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DETERMINANTS OF FOREIGN DIRECT INVESTMENT

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ABSTRACT

Empirical studies of bilateral foreign direct investment (FDI) activity show substantial differences in specifications with little agreement on the set of covariates that are (or should be) included. We use Bayesian statistical techniques that allow one to select from a large set of candidates those variables most likely to be determinants of FDI activity. The variables with consistently high inclusion probabilities are traditional gravity variables, cultural distance factors, parent-country per capita GDP, relative labor endowments, and regional trade agreements. Variables with little support for inclusion are multilateral trade openness, host country business costs, host-country infrastructure (including credit markets), and host-country institutions. Of particular note, our results suggest that many covariates found significant by previous studies are not robust.

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1. Introduction

Empirical analyses of the factors determining foreign direct investment (FDI) across countries have employed a variety of econometric specifications. Many previous studies of cross-country FDI activity have used a gravity equation, which mainly controls for the economic size of the parent and host countries, the geographic distance separating the countries, and proxies for certain economic frictions. Like trade flows, this specification does a reasonably good job of fitting the observed data, but leaves one wondering if such a parsimonious specification captures all relevant factors.

Recent papers by Carr, Markusen and Maskus (2001) and Bergstrand and Egger (2007) have developed theoretical models of multinational enterprise's (MNE's) foreign investment decisions that suggest additional possible factors that determine FDI patterns. These studies point out a number of modifications to a standard gravity model that may be necessary to accurately explain FDI patterns. First, while gravity variables may adequately capture "horizontal" motivations for FDI, where firms look to replicate their operations in other countries to be more proximate to consumers in those markets, additional controls are necessary to allow for "vertical" motivations of FDI, where firms look for low-cost locations for labor-intensive production. For example, these studies introduce measures of relative labor endowments in the host country with the expectation that countries with relatively high shares of unskilled labor will be attractive locations for MNEs due to lower wages. In addition, these studies show that FDI decisions by MNEs are complex enough that interactions between key variables (e.g., GDP and skilled labor endowments) may be necessary to account for nonlinear effects of these variables on FDI patterns. Head and Ries (2008) differs from these previous studies by modeling FDI as arising from decisions by firms to acquire and control foreign assets (i.e., cross-border mergers and acquisitions), rather than development of new (or greenfield) plants. Their analysis of FDI patterns highlights the potential role of common culture and language between countries.

While these prior studies have been important in deepening our understanding of the factors that determine cross-country FDI patterns, they have generally focused on regression models involving specific sets of covariates determined by the researcher and the particular theoretical framework for FDI they chose to examine. By conditioning on a particular regression model specification, this practice ignores uncertainty regarding the model specification itself, which can have dramatic consequences on inference.[1] Most notably, inference regarding the effects of included covariates can depend critically on what other covariates are included versus excluded.

In this paper, we take a Bayesian approach to confront uncertainty regarding the appropriate set of covariates to include in a regression model explaining FDI activity. From a Bayesian perspective, incorporating such uncertainty is conceptually straightforward. The choice of covariates, or "model", is treated as an additional parameter that lies in the space of potential models, which allows us to compute the posterior probability that each potential model is the true model that generated the data. Posterior distributions for objects of interest, such as the effect of a particular covariate, are then averaged across alternative models, using these posterior model probabilities as weights. This procedure, known as Bayesian Model Averaging (BMA), produces inferences that are not conditioned on a particular model.

Although conceptually straightforward, BMA is practically difficult when the set of possible models is large, as direct calculation of posterior probabilities for all models becomes infeasible. In our application, we have a large set of potential covariates, which yields an

[1] For discussion and examples, see Leamer, 1978; Hodges, 1987; Moulton, 1991; Draper, 1995; Kass and Raftery, 1995; Raftery, 1996; and Fernandez, Ley and Steel, 2001a.

extremely large set of possible models ($>1.4 \text{ x } 10^{17}$). To sidestep this difficulty, we use techniques designed to obtain random draws of models from the probability distribution defined by the posterior model probabilities. Such draws are made possible even when the posterior model probabilities are unknown by using the MC^3 algorithm of Madigan and York (1995). These random model draws are then used to construct estimates of the posterior model probabilities.

Our set of potential FDI determinants is meant to be comprehensive, and includes a combination of covariates proposed by the previously mentioned studies, as well as other prior literature on FDI. We mainly examine cross-sectional patterns for the year 2000.[2] We examine both levels and log-linear regressions, placing more weight on our results for the log-linear regressions because most previous studies have used a logarithmic transformation to address skewness in the FDI variable. We also examine three different measures of FDI – FDI stock, affiliate sales, and cross-border merger and acquisition activity – in order to better compare with a broader set of prior studies. At the end, we also explore a specification that first differences across 1990 and 2000 to control for bilateral-country-pair fixed effects.

Our analysis indicates that many of the covariates used in prior FDI studies (and often found statistically significant) do not have a high probability of inclusion in the true FDI determinants model once we consider a comprehensive set of potential determinants using BMA. A fairly parsimonious covariates set is suggested by our analysis. The covariates with consistently high inclusion probabilities are traditional gravity variables, cultural distance factors, parent-country per capita GDP, relative labor endowments, and regional trade agreements. Variables with little support for inclusion are multilateral trade openness, host-

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[2] This year maximized our ability to use data from datasets that have not been updated recently with data sets that were not collected prior to 2000.

country business costs, host-country infrastructure (including credit markets), and host-country institutions.

The remainder of the paper proceeds as follows. The next section reviews previous empirical literature on the determinants of FDI, and makes the case that the appropriate model specification for explaining FDI patterns is far from settled. Section 3 then lays out the BMA methodology we use to assess model uncertainty. Section 4 describes the data and its sources, while Section 5 reports the results and compares to the existing literature. Section 6 concludes.

2. Prior FDI Literature

There is little consensus on how to empirically model bilateral FDI patterns, with many past empirical FDI papers using a base model consisting of gravity-type covariates (country-level GDP and distance) because of its popularity for explaining trade flows. As mentioned in the introduction, there have been a few recent efforts to develop specifications based on theoretical models – namely, the knowledge-capital (K-K) model developed by James Markusen and co-authors, which was brought to data in Carr, Markusen, and Maskus (2001); Bergstrand and Egger's (2007) model incorporating physical capital; and Head and Ries' (2008) model of acquisition FDI.

There is little consistency in the covariates that are postulated to explain worldwide FDI patterns across these three papers. To see this, the first three columns of Table 1 lists the covariates used in each of these papers. Distance between countries is the only covariate common to all three studies. There are 22 different covariates between the three studies, even though each study only averages about 10 covariates. While all three specifications postulate a role for economic size and trade frictions as driving forces of FDI, it is surprising how differently they construct and define variables meant to proxy for these common factors.

Of course, there have been many other papers that have empirically examined FDI patterns using specifications that differ from these three papers. Columns 4-8 of Table 1 list the covariates used in a number of other highly-regarded recent papers. Across these eight studies in columns 1 through 8, there are a combined 47 covariates. However, no covariate is shared by all eight studies and, on average, a covariate is only used in 1.7 of the eight studies. Interestingly, almost 85% of the covariates included in these 8 studies are found to be statistically significant. Given that the average study includes very few of the total set of possible covariates, the possibility of spurious correlations is quite real.

In addition to the substantial differences in covariates used across FDI studies, there are also differences across studies in whether variables are logged or not, or whether panel data were used. (These are noted in the first few rows of Table 1). Given these wide differences in specifications, there clearly is no consensus on how to specify the determinants of bilateral FDI patterns.

The final paper documented in Table 1 (last column) is Chakrabarti (2000). This paper is similar to ours in its motivation to understand which covariates are more likely to be robust determinants of bilateral FDI. However, the analysis considers a surprisingly small set of possible covariates, perhaps because it came before some of the recent advances in the literature. Also, it follows a different methodology (extreme bounds analysis) than ours, feasible implementation of which requires the model space be restricted *a priori*. The approach we take to implement BMA requires no such restriction, and is designed to identify and explore relevant portions of the entire model space. That said, Chakrabarti (2000) serves as a potential warning signal for the literature and motivation for further study, as it finds that most of the covariates investigated are not statistically robust using typical extreme bounds criteria.

On a final note, Eicher, Helfman, and Lenkoski (2010) is concurrent work that is similar to ours in its use of BMA to evaluate an extensive set of potential FDI determinants (including many of those included in Table 1). However, they focus on determinants of FDI flows, whereas our focus is on the (static) cross-country FDI patterns, which has been the focus of most previous studies because it connects directly to the main general equilibrium theories of multinational firm behavior and FDI. An additional focus of Eicher, Helfman, and Lenkoski (2010) is modeling the selection issue of whether there is any FDI activity between bilateral country pairs in the first place. Since virtually all prior FDI studies do not address this issue, and our primary focus is on directly comparing our BMA results to these prior studies, we do not explore this issue here.

3. Methodology

3.1 The FDI Determinants Model and Bayesian Model Averaging

To study the determinants of bilateral foreign direct investment (FDI) we focus on the linear regression model:

$$Y = \alpha\iota_N + X_j\beta_j + \varepsilon \,, \qquad (1)$$

where Y is an N x 1 vector holding the measure of bilateral foreign direct investment, ι_N is an N x 1 vector of 1's, X_j is a N x k_j matrix of FDI determinants, and ε is a an N x 1 vector of independent, normally distributed, disturbances, each with mean zero and variance σ^2. We are interested in the realistic case where there is uncertainty about the appropriate variables to include in X_j. In particular, suppose there are K potential determinants of FDI, collected in the N

x K matrix X, and the variables in X_j are chosen as a subset of X, so that $k_j \leq K$. We assume that the only aspect of model uncertainty in (1) is the selection of X_j, so that a particular selection of X_j defines the j^{th} model, denoted M_j. If we place no restrictions on the combinations of the variables in X that can enter the regression model, there are $R = 2^K$ different models to consider.

The Bayesian approach to comparing alternative models is based on the posterior probability that M_j is the true model that generated the data:

$$\Pr(M_j \mid Y) = \frac{f(Y \mid M_j)\Pr(M_j)}{\sum_{i=1}^{R} f(Y \mid M_i)\Pr(M_i)}, \quad j = 1,\ldots,R, \tag{2}$$

where (2) follows directly from Bayes' rule. In (2), $\Pr(M_j)$ is the researcher's prior probability that M_j is the true model, while $f(Y \mid M_j)$ is the so-called marginal, or integrated, likelihood function:

$$f(Y \mid M_j) = \int f(Y \mid \alpha, \beta_j, \sigma, M_j)\, p(\alpha, \beta_j, \sigma \mid M_j)\, d\alpha\, d\beta_j\, d\sigma, \tag{3}$$

where $f(Y \mid \alpha, \beta_j, \sigma, M_j)$ is the likelihood function for M_j and $p(\alpha, \beta_j, \sigma \mid M_j)$ is the researcher's prior density function for the parameters of M_j. In words, the marginal likelihood function is the likelihood function integrated with respect to the researcher's prior density function. It thus has the interpretation of the average value of the likelihood function, and therefore the average fit of the model, over different parameter values, where the averaging is done with respect to the prior density of model parameters.

The posterior model probabilities in (2) can be used to confront the model uncertainty present in the FDI determinants regression. One approach for using $\Pr(M_j \mid Y)$ is to select the model with highest posterior probability, and then make inferences about the effects of alternative FDI determinants based on this "best" model alone. However, this approach (which mimics much of the model selection literature based on hypothesis tests and information criteria) ignores information in models other than the chosen model, and thus does not yield inferences that fully incorporate model uncertainty. When the posterior model probability is dispersed widely across a large number of models, basing inferences on a single model can yield grossly distorted results.

Instead of basing inference on a single, highest probability model, BMA proceeds by averaging posterior inference regarding objects of interest across alternative models, where averaging is with respect to posterior model probabilities. Specifically, for a generic object of interest, denoted λ, the BMA posterior distribution is calculated as:

$$p(\lambda \mid Y) = \sum_{j=1}^{R} p(\lambda \mid Y, M_j)\Pr(M_j \mid Y), \tag{4}$$

where $p(\lambda \mid Y, M_j)$ represents the posterior distribution for λ conditional on M_j. The BMA posterior distribution follows from direct application of rules of probability, and is thus the obvious solution to incorporate model uncertainty into inference from the Bayesian perspective.[3] It is worth emphasizing that $p(\lambda \mid Y)$ is not conditioned on a particular model being the true model, but is instead only conditioned on the data. That is, BMA has integrated out uncertainty regarding the identity of the true model.

[3] For an introduction to BMA and a review of related literature, see Hoeting, Madigan, Raftery and Volinsky (1999).

For common choices of λ, the model dependent posterior distribution, $p(\lambda \mid Y, M_j)$, will often be available analytically. For example, in our application we are particularly interested in whether or not particular FDI determinant variables belong in the true model. In this case, $p(\lambda \mid Y, M_j)$ is simply an indicator function of whether or not the variable or variables of interest are included in X_j. The corresponding BMA posterior distribution is then the posterior probability that a particular variable or variables belongs in the true model, which is often referred to as an "inclusion probability". As another leading example, the object of interest may be the slope coefficient of a particular variable on FDI. In this case, $p(\lambda \mid Y, M_j)$, refers to the posterior distribution for a regression slope coefficient, which will be available analytically for the models considered in our application.

3.2 Calculating the Posterior Model Probabilities

To implement BMA, we require the posterior model probabilities. From (2) and (3), calculation of these probabilities requires a specification for both the prior model probability, $\Pr(M_j)$, and the prior density function for the parameters of M_j, $p(\alpha, \beta_j, \sigma \mid M_j)$, $j = 1, \ldots, R$. Our prior model probability is uniform with respect to all alternative models:

$$\Pr(M_j) = \frac{1}{R}. \tag{5}$$

This prior specification, which is a common choice in BMA applications, implies that the prior probability that any single variable belongs in the true model is 50%.

Specification of prior parameter densities poses a more significant challenge. One approach is to elicit prior densities for the parameters of each model individually. However, this becomes intractable when the space of potential models is large, as will be true for the FDI determinants model. In such cases, it is useful to use prior parameter densities that are "automatic", in that they are set in a formulaic way across alternative models. One simple, and seemingly attractive, way to do this is to use non-informative priors for the parameters of all models under consideration. Unfortunately, the use of non-informative priors for those parameters not common to all models will yield posterior model probabilities that mechanically favor models with fewer parameters over those with more. For our application, the slope parameters β_j are not common to all models, as they depend on the set of variables included in X_j. Thus, using non-informative priors for β_j is not an option, as it will paradoxically generate model comparison results that are solely a consequence of the prior. This is not the case for parameters that are common to all models, for which non-informative priors yield posterior model probabilities that are not a function of the prior, but only of sample information. For this reason, non-informative priors are a popular choice for parameters common to all models.

For our analysis, we use two different automatic procedures for setting priors. For our primary analysis, we use the priors suggested by Fernandez, Ley and Steele (2001a), hereafter FLS, who provide an automatic procedure for setting parameter prior densities for a group of linear regression models that differ only with respect to the choice of covariates. This procedure is designed for the case where the researcher wishes to use as little subjective information in setting prior densities as possible, and was shown by FLS to have both good theoretical properties and to perform well in simulations for the calculation of posterior model probabilities. As a robustness check, we also present results for a prior advocated by Eicher, Papageorgiou and Raftery (2007). We will describe the FLS prior in detail here, while the alternative prior is discussed in Section 5.5.

The FLS procedure begins by factoring the prior parameter density function as follows:

$$p(\alpha, \beta_j, \sigma \mid M_j) = p(\beta_j \mid \alpha, \sigma, M_j)\, p(\alpha, \sigma \mid M_j). \tag{6}$$

For parameters common to all models, namely α and σ, FLS use the standard, improper non-informative prior density for location and scale parameters:[4]

$$p(\alpha, \sigma \mid M_j) \propto \sigma^{-1}. \tag{7}$$

To set $p(\beta_j \mid \alpha, \sigma, M_j)$, a non-informative prior is not used, as the slope parameters are not common across all models. Instead, FLS use the natural conjugate Normal-Gamma prior density:

$$\beta_j \mid \sigma, M_j \sim N(\beta_j^0, \sigma V_j^0). \tag{8}$$

This natural conjugate form is advantageous as it allows for analytical calculation of the integrals in (3), which greatly speeds computing time. We set the prior mean, β_j^0, to a k_j x 1 vector of zeros. This centers the prior distribution for all model slope parameters on values consistent with the FDI determinants in X_j having no effect on FDI. To set the prior variance-covariance matrix, FLS suggests the *g*-prior specification of Zellner (1986):

$$V_j^0 = (g X_j' X_j)^{-1}. \tag{9}$$

This prior specification is useful, as it reduces the input from the researcher to a single

[4] This prior specification is independent of the model, and thus assigns a common prior density for the intercept and conditional variance parameters across models. To ensure that the model intercept has the same interpretation across all models, we demean the FDI determinant variables before inclusion in the regressions. This gives the intercept parameter the role of the unconditional mean of the bilateral FDI measure for all models.

hyperparameter, g, rather than needing to specify the entire k_j x k_j matrix V_j^0. FLS discuss theoretical motivations for alternative choices of g, and based on this theory and extensive Monte Carlo experiments suggest the following strategy for setting g:

$$g = \begin{cases} \dfrac{1}{K^2} & \text{if } N \leq K^2 \\ \dfrac{1}{N} & \text{if } N > K^2 \end{cases} . \qquad (10)$$

In the FDI determinants application we have $N \leq K^2$, and thus set $g = 1/K^2$.

Given these specifications for the prior densities, posterior model probabilities are conceptually straightforward to calculate. In particular, model probabilities can be computed directly by calculating the marginal likelihood for all possible models, each of which are available analytically for the linear regression model in (1) and the parameter prior densities in (7-10). However, when *K* is large, the size of the model space makes direct calculation of $\Pr(M_j \mid Y)$ based on (2) practically infeasible. For example, we will consider *K* = 56 potential FDI determinants, meaning there are greater than $R = 7 \text{ x } 10^{16}$ possible models to consider. Even if each model could be considered in $1/100{,}000^{\text{th}}$ of a second, an ambitious estimate at current computing speeds, it would still take over 22,000 years to evaluate all possible models.

When the model space becomes too large for direct calculation of posterior model probabilities, a popular alternative approach is to estimate these probabilities by sampling the model space. In particular, define a model indicator that takes on values from 1,…,*R*, with a value of *j* indicating that model M_j is the true model, and assume that this model indicator follows a multinomial probability distribution with probabilities given by $\Pr(M_j \mid Y)$. Further, suppose that we are able to obtain random draws of this model indicator from its probability distribution. It is then possible to construct a simulation-consistent estimate of $\Pr(M_j \mid Y)$ as the proportion of the random draws for which model M_j was drawn. In particular, we can construct the following estimate of $\Pr(M_j \mid Y)$:

$$p_j = \frac{\sum_{s=1}^{S} I_s}{S}, \qquad (11)$$

where S is the number of random draws of the model indicator, and I_s is an indicator function that is one if the s^{th} draw of the model indicator was j. Note that (11) will estimate $\Pr(M_j \mid Y)$ to be zero if M_j is never drawn. However, assuming a large number of simulations are conducted, it will be exactly these models that are likely to have very low posterior model probability. Thus, estimates of $\Pr(M_j \mid Y)$ constructed by simulating from the model space provide an efficient approach to identifying the set of models with relatively high posterior probability.

Note that if we condition on $\Pr(M_j \mid Y)$ equaling zero if M_j is never drawn, equation (2) suggests an alternative, approximation-free approach to evaluating the posterior model probabilities for the visited models:

$$p_j = \frac{f(Y \mid M_j)\Pr(M_j)}{\sum_{i \in \Delta} f(Y \mid M_i)\Pr(M_i)}, \quad j \in \Delta, \qquad (12)$$

where Δ denotes the set of models that are visited by the sampler. As this set of models will be feasible to consider individually, the summation in the denominator of (12) will be feasible whereas the summation in the denominator of (2) was not. If the models that are never visited by the sampler are assumed to have zero probability, model probabilities based on (12) will be exact, while those based on (11) will contain estimation error. All results presented for our FDI determinants analysis use model probabilities based on (12).

To simulate from the model space, we use the Markov Chain Monte Carlo Model Composition (MC^3) algorithm of Madigan and York (1995). This approach relies on the Metropolis-Hastings algorithm, which can be used to provide random samples from any probability distribution provided it is known up to a proportionality constant, which, by inspection of (2), is true for $\Pr(M_j \mid Y)$. MC^3 was implemented by Raftery, Madigan and Hoeting (1997) for BMA in linear regression models, and has been used in a number of economic applications involving linear regression (e.g. Fernandez, Ley and Steele, 2001a, 2001b).[5]

The MC^3 algorithm requires an arbitrary model to initialize the sequence of model draws. Given this initial model, model draws obtained from the algorithm form a Markov chain that converges to draws from $\Pr(M_j \mid Y)$. An important issue with such Markov-chain based samplers is assessing the convergence of the chain. In producing the results described in Section 5 below, we assume that 200,000 draws is sufficient to ensure convergence, and then base our estimates of posterior model probabilities on 1 million additional draws. We performed three checks to ensure convergence of the sampling procedure. First, results from an independent simulation using a longer convergence sample of 400,000 draws were very similar to those based on the shorter convergence sample. Second, our results are insensitive to two widely dispersed initial models, one with no FDI determinants, i.e. $k_j = 0$, and one with all possible FDI determinants, i.e. $k_j = K$. This insensitivity of results to the size of the convergence sample and

[5] For details of the implementation of MC^3 in the context of a linear regression model, see Koop (2003).

the initialization of the chain suggests the sampler has converged. Finally, Fernandez, Ley and Steele (2001a) suggest using the correlation between probabilities based on (11) and (12) as a check on the convergence of the sampler. For all results we present, the correlation between these two estimates of the model probabilities was above 0.99.

4. Data

Measurement of FDI and related activity is far from ideal. Unlike trade flows, reliable measures of FDI are unavailable for many countries. Relatedly, there is no common source for FDI data, and prior studies have therefore employed a number of different measures of FDI. As we wish to compare our results to these prior studies, we have collected data on three different FDI measures that have been typically used.

Our first source of cross-country FDI activity is bilateral FDI stocks reported by members of the Organization of Economic Cooperation and Development (OECD), which is the most comprehensive source of reliable data on total FDI stocks of which we are aware.[6] The OECD provides excellent coverage of FDI activity between OECD countries. It also has some coverage of FDI between OECD and non-OECD countries, though many transactions with small non-OECD countries are missing. The OECD does not report any observations of FDI between countries that are both non-OECD. The FDI stock data will be the benchmark measure of FDI used in our study, but we will also compare and contrast our results when using two alternative measures of FDI activity, described next.

Some studies (e.g., Carr, Markusen, and Maskus, 2001, and Bergstrand and Egger, 2007) have stressed the use of affiliate sales as the most appropriate measure of actual multinational firm activity in a host country, as FDI stock data can be significantly affected by financial

[6] These data can be obtained from SourceOECD: www.sourceoecd.org.

transactions of a firm not related to current productive activity. Unfortunately, affiliate sales data are much less available than FDI stock data. Braconier, Norback, and Urban (2005) have collected the most extensive database of cross-country affiliate sales of which we are aware, and have graciously provided this to us. Their database provides information on outward affiliate sales involving 56 different parent countries and 85 different host countries over roughly four different years from the late 1980s to 1998. Despite this, the number of observations is much smaller than with the FDI stock data.[7]

Finally, we employ data on cross-border mergers and acquisitions (M&As), which have been used in such studies as Rossi and Volpin (2004) and Head and Ries (2008). These data come from Thomsen's SDC Platinum database on M&A activity, which is meant to be a comprehensive census of worldwide M&As above a $1 million threshold since the early 1990s. While this amount of country coverage in the M&A data clearly dominates the other two measures of FDI activity, the M&A measure also has relative disadvantages. First, it measures only one type of FDI, though M&A does account for the majority of worldwide FDI activity. Second, because many of the transactions are between private firms, over half of the M&As in the database do not have any recorded value. Thus, we rely on counts of the number of M&As occurring between country pairs.[8] More specifically, we use cumulated sums of counts of prior and current-year M&As by country pair to create a measure analogous to cross-country FDI

[7] We refer the reader to Braconier, Norback, and Urban (2005) for further detail on country coverage and data sources.

[8] Prior studies, including Rossi and Volpin (2004) and Head and Ries (2008), assumed that the missing M&A transactions' values were random and summed up remaining observations of values to create their measure of cross-border M&A activity. There are some obvious advantages and disadvantages with using M&A count versus (non-missing) value data. One clear disadvantage for our purposes was how many missing observations are created when using the value data -- many of the bilateral-country pairings show M&A activity, but the value data for all the M&A transactions for that pairing are missing. For this reason, and because the correlation between the M&A counts and values by bilateral-country pairs is 0.96, we use the M&A count data.

stocks. Head and Ries (2008) also use cumulated measures of M&A activity and find a quite high correlation (greater than 0.80) between the FDI stock and M&A measures of FDI activity.

It is important to note that virtually all theory and empirics of worldwide FDI has focused on the (static) cross-country patterns, rather than the dynamics of worldwide FDI flows. We follow this pattern and primarily focus on data for the year 2000, since it comes before the world recession following the events of 9/11, and is the most recent data we have for the affiliate sales database. For those FDI measures where it was available, we also collected data for 1990. This allowed us to check the robustness of our results, as well as allows us to examine specifications where we first difference the data to control for country-pair fixed effects.

The set of potential covariates we consider is intended to be comprehensive and is listed in Table 2. The variables in Table 2 are grouped into broad categories of factors that plausibly determine FDI. We have included all covariates from previous studies listed in Table 1 with only a few exceptions. First, we do not include exchange rate variables or changes in recent consumer prices, as we wish to examine the long-run determinants of FDI decisions, leaving examination of dynamic, short-run changes for a future work. Second, bilateral trade flows are clearly endogenous and so we do not include this covariate as some studies have done. Finally, there are a few variables where available data are so limited (e.g., wage data) that we feel the cost in terms of reduced sample size is too great.

We also include a number of additional variables. First, a few recent studies have found that geographic spatial issues are important for understanding bilateral FDI patterns (see Baltagi et al., 2007, and Blonigen et al., 2007). To account for such spatial features of the data to some extent, we include a remoteness variable for both the host and parent country, which is constructed as the distance-weighted average of all other countries' GDP.[9] Possible agglomeration effects within countries also led us to add a measure of urban concentration for both the host and parent country. Previous studies have hypothesized that endowments may matter, particularly if FDI is motivated to find lower cost locations (i.e., vertically-motivated FDI). However, these studies have only included measures of relative labor and capital endowments. We include measures of land and oil as well. Business costs in the host country have been included in some previous studies, but they often use proxies that have limited country coverage which we found significantly reduce the potential sample. Thus, we rely on relatively recent measures of host-country business costs collected by the World Bank that measure the average time it takes to enforce a contract, register property, start a business, and resolve an insolvency. We also include measures from the World Bank's World Development Indicators on communications infrastructure, which previous studies have not included, but plausibly could affect FDI decisions.

These additions and subtractions from the combined set of regressors from previous studies leaves us with 56 variables to examine as potential covariates with FDI. The data sources for our variables are primarily the Penn World Tables, the World Development Indicators database, and the Gravity database at CEPII (www.cepii.org). A full list of data sources is available from the authors upon request.

5. Results

Because previous studies have employed a variety of FDI measures and specifications (e.g., logging variables or not), the reported results below proceed through a number of possible

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[9] Combining spatial econometric techniques with the BMA approach has not been done before to our knowledge, but would likely be quite difficult to implement.

combinations of the FDI measure and variable transformation, before comparing our results to those in previous studies.

5.1. Base Results

We begin with results using our benchmark measure of FDI (FDI stock) as our dependent variable, considering both a specification where all (non-binary) variables are logged and a specification where all variables are not logged. We refer to these as the "log-levels" and "levels" specifications respectively. For each potential covariate, Table 3 reports the inclusion probabilities and the median of the posterior density for the covariate's slope coefficient for both the levels (columns 1 and 2) and log-levels (columns 3 and 4) specifications using our sample of 2000 data. Again, the inclusion probability is the BMA posterior probability that a variable belongs in the true model explaining FDI. For the posterior density for a covariate's slope coefficient, we report the BMA posterior density for the slope coefficient, conditional on that variable belonging in the true model. Note that interactive variables drop out of the log-levels specifications as they generate perfect collinearity in the regression upon taking logarithms.

There are a number of similarities to note across the levels and log-levels specifications. First, it is a relatively small set of variables out of the 56 potential covariates that have high inclusion probabilities in both specifications. Only 13 variables have inclusion probabilities above 50% in the levels specification, while the analogous number of variables is 16 in the log-levels specification. This suggests a fairly parsimonious specification is sufficient to explain cross-country FDI patterns. Second, for both specifications, the types of variables that generally have high inclusion variables are GDP-related variables, distance, cultural distance factors (e.g., common official language), and endowments. However, this means that broad categories of variables are receiving little statistical support, particularly those related to business costs, infrastructure, and institutions in the host country. The one main difference between the two specifications is that the GDP terms receiving support in the levels specifications include non-linear terms, whereas such terms do not find support once the data are logged. This suggests that logging variables is sufficient to handle the inherent skewness in the pattern of cross-country FDI.

Table 4 provides a related analysis where we calculate "group" inclusion probabilities that measure the probability that at least one of the variables in a given group belongs in the true model. For example, the probability that at least one of the variables connected with "Business costs and tax policies" (variables 41 through 46 in Table 2) should be included in the specification is only 26 percent in the levels regression and only 18 percent in the log-levels specification. Since GDP-related terms and distance clearly matter from the results in Table 3, we only report the inclusion probabilities of groupings of our other variables. Table 4 shows that "cultural distance" and "endowment-related terms" have a high group inclusion probability in both the levels and log-levels specifications. Also consistent with our discussion above, inclusion probabilities are low across both specifications for our groupings of host-country business costs, communications infrastructure, financial infrastructure, and legal and political institutions. A difference between the levels and log-levels specifications, as also discussed above, is that the non-linear GDP terms only have high inclusion probabilities (even as a group) in the levels specification. A final difference between the levels and log-levels specification in the group inclusion variables is that trade openness (both bilateral and multilateral) and geography terms beyond distance have reasonably high group inclusion probabilities in the log levels specification, but not the levels specification.

Our results to this point use FDI stock as our measure of cross-country FDI activity. Table 5 next compares results when we use two other measures of FDI that have been used by prior studies – affiliate sales and cross-border M&A activity. The table displays all variables that receive at least 50% in one of our three specifications (FDI stock, affiliate sales, or M&A). For ease in reading the table, we bold the instances where the inclusion probability is 50% or higher. For comparison sake, we only report the results for the log-levels specification and, for the M&A sample, we only use observations for the 902 country-pairs for which we observe the FDI stock variable. (We have many more country-pair observations for the M&A sample that we will analyze and discuss below.) Due to the limited data availability for the affiliate sales data, we use all observations available.

Despite these data issues, many of the patterns found in the FDI stock specification are also found when using these other FDI measures. First, the traditional gravity variables (real GDP of both countries and distance) all have inclusion probabilities of 100% across all three specifications. Parent country real GDP per capita also has a 99% inclusion probability across all three, suggesting that the wealth of the source country is a key determinant. Interestingly, host country real GDP per capita does not have similarly high inclusion probabilities. There is a similar asymmetry in that host country remoteness generally garners high inclusion probabilities across the specifications, whereas parent country remoteness does not. These asymmetric results are an example of empirical patterns our analysis finds that have not been examined by prior theory or empirical studies of FDI to our knowledge.

In general, the M&A and FDI sample share many variables with high inclusion variables beyond the ones we have mentioned, including common official language, colonial relationship, squared skill difference, regional trade agreement, and customs union. We also find it interesting that the M&A sample finds much greater support for the inclusion of a variety of variables related to skilled labor endowment levels and differences.

The FDI stock and affiliate sales specifications find less commonality in the variables that have high inclusion probabilities. We have also produced results for the FDI stock and affiliate sales specifications on a common, overlapping, sample of 253 observations, and found much more similarity in results that mirror those for affiliate sales in Table 5. This suggests that the differences across the affiliate sales and FDI stock specifications in Table 5 are due primarily to the relatively small sample available for the affiliate sales measure. Overall, the general patterns noted in earlier specifications reported above continue to hold – gravity finds very strong support, while cultural distance and endowment variables also find modest support as well. In contrast, there continues to be little support for variables capturing host country business costs, infrastructure, or institutions.

As mentioned, the data on FDI stock and affiliate sales is limited primarily to OECD country pairs, though there is some information on FDI from OECD into less-developed countries, but not on FDI patterns between less-developed countries. On one hand, this selection may not be a significant issue because the vast majority of FDI in the world economy is between the developed economies, which are well-represented in our sample. On the other hand, it is useful to know how FDI determinants may differ when a more representative sample of countries is examined. Our M&A data source has the ability to address this as it is a census of worldwide M&A activity.

Table 6 lists all variables with inclusion variables above 50% for three specifications using logged data for the year 2000. The first two columns of inclusion probabilities are for comparison purposes and are for the FDI stock specification and the M&A specification when limited to the same observations as FDI stock sample. The third column is the M&A specification when we use all observations for which we have available data, which we call the "worldwide" sample, as opposed to the restricted sample, which we call the "OECD" sample. This more than triples the sample size over the other two listed specifications to 3081 observations.

The results from the worldwide M&A sample show a lot of commonalities with the previous results. Gravity variables, cultural distance, and relative skilled labor variables all show very high inclusion probabilities. In fact, 12 of the 15 variables in the OECD M&A sample specification (column 2) also have high inclusion probabilities in the worldwide M&A sample specification. However, the worldwide M&A sample also shows high inclusion probabilities for a few additional variables. These include two variables connected with business costs in the host country (HOST firm tax rates and HOST years to resolve insolvency), variables connected with bilateral treaties (Bilateral investment treaty and double taxation treaty), service sector agreements, and contiguous border. This suggests that these additional variables are important when considering FDI into developing economies and between developing economies, since these are the types of observations that are added when we go from the OECD to the worldwide M&A sample.[10]

5.2. Implications for prior studies

With our BMA results in hand, we now turn to address the fundamental question of how our BMA results compare to those of previous studies. Virtually all of the prior studies include

[10] In the "OECD" sample, all country-pair observations involve at least one OECD country, and 40% of the country-pair observations are between OECD countries. In the "worldwide" sample, 32% of the country-pair observations do not involve at least one OECD country, and only 18% of the country-pair observations are between OECD countries.

gravity related variables and, thus, our results confirm the inclusion of such variables. Common official language also finds robust support in our analysis and is included in five of the prior eight studies in Table 1. Beyond this small set of variables, however, prior studies vary significantly in what they include, and what they include does not necessarily match very well with the variables our analysis finds to have high inclusion probabilities. For example, our analysis finds that parent country wealth (real per capita GDP) has strong and robust support, yet only one study (Head and Ries, 2008) of the eight studies in Table 1 includes this variable. In contrast, four of the studies in Table 1 include host country wealth, yet we find this variable does not have strong support for inclusion. The reason for this asymmetry in wealth effects on FDI is also something that past theoretical papers do not address to our knowledge. Only four of the prior eight studies include variables related to relative skilled labor endowment levels or differences, whereas our analysis finds that such variables should be included. There is little evidence that other relative endowments matter. Colonial relationships, host country remoteness, regional trade agreements, and customs unions are additional variables that find strong support in our analysis, but are rarely included in prior studies. On the other hand, a number of the prior studies include variables connected to host country business costs, infrastructure and institutions, but these do not find support in our analysis. Finally, the studies in Table 1 whose main focus is on a particular hypothesized relationship between a potential covariate and FDI generally do not fare very well in terms of the inclusion probabilities we estimate for the same covariate. This includes Wei (2000) whose focus is on corruption, Stein and Daude (2007) whose focus is on time zone differences and di Giovanni (2005) whose partial focus is on financial market institutions.

5.3. Slope coefficient magnitudes

To this point, we have focused only on inclusion probabilities. In Table 7, we report estimates of the slope coefficient of the variables listed in Table 6. In particular, for the variables and specifications in Table 6, we report the median of the BMA posterior density for the slope coefficient on each variable. As in Table 3, we focus on the BMA posterior density for a variable's slope coefficient, conditional on that variable belonging in the true model. With few exceptions, the coefficient signs are as one would expect and consistent with prior studies. This includes the gravity variables, cultural distance variables, and bilateral trade openness variables. For many of the coefficients, the magnitude of the effect is smaller in the worldwide M&A sample than for the OECD sample, which suggests that FDI responds much less to economic forces for host countries that are less-developed. A few of the coefficients have unexpected signs. One of the more intriguing results is that while the bilateral distance between country pairs lowers FDI (as expected), the remoteness of both the parent and host countries (that is, how far they are from the entire world's markets, not just the other country in the country pair) have positive coefficients. This distinction has not been made before to our knowledge, but certainly deserves future investigation.

5.4. Controlling for country-pair effects

Many prior studies of FDI determinants include country or country-pair effects. A simple way to control for such effects is to difference the data by country-pair combinations. Table 8 provides results from log-linear specifications for a 1990-2000 differenced sample for our FDI stock, OECD M&A and worldwide M&A samples. First-differencing in this manner eliminates a number of time-invariant variables, as is typical. It unfortunately also eliminates a very large portion of the observations, due to many more missing values for variables in 1990. This may be why the FDI stock and OECD M&A samples only have one variable that comes in with an inclusion probability over 50%, though a possible alternative explanation is that bilateral FDI patterns are largely driven by slow-moving or time-invariant factors that are then differenced out of these regressions. However, the worldwide M&A sample still has over 1200 observations and finds 12 variables to have inclusion probabilities over 50%. What we find most important is that these high-inclusion probabilities in the first-differenced worldwide M&A sample are largely the same ones as we have found throughout the many varied permutations we have evaluated in this paper: GDP-related variables, skilled-labor variables, parent-country GDP per capita, and bilateral trade agreements. Distance and cultural distance factors do not show up in this table because first-differencing leaves no (or virtually no) variation from which to identify the impact of these factors.

5.5. Robustness to Alternative Priors

The results presented above were generated for a specific choice of parameter prior distribution, namely those suggested in FLS, as described in Section 3 above. It is well known that BMA results can be sensitive to parameter priors, although for the relatively large sample sizes available in our application, this sensitively should be muted. To verify this, we also present results from an alternative prior specification known as the Unit Information Prior (UIP). The UIP is designed to contain roughly the same amount of information as a typical single observation (Kass and Wasserman, 1995). Eicher, Papageorgiou, and Raftery (2007) argue for the UIP as a reasonable “default” prior based on evidence that it outperforms the prior of FLS for prediction. As discussed in Kass and Wasserman (1995) and Rafery (1995), the UIP suggests a convenient approximation to the marginal likelihood based on the Bayesian Information Criterion (BIC), which makes this prior particularly simple to implement.

Table 9 compares results from the FLS priors to those based on the UIP for the FDI Stock measure of FDI and the log-level specification. The table displays all variables that receive a 50% or higher inclusion probability for at least one of the alternative priors. For ease in reading the table, we bold the instances where the inclusion probability is 50% or higher. The inclusion probabilities suggest that the BMA results are not very sensitive to parameter priors, which again is what we might have expected given the relatively large sample size. In particular, the inclusion probabilities are generally very close in magnitude for the two alternative priors, and there is no case where the two priors yield radically different conclusions regarding the importance of a covariate.

6. Conclusion

The prior literature examining the determinants of FDI is comprised of a limited number of studies that typically propose fairly parsimonious specifications, but which are quite varied in their specifications and FDI measurement. This suggests significant uncertainty in the true model of bilateral FDI patterns. Our approach is to provide some needed systematic investigation of the determinants of FDI by using Bayesian Model Averaging. Our analysis does not support the inclusion of many variables found in prior FDI studies, and suggests that the statistical importance of the main focus variables in many prior studies is not robust to considering a much wider set of covariates. The results also suggest a fairly parsimonious specification of gravity variables, cultural distance factors, parent-country per capita GDP, relative labor endowments, and regional2 trade agreements for modeling FDI.

Of note, our results reflect little support for government policies to encourage FDI, as there is no robust evidence in our analysis that policy variables controlled by the host country (such as multilateral trade costs, business costs, infrastructure, or political institutions) have an effect of FDI. Exceptions include policies that are often negotiated bilateral agreements, including regional trade agreements, bilateral investment treaties, customs unions, and service agreements in the case of M&A. However, we caution that exogeneity of these variables may be more in doubt than many of the other covariates we consider.

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Table 1
Specifications of Prior Studies of FDI Determinants

	Carr, Markusen, Maskus (2001)	Bergstrand and Egger (2007)	Head and Ries (2008)	Eaton and Tamura (1994)	Wei (2000)	di Giovanni (2005)	Stein and Daude (2007)	Chakra-barti (2001)
Data and specifications								
Dependent variable	Sales	Sales	Stock and M&A	Stock	Stock	M&A	Stock	Flows
Variables logged?	No	Yes	Yes	Yes	Yes	Yes	Some	No
Panel data?	Yes	Yes	No	Yes	Yes	Yes	No	No
Two-way or one-way flows?	Two-way	Two-way	Two-way	Two-way	One-way	Two-way	Two-way	One-way
Gravity measures								
PARENT GDP		x				x		
HOST GDP		z			x	x		x
Distance	z	x	x		x	x	x	
Other GDP related terms								
PARENT per capita GDP			x					
HOST per capita GDP			x	x				x
PARENT population			x					
HOST population			x	x	x			
GDP similarity		x						
GDP sum	x	x					x	
GDP difference	x							
GDP per capita differences						x	x	
HOST GDP growth								z
Rest-of-the-world GDP		x						

Other geography measures								
Contiguous border							z	
Time zone differences							x	
Country-level endowments								
Relative skilled-unskilled labor endowments (skill difference)	x	x					x	
Interaction of skill differences and GDP differences	x							
Relative capital-labor endowments		x						
HOST wages					x			z
HOST population density				x				
HOST education levels				x				
Bilateral cultural and colonial linkages								
Common language		x	x		x	x	z	
Colonial links			x				x	
Multilateral trade openness								
HOST trade costs	x							z
PARENT trade costs	x							
HOST trade openness (imports plus exports divided by GDP)								z
HOST trade costs times skill difference term squared	x							
Bilateral trade openness								
BILATERAL transport costs		z						
BILATERAL trade flows/deficit						x		z
Regional trade agreement		x				z	z	

Customs union						z		
Common service sector agreement						x		
Host country FDI/business costs								
HOST FDI costs	x	x						
HOST taxes					x			z
PARENT taxes						x		
PARENT country has tax credit system					z			
Change in HOST consumer prices								z
Bilateral tax and investment agreements								
Tax treaty						x	x	
Investment treaty							z	
Host country communications infrastructure								
Telephone traffic						x	x	
Host country financial infrastructure								
HOST market capitalization						x		
HOST domestic credit						x		
Political environment & institutions								
HOST political stability					x			z
HOST legal institutions							x	
HOST corruption					x			

Exchange rate		
Exchange rates	z	z
Volatility of exchange rates	x	

Notes: An “x” signifies that a variable is included and statistically significant in the majority of specifications reported in the paper. A “z” signifies that a variable is included, but is not statistically significant in the majority of specifications reported in the paper. We exclude from this table variables that Chakrabarti (2001) posited as *ex ante* doubtful and which did not come in statistically significant in that analysis. The type of dependent variable in these studies varied in construction, but can be characterized by data on affiliate sales (which we term “Sales” in the table), FDI stock (“Stock”), FDI flows (“Flows”) and/or counts (or value) of cross-border merger and acquisition activity (“M&A”).

Table 2
Variables

Variable	Definition	Included in previous study listed in Table 1
Dependent variables		
FDI stock	FDI position of PARENT country in HOST country (in millions of U.S. dollars)	
Affiliate sales	Sales of PARENT-owned affiliates in HOST country	
M&A counts	Cumulated counts of PARENT country acquisitions of HOST country targets prior to year of observation	
Gravity measures		
1. PARENT real GDP	Real GDP of PARENT country (in trillions)	X
2. HOST real GDP	Real GDP of HOST country (in trillions)	X
3. Distance	Distance between the two most populous cities in the PARENT and HOST country	X
Other GDP-related terms		
4. PARENT real GDP per capita	Real GDP per capita of PARENT country (constant price: Chain Series)	X
5. HOST real GDP per capita	Real GDP per capita of HOST country (constant price: Chain Series)	X
6. Sum of HOST and PARENT real GDP	Sum of HOST and PARENT real GDP	X
7. Similarity of HOST and PARENT real GDP	Share of HOST real GDP in the sum or HOST and PARENT GDP * Share of PARENT real GDP in the sum or HOST and PARENT GDP	X
8. Squared GDP difference	Squared real GDP difference between HOST and PARENT country	X
9. Squared GDP per capita Difference	Squared real GDP per capita difference between HOST and PARENT country	X
10. HOST urban concentration	Urban population (% of total) in HOST country	
11. PARENT urban concentration	Urban population (% of total) in PARENT country	
Geography measures other than distance		
12. Contiguous border	Dummy variable indicating PARENT and HOST countries are geographically contiguous	X
13. HOST remoteness	Distance of HOST country from all other countries in the world weighted by those other countries' share of world GDP (Does not include host country in calculations)	

14. PARENT remoteness	Distance of PARENT country from all other countries in the world weighted by those other countries' share of world GDP (Does not include host country in calculations)	
15. Time zone difference	Time zone difference between capitol cities of HOST and PARENT countries	X
<u>Relative labor endowments</u>		
16. HOST education level	Average education years in HOST country	X
17. HOST skill level	Percent of employment by skilled labor in HOST country	X
18. PARENT education level	Average education years in PARENT country	
19.PARENT skill level	Percent of employment by skilled labor in PARENT country	
20. Squared education difference	Squared difference in average education years between PARENT and HOST country (proxy for relative skilled labor endowments)	X
21. Squared skill difference	Squared difference in percent of employment by skilled labor between PARENT and HOST country (proxy for relative skilled labor endowments)	X
22. Interaction of GDP differences with education differences	Interaction of GDP differences with education differences	X
23. Interaction of GDP differences with skill differences	Interaction of GDP differences with skill differences	X
<u>Other relative endowment measures</u>		
24. HOST capital per worker	Capital per worker in HOST country	
25. PARENT capital per worker	Capital per worker in PARENT country	
26. Squared difference in capital per worker	Squared difference in capital per worker between HOST and PARENT country	X
27. HOST land area	Land area (sq. km) in HOST country	
28. PARENT land area	Land area (sq. km) in PARENT country	
29. HOST population density	Population divided by land area in HOST country	X
30. HOST is oil country	Indicator variable that the HOST country is a top 10 producer or top 10 exporter of oil	
<u>Cultural distance</u>		
31. Common official language	Indicator variable that PARENT and HOST countries share a common official language	X
32. Common language overlap	Indicator variable that PARENT and HOST countries share a language which at least 9% speak in each country	
33. Colonial relationship	Dummy variable indicating PARENT and HOST countries have had (or do have) a colonial link	X
<u>Multilateral trade openness</u>		
34. HOST trade openness	HOST country openness (imports plus exports divided by GDP) in constant prices (constant	X

	prices, in %)	
35. PARENT trade openness	PARENT country openness (imports plus exports divided by GDP) in constant prices (constant prices, in %)	X
36. Interaction of education differences with HOST trade openness	Interaction of education differences with HOST trade openness	X
37. Interaction of skill differences with HOST trade openness	Interaction of skill differences with HOST trade openness	X
<u>Bilateral trade openness</u>		
38. Regional trade agreement	Indicator variable for regional trade agreement between PARENT and HOST countries	X
39. Customs union	Indicator variable for customs union between PARENT and HOST countries	X
40. Service sector agreement	Indicator variable for economic integration agreement in services between PARENT and HOST countries	X
<u>Host country FDI/business costs</u>		
41. HOST time to enforce contract	Time required to enforce a contract (days) in HOST country	
42. HOST time to register property	Time required to register property (days) in HOST country	
43. HOST time to start business	Time required to start a business (days) in HOST country	
44. HOST time to resolve insolvency	Time to resolve insolvency (years) in HOST country	
<u>Host country tax policies</u>		
45. HOST corporate tax	Highest marginal tax rate, corporate rate (%) in HOST country	X
46. HOST is tax haven	Indicator variable that the HOST country is considered a tax haven by the OECD	
<u>Bilateral tax and investment agreements</u>		
47. Bilateral investment treaty	Dummy variable indicating a bilateral investment treaty in place between HOST and PARENT country before July 1 of year	X
48. Double taxation treaty	Dummy variable indicating a double taxation treaty governing “income and capital” in place between HOST and PARENT country before July 1 of year	X
<u>Host country communications infrastructure</u>		
49. HOST telephones	Mobile and fixed-line telephone subscribers (per 100 people) in HOST country	
50. HOST internet users	Internet users (per 100 people) in HOST country	

51. HOST computers	Personal computers (per 100 people) in HOST country	
Host country financial infrastructure		
52. HOST domestic credit	Domestic credit provided by banking sector in HOST country (% of GDP)	X
53. HOST market capitalization	Market capitalization of listed companies (% of GDP)	X
Political environment and institutions		
54. HOST legal institutions	Strength of legal rights index (0=weak to 10=strong) in HOST country	X
55. HOST political rights	Political rights index for HOST country (Ranges from 1 to 7 with highest score indicating the lowest level of freedom)	X
56. HOST civil liberties	Civil liberties index for HOST country (Ranges from 1 to 7 with highest score indicating the lowest level of freedom)	

Table 3
Level and Log-Level Regressions to Explain FDI Stocks in 2000

Variable	Levels: Inclusion Probability	Levels: Posterior Median	Log-levels: Inclusion Probability	Log-levels: Posterior Median
1. PARENT real GDP	100	7712	100	1.48
2. HOST real GDP	100	8780	100	1.38
3. Distance	85	-0.48	100	-0.95
4. PARENT real GDP per capita	93	0.82	100	1.77
5. HOST real GDP per capita	12	0.74	50	0.71
6. Sum of HOST and PARENT real GDP	0	NA	0	NA
7. Similarity of HOST and PARENT real GDP	65	23379	5	-1.17
8. Squared GDP difference	100	-500.94	7	-0.30
9. Squared GDP per capita difference	74	-9.18×10^{-6}	1	0.00
10. HOST urban concentration	1	26.83	94	1.66
11. PARENT urban concentration	1	-37.41	2	-0.35
12. Contiguous border	7	3811.4	1	0.05
13. HOST remoteness	1	0.22	95	1.31
14. PARENT remoteness	4	-0.67	10	0.80
15. Time zone differences	4	-305.14	9	0.15
16. HOST education level	1	-140.55	2	-0.46
17. HOST skill level	71	32098	7	0.81
18. PARENT education level	1	-164.97	54	-0.97
19. PARENT skill level	1	1232.45	1	0.18
20. Squared education difference	1	55.12	8	-0.09
21. Squared skill difference	9	44724	100	1.68
22. Interaction of GDP differences with education differences	99	-3.14	NA	NA
23. Interaction of GDP differences with skill differences	1	-124.84	NA	NA
24. HOST capital per worker	18	-0.27	7	0.50
25. PARENT capital per worker	93	-0.36	94	0.98
26. Squared difference in capital per worker	14	2.09×10^{-6}	2	0.05
27. HOST land area	67	-7.91×10^{-4}	2	-0.08
28. PARENT land area	2	-2.45×10^{-4}	1	-0.01
29. HOST population density	1	-153.16	3	0.18
30. HOST is oil country	2	-2762.54	1	-0.08
31. Common official language	78	7884.79	99	1.27
32. Common language overlap	1	268.73	1	0.06
33. Colonial relationship	47	7975.17	72	1.08
34. HOST trade openness	4	23.69	71	0.73

35. PARENT trade openness	1	7.80	3	-0.26
36. Interaction of education differences with HOST trade openness	1	0.58	NA	NA
37. Interaction of skill differences with HOST trade openness	7	354.38	NA	NA
38. Regional trade agreement	1	1187.19	92	1.17
39. Customs union	1	578.25	64	0.94
40. Service sector agreement	11	4791.78	11	0.69
41. HOST time to enforce contract	2	4.38	1	0.19
42. HOST time to register property	15	-26.25	3	0.12
43. HOST time to start business	13	-37.27	1	-0.08
44. HOST time to resolve insolvency	1	-15.39	8	-0.26
45. HOST corporate tax	2	136.15	51	-0.72
46. HOST is tax haven	1	2841.19	1	0.56
47. Bilateral investment treaty	45	-3335.56	4	-0.25
48. Double taxation treaty	4	-2153.51	25	0.40
49. HOST telephones	58	-98.30	7	-0.86
50. HOST internet users	3	62.20	2	-0.20
51. HOST computers	8	110.70	2	0.09
52. HOST domestic credit	9	33.06	2	0.19
53. HOST market capitalization	3	16.86	5	0.19
54. HOST legal institutions	2	-334.53	3	-0.32
55. HOST political rights	2	2185.30	20	-0.43
56. HOST civil liberties	4	-1801.26	4	-0.03
Sample size	**902**		**902**	

Notes: "Inclusion Probability" refers to the posterior probability that the associated variable is in the true FDI determinants model. "NA" denotes "not applicable" when the variable is not included because it is perfectly collinear with other variables once logged.

Table 4
Group Inclusion Probabilities

Group	2000 Levels	2000 Log Levels
Nonlinear GDP terms	100	13
Geography besides pure distance	24	95
Endowment-related terms	100	100
Multilateral trade openness	17	60
Bilateral trade openness	22	88
Cultural distance	99	100
Business costs and tax policies	26	18
Communications infrastructure	31	16
Financial infrastructure	17	13
Legal and political institutions	8	26

Notes: "Group Inclusion Probabilities" are the probabilities that at least one of the variables from the group indicated in the first column belongs in the true FDI determinants model.

Table 5
Inclusion Probabilities Above 50% Using Alternative Measures of FDI
(Logged 2000 Data)

Variable	**FDI Stock**	**Affiliate Sales**	**Cross-border M&A**
PARENT real GDP	**100**	**100**	**100**
HOST real GDP	**100**	**100**	**100**
Distance	**100**	**100**	**100**
PARENT real GDP per capita	**100**	**99**	**100**
Squared skill difference	**100**	13	**79**
Common official language	**99**	8	**100**
HOST remoteness	**95**	**100**	**83**
HOST urban concentration	**94**	2	12
PARENT capital per worker	**94**	6	1
Regional trade agreement	**92**	37	**100**
Colonial relationship	**72**	2	**88**
HOST trade openness	**71**	3	2
Customs union	**64**	22	**97**
PARENT education level	**54**	21	2
HOST corporate tax	**51**	**78**	5
HOST real GDP per capita	**50**	2	3
Squared GDP per capita difference	1	**98**	2
HOST legal institutions	3	**65**	2
HOST time to start business	1	**64**	1
Squared education difference	8	2	**98**
PARENT remoteness	10	1	**94**
PARENT urban concentration	2	1	**91**
PARENT skill level	1	4	**89**
HOST skill level	7	3	**66**
Sample size	**902**	**395**	**902**

Notes: The table displays all variables that have at least a 50% inclusion probability in one of the listed specifications. Instances where the inclusion probability is 50% or higher are in bold type.

Table 6
Inclusion Probabilities Above 50% for OECD and Worldwide Samples
(Logged 2000 Data)

	OECD Sample		Worldwide Sample
Variable	**FDI Stock**	**Cross-border M&A**	**Cross-border M&A**
HOST real GDP	**100**	**100**	**100**
PARENT real GDP	**100**	**100**	**100**
Distance	**100**	**100**	**100**
PARENT real GDP per capita	**100**	**100**	**100**
Squared skill difference	**100**	**79**	29
Common official language	**99**	**100**	**100**
HOST remoteness	**95**	**83**	**100**
HOST urban concentration	**94**	12	2
PARENT capital-to-labor endowment	**94**	1	8
Regional trade agreement	**92**	**100**	**100**
Colonial relationship	**72**	**88**	**100**
HOST country trade openness	**71**	2	1
Customs union	**64**	**97**	**100**
PARENT education level	**54**	2	**74**
HOST corporate tax	**51**	5	**100**
HOST real GDP per capita	**50**	3	2
Squared education difference	8	**98**	**79**
PARENT remoteness	10	**94**	**100**
PARENT urban concentration	2	**91**	**100**
PARENT skill level	1	**89**	39
HOST skill level	7	**66**	23
Bilateral investment treaty	4	21	**100**
Double taxation treaty	25	2	**100**
HOST education level	2	2	**100**
HOST years to resolve insolvency	8	46	**90**
Service sector agreement	11	4	**93**
Contiguous border	1	1	**84**
Observations	902	902	3081

Notes: The table displays all variables that have at least a 50% inclusion probability in one of the listed specifications. Instances where the inclusion probability is 50% or higher are in bold type.

Table 7
Posterior Median Slope Coefficients for OECD and Worldwide Samples
(Logged 2000 Data)

	OECD Sample		Worldwide Sample
Variable	**FDI Stock**	**Cross-border M&A**	**Cross-border M&A**
HOST real GDP	**1.38**	**0.91**	**0.61**
PARENT real GDP	**1.48**	**1.05**	**0.82**
Distance	**-0.95**	**-0.60**	**-0.48**
PARENT real GDP per capita	**1.77**	**1.37**	**0.71**
Squared skill difference	**1.68**	**0.77**	0.33
Common official language	**1.27**	**1.15**	**0.50**
HOST remoteness	**1.31**	**1.02**	**0.54**
HOST urban concentration	**1.66**	0.70	0.09
PARENT capital-to-labor endowment	**0.98**	0.08	-0.15
Regional trade agreement	**1.17**	**1.21**	**1.13**
Colonial relationship	**1.08**	**0.81**	**1.26**
HOST country trade openness	**0.73**	0.14	-0.03
Customs union	**0.94**	**1.00**	**0.80**
PARENT education level	**-0.97**	-0.21	**0.39**
HOST corporate tax	**-0.72**	-0.29	**-0.34**
HOST real GDP per capita	**0.71**	-0.19	0.61
Squared education difference	-0.09	**-0.13**	**-0.05**
PARENT remoteness	0.80	**1.12**	**0.48**
PARENT urban concentration	-0.35	**-0.73**	**-0.44**
PARENT skill level	0.18	**0.93**	0.38
HOST skill level	0.81	**0.96**	0.30
Bilateral investment treaty	-0.25	-0.26	**-0.40**
Double taxation treaty	0.40	0.12	**0.33**
HOST education level	-0.46	0.23	**0.67**
HOST years to resolve insolvency	-0.26	0.23	**0.13**
Service sector agreement	0.69	0.62	**0.69**
Contiguous border	0.05	0.08	**0.21**
Observations	902	902	3081

Notes: The table displays the posterior median slope coefficient for all variables that have at least a 50% inclusion probability in one of the listed specifications. Coefficients where the associated inclusion probability is 50% or higher are in bold type.

Table 8
Inclusion Probabilities Above 50% for OECD and Worldwide Samples
(Logged and First-differenced 2000 Data)

	OECD Sample		**Worldwide Sample**
Variable	**FDI Stock**	**Cross-border M&A**	**Cross-border M&A**
PARENT real GDP per capita	**97**	40	3
PARENT urban concentration	3	**90**	**100**
HOST real GDP	3	9	**100**
PARENT real GDP	5	40	**100**
PARENT education level	2	14	**100**
Regional trade agreement	2	5	**100**
Service sector agreement	2	2	**100**
Customs union	3	3	**99**
PARENT remoteness	8	2	**99**
GDP similarity	3	6	**97**
HOST real GDP per capita	3	3	**96**
PARENT skill level	3	2	**96**
HOST skill level	5	38	**85**
Observations	244	244	1246

Notes: The table displays all variables that have at least a 50% inclusion probability in one of the listed specifications. Instances where the inclusion probability is 50% or higher are in bold type.

Table 9
Inclusion Probabilities Above 50% Using Alternative Parameter Priors
(FDI Stock - Logged 2000 Data)

Variable	**FLS**	**UIP**
PARENT real GDP	**100**	**100**
HOST real GDP	**100**	**100**
Distance	**100**	**100**
PARENT real GDP per capita	**100**	**100**
Squared skill difference	**100**	**100**
Common official language	**99**	**98**
HOST remoteness	**95**	**97**
HOST urban concentration	**94**	**98**
PARENT capital per worker	**94**	**97**
Regional trade agreement	**92**	**98**
Colonial relationship	**72**	**90**
HOST trade openness	**71**	**80**
Customs union	**64**	**78**
PARENT education level	**54**	**63**
HOST corporate tax	**51**	**73**
HOST real GDP per capita	**50**	49
Sample size	**902**	**902**

Notes: The table displays all variables that have 50% or higher inclusion probability for at least one of two alternative specifications for parameter priors. Instances where the inclusion probability is 50% or higher are in bold type. Results are for the FDI Stock dataset and log-levels specification. FLS refers to priors suggested by Fernandez, Ley and Steele (2001a), as described in Section 3. UIP refers to the Unit Information Prior of Kass and Wasserman (1995), as described in Section 5.