983-1998. In all specifications, the dependent variable, Ln(FDI), is measured as the real sales by US-owned foreign affiliates which are reported by the Bureau of Economic Analysis.

| Independent Variable | Ln(FDI) | | | |
|---|-----------------------|-----------------------|-----------------------|-----------------------|
| | (1) | (2) | (3) | (4) |
| Ln(Host GDP) | 1.575 (0.091)*** | 1.744 (0.091)*** | 1.568 (0.090)*** | 1.794 (0.087)*** |
| Ln(Host Population) | -0.452 (0.082)*** | -0.608 (0.082)*** | -0.450 (0.081)*** | -0.694 (0.079)*** |
| Ln(Host Trade Cost) | -0.680 (0.061)*** | -0.798 (0.062)*** | -0.671 (0.062)*** | -0.793 (0.058)*** |
| Ln(Host Skill) | 0.248 (0.113)** | 0.174 (0.110) | 0.244 (0.113)** | 0.088 (0.105) |
| Ln(Host Investment Costs) | -0.882 (0.212)*** | -0.983 (0.205)*** | -0.858 (0.213)*** | -0.825 (0.196)*** |
| Ln(Host Distance from US in km) | -0.389 (0.047)*** | -0.406 (0.046)*** | -0.382 (0.048)*** | -0.347 (0.044)*** |
| Trend (1980 = 1) | -0.103 (0.023)*** | -0.093 (0.023)*** | -0.104 (0.023)*** | -0.095 (0.021)*** |
| Trend ² | 0.003 (0.001)** | 0.003 (0.001)** | 0.003 (0.001)** | 0.001 (0.001) |
| Market Potential (i.e., weighted GDPs) | | -0.269 (0.041)*** | | -0.451 (0.047)*** |
| Spatially weighted FDI ^a (i.e., $W \cdot FDI$) | | | 0.056 (0.073) | 0.511 (0.074)*** |
| Constant | -18.652 (0.881)*** | -15.531 (0.975)*** | -18.988 (0.980)*** | -16.516 (0.934)*** |
| Observations | 551 | 551 | 551 | 551 |
| Adj R ² / Log-Likelihood | .83 | .84 | -465.46 | -425.77 |

Standard errors in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

^a Weights, W , are defined as $w_y(d_{i,j}) = 173/d_{i,j} \quad \forall i \neq j$.

Table 4: Spatial Analysis of US Outbound FDI – Sub-samples

In all specifications, the dependent variable, Ln(FDI), is measured as the real sales by US-owned foreign affiliates which are reported by the Bureau of Economic Analysis.

| | Full Sample | OECD | Non-OECD | European OECD |
|---|-----------------------|-----------------------|-----------------------|----------------------|
| Independent Variable | (1) | (2) | (3) | (4) |
| Ln(Host GDP) | 1.794 (0.087)*** | 1.681 (0.152)*** | 2.164 (0.103)*** | 0.888 (0.133)*** |
| Ln(Host Population) | -0.694 (0.079)*** | -0.430 (0.153)*** | -0.939 (0.100)*** | 0.203 (0.131) |
| Ln(Host Trade Cost) | -0.793 (0.058)*** | -1.237 (0.122)*** | -0.525 (0.064)*** | -0.524 (0.112)*** |
| Ln(Host Skill) | 0.088 (0.105) | 0.862 (0.174)*** | -0.477 (0.124)*** | 0.826 (0.152)*** |
| Ln(Host Investment Costs) | -0.825 (0.196)*** | -1.013 (0.204)*** | -0.097 (0.290) | -0.862 (0.199)*** |
| Ln(Host Distance from US in km) | -0.347 (0.044)*** | -0.183 (0.055)*** | -0.356 (0.067)*** | -2.521 (0.235)*** |
| Trend (1980 = 1) | -0.095 (0.021)*** | -0.090 (0.024)*** | -0.256 (0.029)*** | -0.070 (0.021)*** |
| Trend ² | 0.001 (0.001) | -0.001 (0.001) | 0.007 (0.001)*** | 0.002 (0.001) |
| Market Potential (i.e., weighted GDPs) | -0.451 (0.047)*** | -0.298 (0.046)*** | 0.881 (0.146)*** | 0.646 (0.121)*** |
| Spatially weighted FDI ^a (i.e., $W \cdot FDI$) | 0.511 (0.074)*** | 0.695 (0.063)*** | 0.104 (0.090) | 0.106 (0.111) |
| Constant | -16.516 (0.934)*** | -27.590 (1.276)*** | -36.893 (3.232)*** | -8.314 (2.995)*** |
| Observations | 551 | 314 | 237 | 266 |
| Adj R ² / Log-Likelihood | -425.77 | -185.75 | -111.90 | -88.43 |

Standard errors in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

^a Weights, W , are defined as $w_y(d_{i,j}) = 173/d_{i,j} \quad \forall i \neq j$.

Table 5: Industry-Level Analysis of Spatial Patterns in US Outbound FDI

In all specifications, the dependent variable, Ln(FDI), is the real sales by US-owned foreign affiliates in a given industry.

| Independent Variable | Petroleum | Food and kindred products | Chemicals and allied products | Primary and fabricated metals | Machinery, except electrical | Electric and electronic equipment | Transportation equipment | Other manufacturing | Wholesale trade | Services | Other industries |
|---|-----------------------|---------------------------|-------------------------------|-------------------------------|------------------------------|-----------------------------------|--------------------------|----------------------|-----------------------|-----------------------|----------------------|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) |
| Ln(Host GDP) | 0.614 (0.535) | -0.198 (0.541) | 0.533 (0.298)* | 1.100 (0.400)*** | 3.037 (0.486)*** | 1.846 (0.277)*** | -0.214 (0.462) | 0.258 (0.285) | 2.207 (0.165)*** | 1.100 (0.206)*** | 0.684 (0.606) |
| Ln(Host Population) | 0.521 (0.539) | 1.645 (0.526)*** | 0.954 (0.293)*** | 0.778 (0.403)* | -0.925 (0.495)* | -0.443 (0.281) | 3.532 (0.479)*** | 1.325 (0.286)*** | -1.394 (0.165)*** | -0.124 (0.203) | 1.316 (0.608)** |
| Ln(Host Trade Cost) | -0.965 (0.300)*** | -1.291 (0.408)*** | -1.490 (0.237)*** | -1.506 (0.311)*** | -2.119 (0.359)*** | -1.634 (0.180)*** | -3.215 (0.422)*** | -1.602 (0.209)*** | -0.152 (0.145) | -0.085 (0.167) | -0.891 (0.391)** |
| Ln(Host Skill) | 0.911 (0.746) | 0.820 (0.543) | 1.318 (0.325)*** | 0.310 (0.482) | 0.027 (0.586) | -0.658 (0.302)** | -0.425 (0.580) | 1.766 (0.308)*** | -0.324 (0.190)* | 0.020 (0.226) | 4.142 (0.609)*** |
| Ln(Host Investment Costs) | -0.563 (0.902) | -6.109 (0.852)*** | -4.811 (0.521)*** | -8.686 (0.734)*** | -14.161 (0.873)*** | -5.733 (0.456)*** | -12.924 (0.944)*** | -3.328 (0.519)*** | -0.302 (0.301) | -2.631 (0.364)*** | -4.334 (1.011)*** |
| Ln(Host Distance from US in km) | -3.765 (0.856)*** | 2.218 (0.761)*** | 3.267 (0.428)*** | -0.611 (0.599) | 1.101 (0.708) | 0.425 (0.402) | 2.712 (0.763)*** | 0.774 (0.434)* | -0.999 (0.250)*** | -0.222 (0.303) | -0.722 (0.769) |
| Trend (1980 = 1) | -0.037 (0.067) | 0.080 (0.087) | -0.060 (0.047) | -0.037 (0.066) | 0.048 (0.089) | -0.102 (0.044)** | -0.074 (0.092) | 0.019 (0.045) | -0.129 (0.029)*** | -0.067 (0.033)** | -0.214 (0.079)*** |
| Trend ² | -0.005 (0.004) | 0.003 (0.005) | 0.002 (0.002) | -0.001 (0.004) | -0.008 (0.005)* | 0.001 (0.002) | 0.003 (0.006) | -0.003 (0.002) | 0.006 (0.002)*** | 0.004 (0.002)** | 0.016 (0.005)*** |
| Market Potential (i.e., weighted GDPs) | 0.406 (0.157)*** | 1.421 (0.342)*** | 0.934 (0.221)*** | 0.863 (0.281)*** | 0.364 (0.284) | -0.056 (0.077) | 0.429 (0.270) | 0.435 (0.129)*** | 1.008 (0.131)*** | 1.778 (0.158)*** | 0.192 (0.195) |
| Spatially weighted FDI a (i.e., $W \cdot FDI$) | -0.720 (0.177)*** | -0.262 (0.161) | 0.191 (0.116)* | -0.446 (0.165)*** | -0.591 (0.159)*** | 0.201 (0.094)** | -0.312 (0.129)** | -0.129 (0.087) | -0.322 (0.157)** | -0.257 (0.120)** | -0.098 (0.137) |
| Constant | -26.437 (9.446)*** | 22.350 (10.826)** | 14.382 (6.830)** | 28.993 (8.819)*** | 74.054 (10.239)*** | 22.636 (5.418)*** | 80.822 (11.355)*** | 4.105 (6.305) | -39.313 (3.859)*** | -26.348 (4.486)*** | -0.062 (11.483) |
| Observations | 142 | 202 | 226 | 194 | 220 | 176 | 152 | 143 | 222 | 229 | 109 |
| Adj R ² / Log-Likelihood | -181.08 | -298.10 | -234.86 | -256.39 | -342.69 | -147.91 | -218.27 | -113.75 | -109.34 | -151.10 | -134.98 |

Absolute values of *t*-statistics are in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

Figure 1: US Outbound FDI in 1992

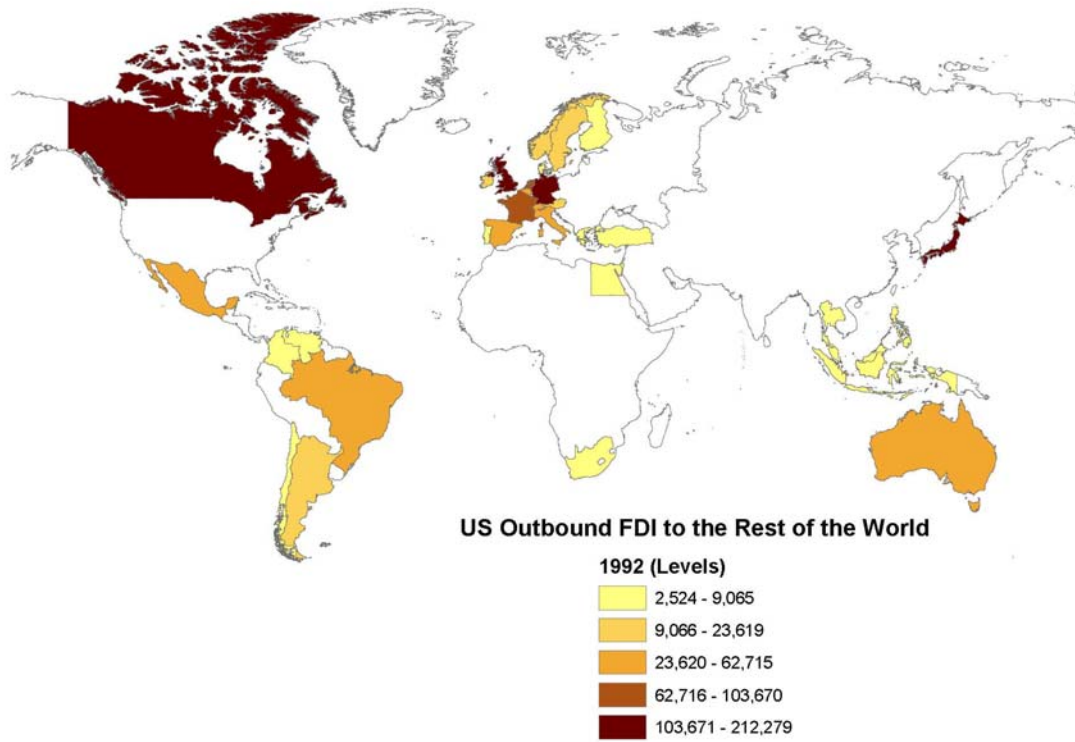


Figure 2: US Outbound FDI to OECD Countries in 1992.

Sample countries included: Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Japan, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, Turkey, United Kingdom.

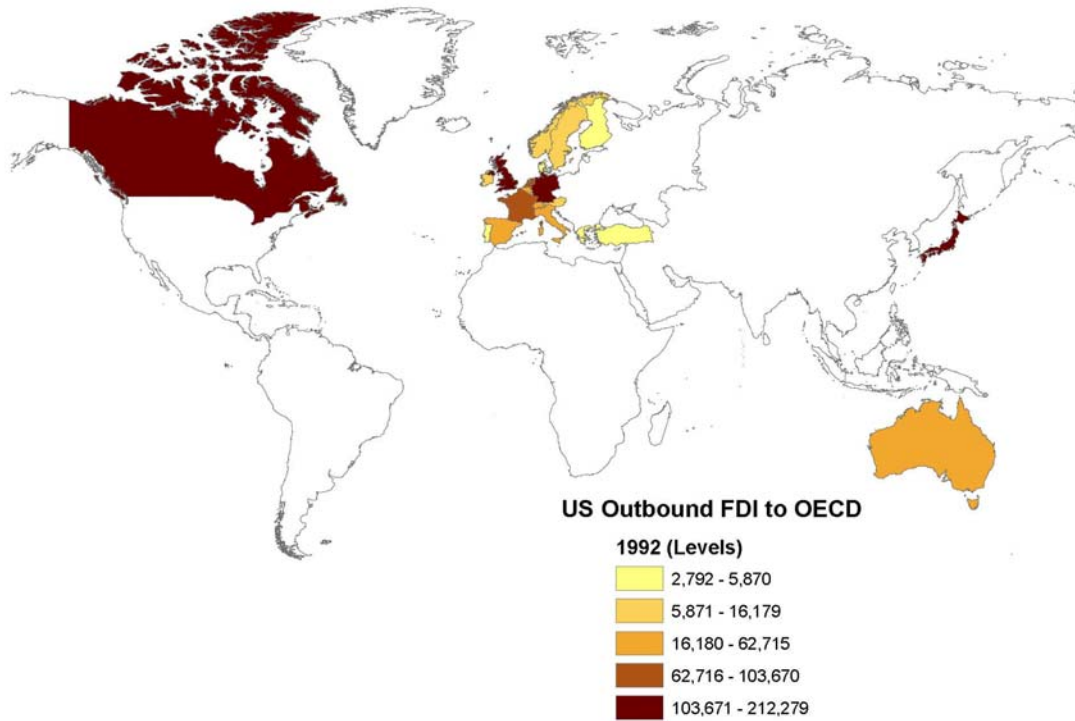
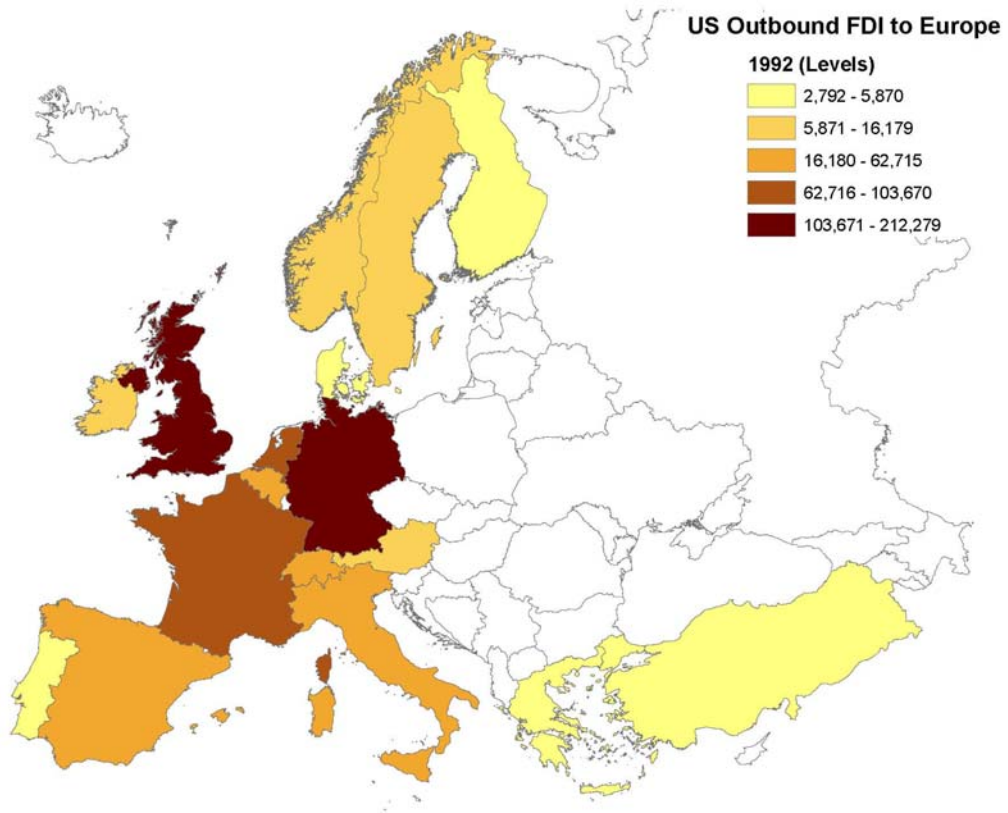


Figure 3: US Outbound FDI to European OECD in 1992.

Sample countries included: Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, Turkey, United Kingdom.



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Appendix A

In the spatial lag models we use in this paper, the error terms are typically assumed to be normally distributed with constant variance, which implies the following log-likelihood function:

$$[6] \quad \log L = -\frac{n}{2} \log(2\pi) - \frac{1}{2\sigma^2} \sum_{i=1}^n \varepsilon_i^2 - \frac{n}{2} \log \sigma^2 + \log |I - \rho W| \quad .$$

Eq. [6] differs from a standard log-likelihood function for a linear regression model with the last term – the Jacobian of the transformation from ε to FDI . The first-order condition for σ^2 implies that $\hat{\sigma}^2 = n^{-1} \sum_{i=1}^n (Y_i - \rho \cdot W \cdot FDI_i - X_i \beta)^2$, where X represents all our covariates on the right-hand side of Eq. [1] in the text other than the spatial lag term. Substituting this expression into Eq. [6], the log-likelihood function is

$$[7] \quad \log L = -\frac{n}{2} \log(2\pi + 1) - \frac{n}{2} \log \hat{\sigma}^2 + \log |I - \rho W| \quad .$$

The Jacobian term makes estimation difficult as calculating the determinant of the n by n matrix is computationally costly. However, estimation may be simplified by first calculating the eigenvalues of W , ω_i , as $\log |I - \rho W| = \sum_{i=1}^n \log(1 - \rho \omega_i)$. Although calculating eigenvalues of an n by n matrix is also time-consuming, the calculation need only be made once.

Letting $Z = W \cdot FDI$, where $A = (I - \rho W)^{-1}$ and $\theta = (\beta, \rho)'$, the score vector and information matrix implied by Eq. [7] are:

$$[8] \quad \frac{\partial L}{\partial \theta} = \frac{1}{\sigma^2} \begin{pmatrix} X'u \\ Z'u - tr(AW) \end{pmatrix} = G$$

and,

$$[9] \quad -E \frac{\partial^2 L}{\partial \theta \theta'} = \frac{1}{\sigma^2} \begin{pmatrix} X'X & X'Z \\ Z'X & Z'Z + \sigma^2 tr(AWAW) \end{pmatrix} = V,$$

respectively. Standard iterative maximum-likelihood estimation procedures use these matrices to calculate the change in θ across iterations: $\theta_{j+1} = \theta_j + V^{-1}G$. The presence of the $tr(AW)$ in Eq. [8] and $tr(AAWW)$ in Eq. [9] imply that the change in coefficients across iterations j and $j+1$ cannot be calculated via a simple regression of ε on X and Z .