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FDI in space: Spatial autoregressive relationships in foreign direct investment

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Abstract

There are a number of theoretical reasons why foreign direct investment (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.

JEL classification: F21; F23.

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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

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nearly 32%. When compared to the 1.5% annual growth in exports and the 0.6% annual increase in world gross domestic product (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.[2]

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 et al. (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 of final goods from the affiliate in the host country.[3,4] 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 et al. (forthcoming) and termed "complex vertical." While both of these forms of FDI would involve exports to third markets, the difference is that complex-vertical MNE activity would be associated with exports of intermediate inputs from affiliates to third market for further (or final) processing, before being shipped to its final destination. However, 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.[5]

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

[2] Recent work by Carr et al. (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.

[3] Consistent with this, anecdotal evidence suggests that as much as 94% of US affiliate production in Ireland is intended for export, 76% of which is bound for the European Union (CSO, 2004).

[4] Ekholm et al. (2003) also distinguish between export-platform firms, differentiating between "horizontal export platforms" in which all subsidiary output is sold in the third country and "vertical export platforms" in which subsidiary output is sold both in the third country and in the parent country. Since we control separately for the size of third countries and the parent country, we do not distinguish between these in our discussion.

[5] Blomström and Kokko (1998) provide a more detailed discussion of how agglomeration economies may arise in the context of FDI, and we discuss this more below.

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 (or third-region) effects—much less, general interdependence across multiple host markets—is sparse. Head et al. (1995) look for evidence of agglomeration externalities in determination of Japanese FDI location in the US by examining patterns of related producers in states adjacent to the US state chosen by a Japanese affiliate. Their 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. Head and Mayer's (2004) analysis of Japanese FDI patterns into developed Europe examines the effect of market potential using measures that include not only the host region's GDP, but also GDP of adjacent regions weighted by distance and other trade frictions. They find that regions with higher market potential attract more FDI and that this effect is robust to a variety of alternative measures of market potential and inclusion of agglomeration measures as in Head et al. (1995). While the discrete choice models used in Head et al. (1995) and Head and Mayer (2004) allow for potential interdependence of FDI decisions, such models impose significant restrictions on the data, (e.g., the assumption of the independence of irrelevant alternatives). Furthermore, they limit one to examining a discrete measure of FDI choice, not the magnitude of the FDI activity.[6] 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 that a region's FDI is positively correlated with FDI into neighboring regions (a positive spatial lag), which is attributed to agglomeration economies. The only other paper to use spatial econometric techniques to examine FDI patterns is Baltagi et al. (forthcoming) whose approach is more closely related to ours.[7] 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 what extent does omission of spatial interactions bias the coefficients on the

[6] Ekholm et al. (2003) also present empirical work examining the extent to which subsidiary sales are geared towards the parent, host, or third countries. Like our results, they find that the evidence of export-platform FDI depends on the geography of the host country under consideration, with a particular importance given to trade agreements.

[7] 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.

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. Furthermore, after controlling for country-specific dummy variables, estimated effects of spatial terms are often insignificant. This result is analogous to Feenstra's (2002) finding that fixed effects can adequately control for third-country effects in gravity trade models, which Anderson and Van Wincoop (2003) show are crucial in modeling trade in the gravity framework. However, our analysis also reveals that both the traditional determinants of FDI and the estimated spatial interdependence are 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 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 from MNE motivations

There are a variety of MNE 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 the spatial econometrics literature refers to 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.[8] 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.

[8]Contemporaneous only from the econometrician's perspective, given that the sequential observations are only observed in aggregate on an annual basis.

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. The decision to undertake horizontal FDI is governed by the "proximity–concentration tradeoff" in which proximity to the host market avoids trade costs but incurs the added fixed cost of building a second production facility.[9] In its simplest form, such a model would not be associated with any 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 MNE will choose the most preferred destination market and use it as a platform to serve other markets through exports. Note that using a single, well-located subsidiary provides a great deal of the proximity benefits of the pure horizontal firm without incurring additional plant-level fixed costs. This desire to economize on plant-level costs 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 surrounding-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 surrounding-market potential should be insignificant in a well-specified model of this form of FDI, since the output of the subsidiary is simply shipped back to the parent country, leaving the characteristics (and FDI activities) of surrounding markets without explanatory power.

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 et al., forthcoming; 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, including the location of immobile resources (e.g., mining of natural resources). 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.

Table 1 summarizes the signs one would expect to find in the data if activity were being driven by each of these various forms of MNE behavior at the firm level. Since there may

[9] See Brainard (1997) for discussion of and evidence for this tradeoff in a two-country setting.

Table 1
Summary of hypothesized spatial lag coefficient and surrounding-market potential effect for various forms of FDI

FDI motivation	Sign of spatial lag	Sign of surrounding-market potential variable
Pure horizontal	0	0
Export-platform	–	+
Pure vertical	–	0
Vertical specialization	+	0

be a mixture of these motivations behind the country- and industry-level data we observe, our empirical work below will identify only net effects. Thus, we cannot directly test for the existence of one form over the other. However, confirmatory evidence of one dominant form of MNE activity in the data is possible given unique sign patterns across the various forms.

Our main goal in this section has been to simply illustrate how MNE 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 ignoring spatial interdependence of FDI decisions, straightforward methods of dealing with this potential bias, and the sensitivity of spatial relationships across various sub-samples of our data.

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 describe the data for the sample of countries we use in our analysis.

3.1. Spatially-dependent FDI

In general, one would be interested in fitting data with a spatial model for one of two reasons.[10] 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.[11] Second, and of particular interest in examining connections to the MNE motivations discussed above, the estimation of a spatial autoregressive or "spatial lag" model accounts 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

[10]See Anselin (1988) for detailed discussion.

[11]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 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.

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.[12]

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

$$\mathrm{FDI} = \alpha_0 + \alpha_1 \text{ Host Variables} + \varepsilon, \tag{1}$$

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 leads to well-behaved residuals given the skewness common to FDI data. Such a log-linear model also allows for interactions of the underlying linear forms of the variables, as found in Carr et al. (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 et al. (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).

[12]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.

While the standard specification would include characteristics of the parent country (e.g., 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—*Surrounding-Market Potential* and the spatially lagged dependent variable, $W \cdot \mathrm{FDI}$. In particular, we estimate

$$\begin{aligned}\mathrm{FDI} = {} & \alpha_0 + \alpha_1 \text{ Host Variables} + \alpha_2 \text{ Surrounding-Market Potential} \\ & + \rho \cdot W \cdot \mathrm{FDI} + \varepsilon. \end{aligned} \tag{2}$$

We define the surrounding-market potential variable broadly, where for a country j it is defined as the sum of inverse-distance-weighted GDPs of all other $k \neq j$ countries in the world for which we can obtain GDP data, by year. While similar in spirit to the Harris (1954) measure of market potential of neighboring regions which Head and Mayer (2004) find has the best explanatory power in their analysis, our surrounding-market potential variable differs from previous studies by not including the host region's GDP, which we will include as a separate regressor. We do this in order to better identify various forms of MNE activity. For example, while the host region's GDP is likely an important factor for both pure horizontal and export-platform MNE activity, the market potential *surrounding* a host region should only have an impact on export-platform MNE decisions. As we will show below, the data clearly reject a common coefficient on host GDP and surrounding-market potential, which is the imposed restriction of previous studies when combining these into one market potential variable. We use the same functional form on distance for constructing the surrounding-market potential variable as we will use for our construction of the spatial lag term which we discuss next.[13]

The addition of $\rho \cdot W \cdot \mathrm{FDI}$ 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 the spatial relationship in FDI captured by W. It is important to recognize that $\rho \cdot W \cdot \mathrm{FDI}$ captures the proximity of the observed host to other host countries; $W \cdot \mathrm{FDI}$ should therefore not be confused with the standard gravity distance that measures the distance between the parent and 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

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

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

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 $W_{1983} = W_{1984} = \cdots = W_{1998}$.[14] With our sample of FDI over years 1983 through 1998, the full weight matrix, W, is given by

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

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 km separating Brussels and Amsterdam) receives a weight of unity and all other distances within the sample receive a weight that declines according to

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

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 kth column of row j indicates that the kth observation will be used to adjust the prediction of the jth observation $(j \neq k)$.[15] 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, $W \cdot \mathrm{FDI}$, then has the simple interpretation of row-sums being a proximity-weighted average of FDI into alternative countries.[16]

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 kth 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 established literature in spatial econometrics by estimating the model Eq. (2) using maximum likelihood (ML) methods. Such methods are described in more detail in Appendix A.

[14] 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.

[15] 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.

[16] Note that we do not row-standardize our surrounding-market potential variable, implying that this is the overall size of the distance-weighted third country GDPs. Using this non-standardized surrounding-market potential makes it more comparable to that used by Head and Mayer (2004).

3.3. Sample data

We begin our estimations with a panel of annual data on US outbound FDI activity into the 35 host country destinations for the period 1983 through 1998.[17] 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.

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 (Blonigen et al., 2005). 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 et al. (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.[18]

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.[19] 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 GDP and population data come from Penn World Tables (PWT), which reports such data for 1950 through 2000.[20] 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.

Host country skill is measured by average years of schooling for those over age 25, reported every five years for 1960–2000.[21] 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.[22] Missing data from this source forces us to exclude Iceland and New Zealand. As such, our final sample spans from 1983 to 1998 for

[17]Limiting to these 35 FDI destinations is primarily due to electronic processing constraints of estimating these spatial lag models and the lack of investment barrier data. However, we note that these top 35 destinations accounted for more than 94% of all US FDI activity in 1992.

[18]Blonigen et al. (2005) provide an initial set of theoretical and empirical results regarding spatial interactions in US inbound FDI.

[19]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.

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

[21]Acquired from Barro and Lee (2001), International Data on Educational Attainment.

[22]For more information see http://www.beri.com.

Table 2
Descriptive statistics

Variable	Mean	Standard deviation	Minimum	Maximum
FDI	41,686	61,604	964	350,173
Host GDP ($billions)	392	490	24	3120
Host population (thousands)	40,259	41,921	2.681	203.678
Host trade costs	0.025	0.018	0.003	0.110
Host skill	7.334	2.239	2.642	11.844
Host investment costs	55.320	12.238	33.000	82.667
Host distance from US in km	8327	3855	734	16,371
Surrounding-market potential ($billions)	811	667	116	3360

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 of 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.Sample countries (where * denotes OECD country) include: 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.

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.[23] Table 2 provides a list of the 35 included countries, as well as summary statistics of the variables in our data from 1983 through 1998.

4. Empirical results

In this section, we begin by presenting our initial results using our full sample to explore spatial interactions in the data and gauge the bias on the coefficient estimates of traditional FDI determinants when one does not control for such spatial relationships. The heterogeneity of countries in the full sample makes it less likely that the spatial terms would identify one form of MNE activity as prevalent. Thus, the rest of the section refines our data into alternative sub-samples in order to more narrowly focus on the likely types of FDI motivations. Following this, we disaggregate by industry within a given sub-sample—US activity into OECD countries in Europe—to highlight the fact that aggregation across industries also masks variation in the evidence for different types of FDI.

[23]These data were obtained from the website of Centre d'Etudes Prospectives et d'Informations Internationales, http://www.cepii.fr/anglaisgraph/bdd/distances.htm.

4.1. Base results

Table 3 presents our initial results using our full sample of country-level data. We present five 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 (3) present OLS estimates that separately include the traditional market potential variable (i.e., that which combines host-country GDP with the measure of surrounding-market potential) and surrounding-market potential variable, respectively. These two columns allow us to examine the results from a traditional market potential variable to one that allows host GDP and surrounding-market potential to have separate impacts. Column (4) provides ML estimates of the full specification of Eq. (2), which includes host GDP and surrounding-market potential as separate variables, as well as a spatial lag on FDI. Finally, Column (5) of Table 3 adds country dummy variables to our specification in Column (4), controlling for unobserved country-specific heterogeneity.

A number of interesting observations can be made from results in Table 3. A first observation is the very strong rejection in the data that host GDP and surrounding-market potential have identical effects on FDI activity. As shown in the Column (3) estimates, host GDP has a strong positive and significant coefficient (an elasticity of 1.8, given the variables are in logarithm), while surrounding-market potential has a significant negative coefficient. This unexpected result is inconsistent with all of the MNE motivations we discuss and presents an apparent puzzle. We will come back to alternative hypotheses for this result below, including consideration of omitted variable biases that may be controlled for by including country dummies. Regardless, a traditional market potential variable which restricts the coefficient to be identical on these two terms, as in Column (2), results in an insignificant coefficient and a significant decrease in the R^2 from 0.87 to 0.74. Coefficients on other control variables differ significantly when imposing this restriction as well. Thus, the data clearly reject the market potential variable traditionally used in the literature in favor of including separate terms for host-country GDP and the surrounding-market potential.

The second observation is that our spatial lag term, first included in Column (4), is significant and positive. A positive spatial lag is consistent with complex-vertical motivations for MNE activity and/or other positive production externalities amongst US foreign affiliates across countries. Thus, we find evidence for the importance of spatial interdependence in the data through both the spatial lag and surrounding-market potential terms. Interpretation of the coefficient estimate is that there is approximately a 5% increase in FDI into a host country for a 10% increase in the distance-weighted FDI going into surrounding markets. We find it surprising and important that the other control variables, including the surrounding-market potential variable, are relatively unaffected by inclusion of the spatial lag—Columns (3) and (4) estimates are qualitatively identical—despite the statistical and economic significance we report. In general, this is reassuring evidence of the validity of previous empirical studies of cross-country FDI that have not considered spatial patterns.

The final set of observations in Table 3 estimates regard the last column where we include a set of country-level dummy variables. As is well known, such variables control for time-invariant unobserved effects specific to each country in our panel data. As such, it is possible that the spatial effects we find will be subsumed into these country dummies if

Table 3
Spatial analysis of US outbound FDI—full sample

Independent variable	Full sample				
	(1)	(2)	(3)	(4)	(5)
Ln(host population)	−0.452*** [0.082]	0.871*** [0.041]	−0.666*** [0.075]	−0.693*** [0.071]	−1.023*** [0.134]
Ln(host trade cost)	−0.680*** [0.061]	−0.213*** [0.069]	−0.935*** [0.059]	−0.944*** [0.055]	−0.792*** [0.075]
Ln(host skill)	0.248** [0.113]	1.186*** [0.127]	0.244** [0.101]	0.221** [0.095]	0.098 [0.130]
Ln(host investment costs)	−0.882*** [0.212]	−3.533*** [0.226]	−1.069*** [0.190]	−0.970*** [0.179]	−0.699*** [0.157]
Ln(host distance from US in km)[a]	−0.389*** [0.047]	−0.729*** [0.062]	−0.622*** [0.046]	−0.627*** [0.044]	
Trend (1980 = 1)	−0.103*** [0.023]	−0.005 [0.029]	−0.058*** [0.021]	−0.055*** [0.020]	−0.059*** [0.019]
Trend^2	0.003** [0.001]	0.002 [0.002]	0.002* [0.001]	0.000 [0.001]	0.002*** [0.001]
Ln(host GDP)	1.575*** [0.091]		1.827*** [0.083]	1.846*** [0.078]	1.115*** [0.090]
"Traditional" market potential (i.e., Ln(host + weighted GDPs))		−0.005 [0.095]			
Surrounding-market potential (i.e., Ln(weighted GDPs))			−0.714*** [0.060]	−0.929*** [0.063]	−0.059 [0.211]
Spatially weighted FDI[b] (i.e., *W* FDI)				0.504*** [0.067]	0.144* [0.078]
Constant	−18.652*** [0.881]	−9.823*** [1.753]	−6.486*** [1.288]	−6.485*** [1.211]	−6.589* (3.552)
Country dummies	No	No	No	No	Yes
Observations	551	551	551	551	551
Adj R^2/Wald Chi^2	0.83	0.74	0.87	3430.6	28776.9

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

[a] Recall that distance is time invariant.

[b] Weights, W, are defined as $w_y(d_{i,j}) = 173/d_{i,j} \forall i \neq j$.

such spatial interactions are relatively stable over time.[24] In fact, there is an analogy in the international trade literature in Feenstra's (2002) finding that third-country interdependence in gravity model estimation delineated by Anderson and Van Wincoop (2003) can be adequately accounted for in a panel setting with country-level fixed effects. In our data, the inclusion of country dummies substantially eliminates the statistical and economic significance of the spatial terms. The surrounding-market potential variable is now statistically zero and the spatial lag coefficient falls to just 0.144, though still statistically significant. We note that we cannot identify whether the spatial effects are present but stable over time, so that they are subsumed into the country dummies, or whether our spatial terms were simply correlated with unobserved country effects. However, it is particularly noteworthy that when including country dummies the surrounding-market potential term has an insignificant coefficient rather than the more-puzzling negative. Alternatively it may be that controlling for unobserved country heterogeneity eliminates a bias in this variable. Regardless, we find that spatial effects, to the extent they exist, are properly thought of as cross-sectional in nature, largely controlled for by using country-fixed effects. We revisit this issue though in other sub-samples below. On a final note, the coefficient estimates on the other control variables change much more with the inclusion of country dummies than when we simply add spatial terms, which is consistent with time-invariant unobserved effects being quite significant in determining FDI patterns.

4.2. Spatial patterns in the sub-samples of the data

4.2.1. OECD versus non-OECD results

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 Fig. 1 illustrates, this has important implications for the spatial distribution of US outbound FDI. We therefore refine our analysis by considering alternative samples that first split the sample into OECD and non-OECD countries and then examine a sample of only European OECD countries. These results are reported in Table 4. For each sub-sample, we report specifications analogous to columns (4) and (5) in Table 3, which allow the comparison of specifications without and with country dummies, respectively.

Beyond this issue of geography, a primary motivation for splitting the sample between OECD and non-OECD countries is 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. Separating the sample in this way may then provide sharper results with respect to our spatial terms, in particular.

The first two columns of Table 4 provide results from the OECD sub-sample, where we find results that are quite similar to their counterparts from the full sample (i.e., columns

[24]This may be quite likely a priori since a component of these terms is distance, which clearly does not change over time. This is indeed what Baltagi, Egger, and Pfaffermayr (forthcoming) find in their fixed effects estimates.

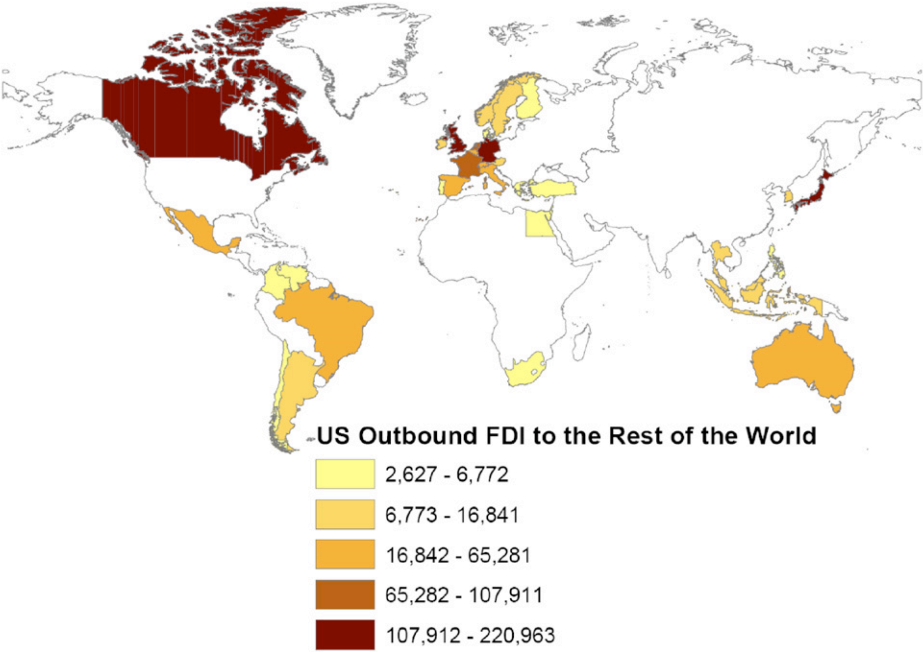

Fig. 1. US outbound FDI in 1992. Sample countries included (where * denotes OECD country): Argentina, Australia*, Austria*, Belgium*, Brazil, Canada*, Chile, Columbia, Denmark*, Egypt, Finland*, France*, Germany*, Greece*, Indonesia, Ireland*, Italy*, Israel, Japan*, Korea, Malaysia, Mexico, Netherlands*, Norway*, Philippines, Portugal*, Singapore, South Africa, Spain*, Sweden*, Switzerland*, Thailand, Turkey*, United Kingdom*, Venezuela.

(4) and (5) in Table 3). In particular, as in the full-sample results, we find a significant negative effect of surrounding-market potential and a significant positive spatial lag when we do not include country dummies. Both spatial terms are insignificant once the country dummies are included. All together, this suggests that when restricting the data to the developed world (which is approximately 88% of US outbound FDI in our sample), filtering out time-invariant effects appears to sufficiently control for spatial effects that exist in the cross section of countries. While not reported here for brevity, the traditional control regressors are generally invariant to the inclusion of spatial terms in both sub-samples (OECD and non-OECD).[25] Additionally, in unreported results we find that the use of a traditional market potential variable, that restricts the coefficients on host GDP and surrounding-market potential, is rejected in both sub-samples. These are important results that are consistent with our full sample results.

While most of the estimates for the non-OECD sub-sample in columns (3) and (4) are qualitatively similar, there are a few important differences. First, the host skill variable is negative in the non-OECD sample (before controlling for fixed country effects), while positive and statistically significant in the OECD sample. This likely points out very

[25]On the other hand, as shown by comparing columns (1) and (2), the magnitude and even the sign of some of the traditional controls are significantly affected by whether one includes country dummies or not.

Table 4
Spatial analysis of US outbound FDI—sub-samples

Independent variable	OECD		Non-OECD		European OECD	
	(1)	(2)	(3)	(4)	(5)	(6)
Ln(host population)	−0.348** [0.139]	0.688** [0.289]	−1.002*** [0.094]	0.206 [0.127]	0.224 [0.140]	1.720*** [0.282]
Ln(host trade cost)	−1.540*** [0.102]	−0.335*** [0.105]	−0.766*** [0.069]	−0.891*** [0.096]	−0.836*** [0.121]	−0.681*** [0.100]
Ln(host skill)	0.871*** [0.156]	0.884*** [0.180]	−0.425*** [0.122]	0.222 [0.179]	1.084*** [0.160]	0.076 [0.168]
Ln(host investment costs)	−1.286*** [0.184]	−0.739*** [0.153]	0.007 [0.279]	−0.772*** [0.257]	−1.326*** [0.204]	−0.476*** [0.151]
Ln(host distance from US in km)[a]	−0.456*** [0.048]		−0.412*** [0.068]		−2.671*** [0.252]	
Trend (1980 = 1)	−0.029 [0.023]	−0.098*** [0.017]	−0.103*** [0.025]	−0.033 [0.035]	−0.049** [0.024]	−0.132*** [0.020]
Trend 2	−0.002** [0.001]	0.002*** [0.001]	0.005*** [0.001]	0.004*** [0.001]	−0.000 [0.001]	0.002*** [0.001]
Ln(host GDP)	1.678*** [0.137]	1.951*** [0.141]	2.005*** [0.102]	1.297*** [0.131]	1.019*** [0.143]	1.943*** [0.141]
Surrounding-market potential (i.e., Ln(weighted GDPs))	−0.922*** [0.080]	0.112 [0.108]	−0.831*** [0.119]	−1.505*** [0.429]	−0.049 [0.190]	0.539*** [0.178]
Spatially weighted FDI[b] (i.e., $W \cdot$ FDI)	0.689*** [0.062]	−0.012 [0.057]	0.069 [0.090]	0.082 [0.072]	0.461*** [0.096]	−0.013 [0.056]
Constant	−15.259*** [1.700]	−41.478*** [4.657]	−0.457 [2.955]	5.442 [7.407]	−2.577 [3.406]	−58.126*** [3.625]
Country dummies	No	Yes	No	Yes	No	Yes
Observations	314	314	237	237	266	266
Wald Chi^2	4091.7	48550.5	972.6	4668.3	3566.5	42523.7

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

[a]Recall that distance is time invariant.

[b]Weights, W, are defined as $w_y(d_{i,j}) = 173/d_{i,j} \forall i \neq j$.

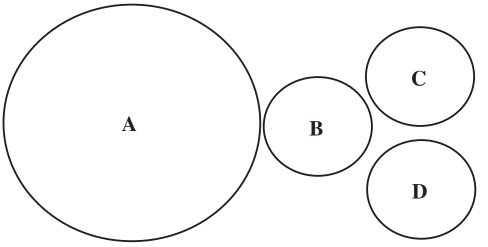

Fig. 2. Spatial grouping of four countries where size of circle represents size of country's market.

different motivations for FDI across these countries, with FDI attracted to low-skill locations within non-OECD countries because of its correlation with low wages, but attracted to high-skill locations (despite its correlation with wages) for FDI into developed OECD countries.

The spatial terms also reveal an important difference between the two sub-samples. In both, the spatial lag is insignificant after country dummies are included. However, while the negative coefficient on surrounding-market potential becomes statistically insignificant with the inclusion of country dummies in the OECD sample, it remains statistically negative and grows in absolute magnitude in the sample of non-OECD countries. These coefficient estimates on the spatial terms do not correspond to a particular MNE model and the negative coefficient on the market potential variable is particularly puzzling.

4.2.2. *Border effects and surrounding-market potential*

A possible resolution, as suggested by a referee, is the role of border costs between countries.[26] Suppose a MNE wishes to serve a region of neighboring countries with export-platform affiliate sales rather than with exports, where one country is quite large in market size relative to the others, but not centrally located within the group of countries, as depicted by Country A in Fig. 2. If there are no border costs between the countries—only transport costs—the MNE would locate its affiliate centrally, in Country B, which would have the largest distance-weighted surrounding-market potential. Now suppose that border costs are significant between the countries, though not so significant as to eliminate the MNE's desire to serve the region from a single export-platform affiliate. In this case, the MNE is more likely to locate in Country A in order to have access to the largest market free of border costs. However, given the construction of the variable, Country A has the smallest surrounding-market potential of the four countries! Furthermore, Country B, with its large surrounding-market potential due to its proximity to A, stands to lose the most FDI as border costs rise. In these ways, border costs can actually lead to a predicted negative relationship between surrounding-market potential and MNE activity. This simple hypothesis also echoes the results of Ekholm et al. (2003), which suggests that the

[26]An alternative hypothesis for the negative sign on the surrounding market potential coefficient is the negative competitive impacts from firms in these neighboring markets. This could occur if firms in neighboring countries have greater competitive advantages to serving the host market than the US firms. However, if such competitive forces were indeed a dominant factor, by the same reasoning one could then also expect a negative coefficient on host GDP term, which is not a feature of our results.

potential of export-platform FDI is likely greatest between members of free trade agreements.

We examine this hypothesis in two ways. First, as the negative coefficient on the surrounding-market potential variable appears robust to the inclusion of country dummies in the non-OECD sample, we attempt further investigation with the addition of an interaction between our surrounding-market potential variable with the trade-cost measure. If the border-costs hypothesis is correct, we would expect a negative coefficient on this interaction term, suggesting that with greater trade costs the negative relationship between surrounding-market potential and MNE activity might be exaggerated. In the above example, as border costs rise, increasing our trade cost measure for country B, its proximity to A implies that it receives even less FDI than before. In a full specification including country dummies, the inclusion of this interaction term does yield a statistically significant negative coefficient, providing confirmatory evidence for this interpretation of negative effect of surrounding-market potential.

Perhaps an even more compelling exercise is to analyze MNE activity for a group of neighboring countries in our sample with little to no border costs—the European OECD countries in our sample. If the border-cost hypothesis is correct, we should find no evidence for a negative effect of surrounding-market potential on MNE activity. We turn to this analysis in the next section.

4.2.3. European OECD sub-sample results

Results from a sample of European OECD countries are shown in columns (5) and (6) of Table 4. A primary difference between this sample and the other samples is that the surrounding-market potential variable is never significantly negative and is positive and significant when capturing cross-sectional variation in FDI with the inclusion of country dummies. The sign pattern on the spatial terms in the country-dummies specification, with a negative spatial lag coefficient, is consistent with export platform motivations, though the spatial lag is statistically insignificant. As with other samples, control variables are relatively invariant to inclusion of spatial terms in this sample, even when these terms are statistically significant, but fairly sensitive to the inclusion of country dummies. Importantly, the data again reject restricting the coefficients on host-country GDP and surrounding-market potential to be the same although we note that we obtain a fairly similar coefficient estimate on the traditional market potential variable (which combines both host and surrounding-market GDPs) to that of Head and Mayer (2004) when our sample only covers European OECD countries and we weight countries as in their data.

The insignificant spatial lag for the European sample is somewhat surprising, as other studies (e.g., Ekholm et al., 2003; Head and Mayer, 2004) have found some evidence for export-platform motivations of MNE activity in Europe, albeit using different data samples and methodologies. One possible explanation is aggregation bias from using country-level data. If all US firms were choosing the same country (or handful of countries) to serve as export platforms we would expect a negative spatial lag. However, heterogeneity across industries likely implies attractions to different export-platform locations. If export-platform FDI was occurring, but industries were picking different locations for these platforms, our estimates from aggregate data would pick up the importance of surrounding-market potential, but no negative spatial lag. It is also possible that even in these developed countries some industries are primarily motivated by vertical specialization chains, which would tend to make the spatial lag positive in sign,

Table 5
Industry-level analysis of spatial patterns in US outbound FDI

Independent variable	Petroleum	Food and kindred products	Chemicals and allied products	Primary and fabricated metals	Machinery, except electrical	Electric and electronic equipment	Transport-ation equipment	Other manufac-turing	Wholesale trade	Services	Other industries
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Ln(host GDP)	1.395***	−0.267	0.126	1.109	1.326	2.209***	2.094*	−0.155	2.737***	1.420***	−5.053***
	[0.530]	[0.607]	[0.486]	[0.880]	[0.917]	[0.517]	[1.123]	[0.435]	[0.262]	[0.444]	[1.547]
Ln(host population)	3.904**	8.552***	6.795***	16.099***	−2.795	1.087	11.356***	6.701***	4.782***	−3.949***	−23.681**
	[1.786]	[1.652]	[1.259]	[2.278]	[2.396]	[1.282]	[2.920]	[1.191]	[0.961]	[1.218]	[9.698]
Ln(host trade cost)	−0.243	1.983***	−0.326	2.695***	5.128***	−0.308	−0.442	−0.656*	−1.192***	0.025	−2.020
	[0.459]	[0.551]	[0.465]	[0.830]	[0.800]	[0.580]	[1.264]	[0.381]	[0.239]	[0.393]	[1.679]
Ln(host skill)***	0.436	9.847***	2.295***	4.981***	6.368***	1.291	−0.703	−1.055*	1.826***	1.613***	−12.993***
	[0.603]	[0.843]	[0.686]	[1.546]	[1.348]	[1.035]	[2.021]	[0.605]	[0.351]	[0.597]	[4.287]
Ln(host investment costs)	−0.212	−0.069	−1.114**	−5.001***	−2.068**	−0.015	−1.925	−1.740***	−0.489*	−0.194	−6.592***
	[0.649]	[0.627]	[0.507]	[1.030]	[0.977]	[0.554]	[1.413]	[0.444]	[0.274]	[0.556]	[1.701]
Trend (1980 = 1)	−0.194**	−0.158*	−0.104	−0.640***	0.126	0.339***	−0.220	0.088	−0.051	−0.199***	0.168
	[0.077]	[0.087]	[0.071]	[0.114]	[0.136]	[0.091]	[0.179]	[0.077]	[0.036]	[0.065]	[0.196]
Trend^2	0.004**	0.002	0.003*	0.014***	0.004	−0.005**	−0.004	−0.002	−0.003***	0.008***	0.011**
	[0.002]	[0.002]	[0.002]	[0.003]	[0.004]	[0.002]	[0.005]	[0.002]	[0.001]	[0.002]	[0.005]
Surrounding-market potential	0.363	3.131***	1.159*	5.436***	−1.103	−5.458***	2.426	−0.220	−0.594*	2.160***	3.400
(i.e., weighted GDPs)	[0.766]	[0.805]	[0.663]	[1.098]	[1.236]	[0.995]	[1.924]	[0.679]	[0.326]	[0.605]	[2.092]
Spatially weighted FDI[a]	0.226**	−0.247**	0.084	−0.304***	−0.081	−0.077	−0.054	−0.084**	−0.067	−0.082	−0.152
(i.e., $W \cdot FDI$)	[0.099]	[0.115]	[0.085]	[0.117]	[0.101]	[0.069]	[0.081]	[0.041]	[0.082]	[0.109]	[0.106]
Constant	−65.067***	−142.60***	−93.727***	−291.97***	27.432	65.556***	−195.183***	−54.030***	−83.004***	−34.225**	227.983**
	[19.189]	[22.280]	[16.871]	[28.661]	[31.160]	[23.817]	[48.530]	[17.516]	[10.693]	[15.959]	[89.778]
Observations	140	198	220	191	214	171	149	139	216	222	105
Adj R^2/Log-likelihood	−6.401	−90.26	−63.86	−139.8	−192.4	−40.39	−145.3	13.89	73.74	−45.92	−95.92

Absolute values of t-statistics are in parentheses: *significant at 10%; **significant at 5%; **significant at 1%.
In all specifications, the dependent variable, Ln(FDI), is the real sales by US-owned foreign affiliates in a given industry.
[a]Weights, W, are defined as $w_y(d_{i,j}) = 173/d_{i,j} \quad \forall \ i \neq j$.

counterbalancing the effect of industries pursuing export-platform strategies.[27] In the next section we turn to data on industry-level outbound US FDI by country for the European OECD sample, motivated in part to further disentangle MNE motivations from the data.

4.3. Examination of disaggregated country-industry level data

Table 5 presents results when we estimate our empirical specification for US MNE activity in European OECD countries by individual economic sectors categorized by the BEA. Publicly available data on US FDI activity has limitations in how disaggregated such data can be reported and these categories represent the finest level of disaggregation for which we can get public data by country and industry on an annual basis.

Our time period, sample countries, and control variables match those for the European OECD regression above. Given the importance suggested above, we also include country dummies in all specifications. 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. As one may expect, there is substantial heterogeneity in estimates across sectors though these differences are mainly in the magnitude of estimated parameters, not their sign.

Importantly, we find stronger evidence of export-platform activity in the European-OECD sample when adopting these more disaggregated sector-level data. Five 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. For two of these, ‘‘food and kindred products’’ (Column 2) and ‘‘primary and fabricated metals’’ (Column 4), both of these spatial variables are also statistically significant. The coefficient on market potential is non-negative in nine of the 11 sectors and significantly positive 4 times. The spatial lag is likewise non-positive 10 out of eleven times and significantly negative three times. The one exception to this is ‘‘Petroleum,’’ (Column 1). However, given that a great deal of this industry is likely tied to the geographic proximity of oil fields, such may not be surprising.

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

[27] For example, micro-level evidence by Feinberg and Keane (2001) and Hanson et al. (2005) find substantial vertical activity going on only for certain manufacturing sectors (such as electronics) and host countries.

terms to capture spatial interdependence, even though such interdependence is estimated to be significant 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 and level of disaggregation are quite important in trying to separate evidence supporting different motivations for FDI.

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 et al. (forthcoming) 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 and disaggregate our data we find evidence suggestive of export-platform FDI for most industries within the developed European countries.

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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:

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

Eq. (A.1) 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. (A.2) in the text other than the spatial lag term. Substituting this expression into Eq. (A.1), the log-likelihood function is

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

The Jacobian term makes estimation difficult as calculating the determinant of the $n \times n$ 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 $n \times n$ matrix is also time-consuming, the calculation need only be made once.

Letting $Z = W \cdot \mathrm{FDI}$, where $A = (I - \rho W)^{-1}$ and $\theta = (\beta, \rho)'$, the score vector and information matrix implied by Eq. (A.2) are

$$\frac{\partial L}{\partial \theta} = \frac{1}{\sigma^2} \begin{pmatrix} X'u \\ Z'u - \mathrm{tr}(AW) \end{pmatrix} = G, \tag{A.3}$$

and,

$$-E\frac{\partial^2 L}{\partial \theta\, \partial \theta'} = \frac{1}{\sigma^2} \begin{pmatrix} X'X & X'Z \\ Z'X & Z'Z + \sigma^2\, \mathrm{tr}(AWAW) \end{pmatrix} = V, \tag{A.4}$$

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 $\mathrm{tr}(AW)$ in Eq. (A.3) and $\mathrm{tr}(AAWW)$ in Eq. (A.4) 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.

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