Robust FDI Determinants:*
Bayesian Model Averaging In The Presence Of Selection Bias

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The literature on Foreign Direct Investment (FDI) determinants is remarkably diverse in terms of competing theories and empirical results. We utilize Bayesian Model Averaging (BMA) to resolve the model uncertainty that surrounds the validity of the competing FDI theories. Since the structure of existing FDI data is well known to induce selection bias, we extend BMA theory to HeckitBMA in order to address model uncertainty in the presence of selection bias. We show that more than half of the previously suggested FDI determinants are not robust and highlight theories that do receive robust support from the data. Our selection approach allows us to identify the determinants of the margins of FDI (intensive and extensive), which are shown to differ profoundly. Our results suggest a new emphasis in FDI theories that explicitly identify the dynamics of the intensive and extensive FDI margins.

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1. Introduction

Global FDI flows increased tenfold, or by about $2 trillion, from 1990 to 2008 (UNCTAD, 2009), nevertheless a consensus on robust FDI determinants is still elusive. While remarkably diverse FDI theories have motivated a range of potential FDI determinants, empirical FDI approaches commonly juxtapose only limited subsets of candidate regressors.[1] In light of this model uncertainty, it comes as no surprise that FDI coefficient estimates are well known to be ambiguous and at times contradictory. The most comprehensive FDI survey to date (Blonigen, 2005) summarizes the FDI model uncertainty succinctly: "in the final analysis, the empirical literature on determinants of FDI is still young enough that most hypotheses are still up for grabs."

Using Extreme Bound Analysis, Chakrabarti (2001) provided the first systematic evidence of the fragility of FDI determinants.[2] The ad hoc Extreme Bound approach has since been superseded by statistical theory, which developed Bayesian Model Averaging (BMA) to account for model uncertainty as part of the estimation procedure (Raftery, 1995). The BMA approach is important since Berger and Sellke (1987) have shown that conventional sensitivity analyses overstate significance and confidence intervals in the absence of a full account of model uncertainty. When model uncertainty is not addressed comprehensively, it remains unclear whether a statistically significant FDI determinant remains relevant when alternative specifications/theories are considered. BMA methodology is thus tailor-made to examine the large set of candidate regressors that have been proposed as FDI determinants by alternative FDI theories.

An added complication in FDI empirics is that even the most comprehensive FDI datasets contain large sections of missing data. Selection bias may thus contaminate coefficient estimates, since it is unclear whether the nature of FDI forces the lion's share of investment to occur among OECD countries, or whether this observed FDI pattern is

[1] For example, Blonigen and Piger (2011) note that three key empirical FDI studies include no fewer than 22 different FDI determinants, but with little overlap. Baltagi et al. (2007) include a table that juxtaposes 4 alternative FDI theories that motivate 15 different FDI determinants.

[2] Leamer (1978) suggested Extreme Bound Analysis as an ad hoc sensitivity analysis in the presence of model uncertainty. EBA has been criticized for its lack of statistical foundations; it also restricted Chakrabarti (2001) to a limited number of models.

an artifact of systematically missing observations.[3] To address both model uncertainty and selection bias, we introduce HeckitBMA, which extends the statistical foundations of BMA to include Heckman's (1979) selection bias procedure.

HeckitBMA reveals not only the determinants of the intensive and extensive margins of FDI ("the volume of investment flows" and "the decision to invest", respectively), it also permits us to estimate FDI determinants without having to constrain parameter estimates to be identical across both margins. There is no reason to suspect that the margins of FDI should feature identical determinants, nor that the same determinant has the identical impact for both margins. Our selection criterion is based on Razin, Rubinstein and Sadka (2004), who note that FDI involves fixed costs that give rise to two-part decisions: a marginal productivity condition that determines *how much* to invest, and a total profitability condition that indicates *whether or not* to invest abroad. Previous studies have confirmed the relevance of such FDI fixed costs.[4]

Our results show that the impact of model uncertainty on FDI estimates is substantial and that the Heckman selection methodology is necessary to obtain unbiased and consistent estimates. In the absence of explicit controls for model uncertainty, the conventional Heckit procedure suggests nearly twice as many FDI determinants as HeckitBMA at the extensive margin and 12 additional regressors (33%) at the intensive margin. This is not surprising, since Heckit is not designed to consider models associated with alternative theories. Instead, HeckitBMA discovers much more parsimonious models of FDI that score better as measured by the Bayesian Information Criterion (BIC).

According to HeckitBMA, the intensive margin of FDI is influenced by *country characteristics* such as common history/language, and the absence of corruption and religious/internal conflict in the host country, as well as better democratic/bureaucratic/corruption institutions in source countries. Robust *economic determinants* of greater FDI flows at the intensive margin include common currencies/RTAs (specifically, the dollar and APEC), larger market sizes, and lower taxes

[3] This FDI data issue has been well documented as early as Soto (2000). OECD data covers FDI activity among OECD countries comprehensively, but OECD/Non-OECD coverage is spotty and Non-OECD country-pairs are nonexistent.
[4] Caballero and Engel (1999, 2000), Razin, Rubenstein, and Sadka (2004), Razin and Sadka (2006).

in the host and source countries. In addition, market potential, lower growth, development, and productivity in host countries reduce FDI flows. We highlight that these results are robust across subsamples, but that the OECD samples has a slightly different set of FDI determinants.

In stark contrast, the decision to invest has markedly fewer determinants. Country characteristics that affect the extensive margin are common colonial history/borders, as well as the lack of religious tension in the host and lower corruption in source countries. Economic factors that increase the likelihood of FDI investment include host and source country market size, as well as the hosts market potential and level of development. Greater source country productivity, taxation, or economic tensions decrease the likelihood that FDI is undertaken.

The importance of these FDI determinants is best appreciated once we relate the individual regressors back to specific FDI theories. We find only mixed support for horizontal or export platform FDI theories (Markusen, 1984). Trade agreements and currency unions do not encourage FDI across the board but only in specific instances (e.g., dollarization and APEC membership). Market potential exerts a decisive effect on FDI, but as in Blonigen et al. (2007), we find the effect runs contrary to the theory prediction: a host's proximity to large markets results in *less* FDI – as large, proximate markets *divert* FDI from smaller potential host. Vertical FDI incentives (Helpman, 1984) are not strongly supported as we find that FDI is sensitive to higher levels of development or development differentials. Contrary to the knowledge-capital model (Markusen et al., 1996 and Markusen, 1997), we find no evidence that educational differences exert robust effects on the margins of FDI. HeckitBMA does confirm the Razin et al. (2007a) hypothesis that productivity is a crucial determinant of the decision to invest, together with corporate taxes in source and host countries. Bilateral tax treaties, in contrast, are shown to exert no impact on FDI, supporting the view that such treaties are created not only to facilitate investment, but also to restrict tax evasion and transfer pricing (the latter reduce FDI incentives).

Closely related to our paper is the body of work of Razin and Sadka (2007b), who separate the decision to invest from the quantity of FDI flows. Their pioneering empirical work also consistently documents evidence for selection bias in FDI regressions.[5] We expand their approach to include the large number of regressors that have been suggested by alternative FDI theories. Methodologically, our approach is related to Chakrabarti's (2001) extreme bound analysis and to Blonigen and Piger (2011) who use Bayesian methods to analyze model uncertainty surrounding FDI stocks in a cross section. In contrast, we examine the dynamics of FDI flows from 1988-2000 and control for selection bias.

2. Empirical Methodology

Bergstrand and Egger (2007) provide theoretical foundations that motivate the use of gravity equations to analyze FDI patterns. The gravity equation has become the most popular approach in examining FDI determinants (see Barba Vanaretti and Venables, 2004), suggesting that FDI flows can be modeled according to

$$Y_{ijt} = \alpha_0 + \alpha_t + \beta_1 \log GDP_{it} + \beta_2 \log GDP_{jt} + \beta_3 \log D_{ij} + \beta_4 X_{ijt} + \varepsilon_{ijt} \,, \qquad (1)$$

where the log of bilateral FDI at time t, Y_{ijt}, depends positively on the market size of host, j, and source, i, countries, GDP_{jt}, and GDP_{it}, as well as on their bilateral distance, D_{ij}. Typically a matrix of covariates, X_{ijt}, is included to represent alternative FDI theories. These regressors are motivated at length in Section 4 below. The inclusion of time fixed effects, α_t, is standard to eliminate bias resulting from aggregate global shocks. Time fixed effects also mitigate possible spurious correlation that could be introduced, for example, by the use of the U.S. CPI to deflate FDI flows.

The canonical selection bias framework is given by the system of equations[6]

$$\begin{aligned} Z &= \theta' W + \varepsilon \\ Y &= \beta' X + \eta \text{ (if Z > 0)} \end{aligned} \qquad (1)$$

where Y is the dependent variable, X is a set of covariates, and Z is an unobserved factor that dictates whether Y is observed. Z is determined by a set of variables W, where X and W may share several variables. The error term of (1) is jointly distributed

[5] FDI selection bias is also prominent in Davies and Kristjansdottir (2010), and Balsvik and Haller (2011).
[6] Whenever possible, we suppress subscripts to simplify notation.

$$\begin{pmatrix}\eta \\ \varepsilon\end{pmatrix} \sim N\left(\begin{pmatrix}0 \\ 0\end{pmatrix}, \begin{pmatrix}\sigma_{\varepsilon}^{2} & \sigma_{\eta\varepsilon} \\ \sigma_{\eta\varepsilon} & \sigma_{\varepsilon}^{2}\end{pmatrix}\right). \tag{2}$$

The classical selection bias arises when $\sigma_{\eta\varepsilon}^{2} \neq 0$, which causes the OLS estimates of β that use only the observed values of Y to be biased.

Heckman (1979) proposes a method to correct this bias. His Heckit model first performs a probit regression on Z, which is equal to 1 if Y is observed and 0 otherwise, using W as covariates and yielding vector estimates, $\hat{\theta}$. Once $\hat{\theta}$ is found, $\tilde{Z} = \hat{\theta}'W$ is formed to obtain the Inverse Mills Ratio, $\hat{\lambda} = \phi[\tilde{Z}]/\Phi[\tilde{Z}]$, which is the ratio of the probability density function over the cumulative distribution function of $\tilde{Z}$. In a second stage, those Y that are observed are regressed on X and the Inverse Mills Ratio, $\hat{\lambda}$, yielding the consistent vector estimates, $\hat{\beta}$. The Inverse Mills Ratio (sometimes called "selection hazard") is a function that is motivated by the properties of truncated normal distributions to control for selection bias. When the null hypothesis that the coefficient on the Inverse Mills Ratio is zero is rejected, selection bias is present and OLS estimates are downward biased.

HeckitBMA combines Heckit and BMA methodologies. Just like the Heckit methodology, HeckitBMA processes the data as a two stage estimator, but it also addresses model uncertainty in both stages. The first stage is an application of BMA for logistic regression based on Viallefont, Raftery and Richardson (2001) to form model averaged estimates of Z and λ. Below we introduce the two HeckitBMA stages in detail.

As we introduce HeckitBMA notation, it is helpful to review BMA properties that are implied in stage 1. Let $Z = \alpha + \sum_{i=1}^{p} \theta_i W_i + \varepsilon$, where $W_1, W_2, ..., W_p$ is a subset of $W_1, W_2, ..., W_n$.[7] The set of potential models is comprised of the individual models $\{M_1, ..., M_S\}$. BMA stipulates that the posterior distribution of θ given the data, *D*, is given by the weighted average of the predictive distribution under each model. The specific weights are derived from the models' corresponding posterior probabilities,

[7] For a comprehensive BMA survey, see Raftery (1995) for detailed discussions and derivations.

$$pr(\theta_n \mid D) = \sum_{n \in M_s}^{I} pr(\theta_n \mid M_s, D)\ \pi_s \tag{3}$$

where $pr(\theta_n \mid M_s, D)$ is the predictive distribution given model M_s, and $\pi_s = pr(M_s \mid D)$ is the model's prior probability. The posterior model probability for each first stage model is

$$\pi_s = pr(M_s \mid D) = pr(D \mid M_s) pr(M_s), \text{ where} \tag{4}$$

$$pr(D \mid M_s) = \int pr(D \mid \theta_s, M_s) pr(\theta_s \mid M_s) d\theta_s \tag{5}$$

is the integrated likelihood of model M_s with parameters θ_s. The prior densities for parameters and models are $pr(\theta_s \mid M_s)$ and $pr(M_s)$, respectively.[8]

Posterior model probabilities are also the weights used to establish the posterior means and variances

$$\hat{\theta}^{BMA} = \sum_{s=1}^{S} \pi_s \hat{\theta}_s \tag{6}$$

$$\hat{\sigma}^{BMA} = \sum_{s=1}^{S} \left(Var[\theta_s \mid D, M_s] + (\theta_s)^2 \right) \pi_s - E[\theta_s \mid D]^2 \tag{7}$$

The posterior distribution for a parameter is a mixture of a regular posterior distribution and a point mass at zero, which represents the probability that the parameter equals zero. The sum of the posterior probabilities of the models that contain a variable yields its inclusion probability, which is taken as a measure of the importance of that variable. For instance, for variable W_k we may write,

$$\mu^{BMA}(\theta_{W_k}) = pr(\hat{\theta}_{W_k} \neq 0 \mid D) = \sum_{s \in M_k} \pi_s \tag{8}$$

where M_k is a collection of indices for which $s \in M_k$ implies model M_s does not restrict the parameter θ_k to zero. The general rule developed by Jeffreys (1961) and refined by

[8] We follow the literature with the standard assumption of uniform model priors (so that, ex ante, each model is presumed equally likely). Our parameter prior is the Unit Information Prior (see Raftery, 1995). This prior has been criticized as too conservative (e.g., returning too few effective regressors), but Eicher, Papageorgiou and Raftery (2011) show that in economic applications the prior density is sufficiently spread out to be reasonably flat over the region of the parameter space where the likelihood is substantial. Fernandez, Ley and Steel (2001) propose an alternative prior, which is also popular in economic applications, it is however, significantly more conservative and can have lower predictive performance.

Kass and Raftery (1995) stipulates effect-thresholds for posterior probability. Posterior probabilities < 50% are seen as *evidence against* an effect, and the evidence for an effect is either *weak*, *positive, strong*, or *decisive* for posterior probabilities ranging from 50-75%, 75-95%, 95-99%, and > 99%, respectively. In our analysis, we refer to a regressor as "effective," if its posterior inclusion probability exceeds 50%.

2.1. Selection Bias and HeckitBMA

While BMA has previously been applied in the context of international economics,[9] our specific FDI application requires an extension of the canonical BMA theory to account for selection bias. When the structure of the data suggests the potential of selection bias, the BMA framework in the previous section can be extended to a two-step Heckit model averaging procedure in which estimation is performed. HeckitBMA documents whether the absence of observed FDI flows is the result of randomly missing observations or due to endogenous FDI selection decisions that introduce bias to OLS coefficient estimates in previous FDI studies.

HeckitBMA is a nested BMA approach that establishes the posterior model probabilities in the first stage according to the BMA methodology, determining both π_s and $\tilde{Z}_s$, as well as the first stage fitted values for each model M_s. The methodology then forms the model averaged fitted value according to

$$\tilde{Z}^{BMA} = \sum_{s=1}^{S} \pi_s \tilde{Z}_s \tag{9}$$

and derives from this the Inverse Mills Ratio, $\hat{\lambda}^{BMA} = \phi\left[\tilde{Z}^{BMA}\right] / \Phi\left[\tilde{Z}^{BMA}\right]$.[10]

The second-stage model selection procedure is follows the classical linear regression BMA, as outlined in Hoeting et al. (1997), with the model-averaged inverse

[9] See e.g., Eicher, Henn, and Papageorgiou (2008) and Blonigen and Piger (2011). Other BMA applications in economics include investigations of growth determinants such as Fernandez, Ley and Steel (2001) and Eicher, Papageorgiou and Raftery (2011), Iterative BMA in Eicher, Papageorgiou and Roehn (2007) and 2SLSBMA in Eicher, Lenkoski, and Raftery (2009).

[10] An alternative Bayesian approach to sample selection models involves the imputation of the censored observations (see e.g. Chapter 14 of Koop et al.). On paper, such an approach is appealing, since the posterior distribution can be approximated through the seemingly straightforward application of a Gibbs sampler. However, in practice the requirement that such a large number of missing values be imputed at each step of the sampler may lead to considerable autocorrelation in the Markov Chain (see Omori 2007), thereby causing convergence to be extremely slow, if not practically impossible.

mill's ratio added as an additional variable in each specification. In terms of the priors on the models/parameters we use the Unit Information Prior (UIP), which facilitates the BIC approximation, as outlined in Raftery (1995). Denoting by $L = \{L_1, ..., L_N\}$ the set of second stage models, HeckitBMA uses $\hat{\lambda}^{BMA}$ and the data, D, to derive the second stage posterior model probabilities, $\nu_n = pr(L_n \mid D)$, and estimates, $\hat{\beta}_n$, for each model $L_n \in L$.[11] The HeckitBMA posterior mean and variance are then given by

$$\hat{\beta}^{HeckitBMA} = \sum_{n=1}^{N} \nu_n \hat{\beta}_n \tag{10}$$

$$\hat{\sigma}^{HeckitBMA} = \sum_{n=1}^{N} \left(Var\left[\beta_n \mid D, L_n, \hat{\lambda}^{BMA}\right] + (\beta_n)^2 \right) \nu_n - E\left[\beta_n \mid D, \hat{\lambda}^{BMA}\right]^2 \tag{11}$$

Equation (10) shows that the HeckitBMA estimate is formed as the average of each estimate that results from using the combination of $\hat{\lambda}^{BMA}$ and model L_n in the second stage, weighted by the second stage probabilities. As in traditional BMA, we can calculate the inclusion probabilities as

$$\mu^{HeckitBMA}\left(\beta_{X_k}\right) = pr\left(\hat{\beta}_{X_k} \neq 0 \mid D\right) = \sum_{n \in L_k} \nu_j \tag{12}$$

The HeckitBMA inclusion probability carries the same interpretation as in the conventional BMA methodology. The only difference is that the inclusion probability is now based on estimates and model probabilities that account for selection bias.[12]

3. FDI Theories and Model Uncertainty

This section outlines the model uncertainty surrounding FDI determinants, which requires a brief survey of existing FDI theories. Early FDI theory suggested two distinct motivations for FDI: horizontal FDI, which is undertaken to access markets when firms

[11] Note this implies that the inverse Mills ratio, $\hat{\lambda}^{BMA}$, is not subject to model selection, hence we cannot use its inclusion probability as an indicator for the existence of selection bias. Instead the Mills ratio's Bayesian Credible Interval is used.

[12] To search the model space effectively, we used the Mode Oriented Stochastic Search (MOSS) algorithm developed by Lenkoski and Dobra (2011) and ran it from different starting points to ensure consistent results. The MOSS algorithm is a variant of the Shotgun Stochastic Search (SSS) algorithm (see Hans, et al., 2007) and has been shown to produce better or equal results as MC3 (Raftery et al, 1997) or Leaps and Bounds (Furnival and Wilson, 1974) while being able to handle many more candidate regressors. Our results would be unchanged had we used, for instance, SSS. MOSS essentially reproduces results in Eicher et al., 2011, which had been obtained using either MC3 or the Leaps and Bounds.

encounter trade restrictions, and vertical FDI, which leverages low factor prices in host countries to reduce production costs (see, e.g., Markusen, 1984 and Helpman, 1984). Markusen et al. (1996) and Markusen (1997) unified these two FDI motivations in the knowledge-capital model of FDI. Due to its complexity, closed-form solutions of the knowledge-capital model are elusive and simulated results highlight nonlinearities.

New trade theory provides for additional and more intricate FDI patterns. Ekholm, Forslid and Markusen (2007) and Bergstrand and Egger (2007) suggest export platform FDI is undertaken to serve not only the host country, but also to produce goods that are subsequently exported to neighboring countries. This strand of the literature highlights the importance of a comprehensive account of regional trade agreements in the empirical approach. Vertical interaction FDI is undertaken when subsidiaries in host countries ship intermediate goods back and forth for processing before exporting finished products back to the parent (see, e.g., Baltagi, Egger and Pfaffermayr, 2007).

These theories have been taken to the data with mixed success in a variety of econometric approaches. Carr, Markusen and Maskus (2001) provide evidence in favor of horizontal and vertical FDI that is consistent with the knowledge-capital model. Bergstrand and Egger (2007) introduce a third mobile factor (physical capital) to the knowledge-capital model to highlight the interaction between trade agreements and FDI flows. They find substantial evidence for effects of RTAs on FDI flows, which vanish, however, when transport and investment costs are included.

Yeaple (2003) utilizes affiliate sales to their parent companies to interact factor endowment differences with industry factor intensities. He reports positive evidence for both vertical and horizontal FDI motivations. Coughlin and Segev (2000) focus on export platform FDI by exploring possible regional/spatial FDI patterns to find evidence for export platform FDI and agglomeration externalities. Further support for export platform FDI is provided by Blonigen et al. (2007), who estimate negative FDI effects associated with neighboring-country FDI, using US/EU data.

Finally, Baltagi, Egger, and Pfaffermayr (2007) develop a general model of FDI in a multi-country world. It predicts how neighboring country characteristics (e.g., GDP, trade costs, endowments, etc.) affect FDI in a given host country, depending on the specific FDI motivation (horizontal, vertical, export-platform, etc.). They find mixed evidence and only weak support for export-platform and vertical interaction FDI.

4. Existing Empirical Approaches and Candidate Regressors

The above set of FDI theories and their associated empirical approaches motivate a substantial set of candidate regressors that identify FDI determinants.[13] In this section we outline the set of regressors that have been associated with each of the above mentioned theories as well as the regressors that are commonly added to FDI gravity equations as additional controls (see Table 1 for a summary).

Aside from the typical gravity variables specified in (1), generic regressors such as Language, Border, and Colonial History are usually added to capture country-pair specific effects that might induce/obstruct FDI. In addition, the Real Exchange Rate is included in the gravity model as depreciations in the host country are thought to increase both the intensive and extensive margins of FDI (Goldberg and Klein, 1998). Depreciations reduce the amount of foreign currency needed to purchase assets abroad, and reduce the nominal return to the source in terms of foreign currency. Hence the often insignificant real exchange rate coefficient should not be surprising in large panel FDI studies.

Factor endowments are another key determinant of FDI. GDP Per Capita is commonly included to proxy for FDI that leverages differences in incomes, development, or capital abundance. As a measure of country income level, per capita GDP is expected to increase FDI flows for both source and host countries. As a measure of capital abundance, per capita GDP is predicted to generate positive FDI outflows for source countries and negative flows for host countries, since basic FDI models imply flows from capital-abundant to labor-abundant countries (Egger and Pfaffermayr, 2004). Education differences among country pairs are a proxy for vertical FDI motivations. According to

[13] Note that a number of these determinants, such as real per capita GDP, GDP growth rate, productivity, exchange rate, for both source and host countries may well be suspected to be endogenous (see e.g, Russ 2007 and Bergstrand and Egger 2007) . Also trade and trade agreements may well be endogenous (see e.g, Blonigen 2010 or Aizenman and Noy (2004, 2005). We follow the vast share of the literature that does not address the issue to and do tackle endogeneity and model uncertainty. Previous approaches to resolving endogeneity and model uncertainty include Tsangarides (2004), Chen, Mirestean, and Tsangarides (2009), Mirestean and Tsangarides (2009), as well as Moral-Benito (2009). We leave the empirical execution of a simultaneous account of endogeneity, selection bias and model uncertainty for future research.

the knowledge-capital model, greater educational disparities are expected to promote larger vertical FDI outflows.

Prospective growth, proxied by GDP Growth, signals higher returns, which attract FDI to a host and reduce outflows from a source country (see Rodrick, 1999 and Lim, 2001). Ekholm, Forslid and Markusen, (2007), Blonigen et al. (2007), and Baltagi, Egger and Pfaffermayr (2007) also include Market Potential (the size of proximate third country markets) to indicate each country's attraction as an export platform. Great market potential signals that the country should receive more export platform FDI as the host can serve relatively large markets in its relative proximity. However, the coefficient of this regressor has seldom been reported to be of the right sign, given large and important outliers such as Japan. A third economic factor that is seen to exert crucial influence on FDI returns is Country Productivity (see Rodrik, 1999, Razin, Rubenstein, and Sadka 2004, and Razin, Sadka, and Tong, 2008). Razin, Sadka, and Tong (2008) develop a theory where productivity increases affect FDI setup costs such that an increase in host productivity *reduces* the likelihood of new FDI, but *increases* FDI outflows to existing subsidiaries.

Blonigen (2005) highlights how Corporate Tax Rates and Tax Treaties influence FDI flows while Razin and Sadka (2007b, Ch 10) point out the differential impact of source/host tax rates. Host taxes reduce FDI primarily at the intensive margin and source tax rates increase FDI outflow primarily at the extensive margin. Increases in source countries' corporate taxes induce multinationals to establish new affiliates abroad, but the quantity of production transferred abroad increases when host countries' tax rates decline. Although the number of bilateral tax treaties has increased from 100 to over 2,500 since 1960 (Egger et al., 2006), the empirical evidence regarding their effects is ambiguous (see Davies, 2004 for a survey). Studies often do not differentiate between the intensive and extensive margins; when the margins of FDI are considered, as in Blonigen and Davies (2004) results show strong positive effects of existing tax treaties on FDI, but negative effects of new tax treaties (see also Egger et al., 2006). When Di Giovanni

(2005) examines only the extensive margin of FDI, positive effects of tax treaties are reported.[14]

Financial risk also serves as a central determinant of FDI. Razin, Sadka, and Tong (2008) include crucial risk measures in their econometric analysis. Economic and Political Risk have also featured prominently in recent growth regressions; variables that proxy for such risks are included in regressions to capture factors that impact the return on investment. Carr, Markusen, and Maskus (2001) first included variables that relate to economic and political risk, such as the risk of expropriation. It is usually thought that less risk increases inflows to a host and reduces outflows from a source country.

We also include measures of regional trade agreements and currency unions. There is considerable evidence that currency unions affect FDI, although much of the research has focused on Europe only (see e.g., Petroulas, 2007 and Baldwin et al., 2008). Trade and FDI are well known to be closely related, and Bernard, Jensen, and Schott (2009) find that roughly 50 percent of U.S. trade is intra-firm trade between affiliates of the same MNC. Here the thorny issue is endogeneity; hence we focus on the effects of Regional Trade Agreements (RTAs), which have a clear but not necessarily direct impact on FDI via export platform and/or horizontal/vertical FDI incentives.[15] The ambiguity arises as RTAs might increase FDI to an export platform *within* the RTA, and reduce it to all other members of the RTA. In addition, RTAs alter firms' tariff-jumping FDI incentives to amplify export platform FDI effects (Blonigen, 2002). To separate trade effects that arise within and between RTAs, Eicher, Henn, and Papageorgiou (2008) highlight the importance of controlling for all possible individual RTAs rather than including just one average catch-all RTA effect.

Given the diversity of theories, the common approach has been to focus on specific effects, such as tax treaties, or particular RTAs. Since we are proposing to

[14] The design of tax treaties may also contribute to the ambiguous findings. While treaties reduce withholding taxes and double taxation; Radaelli (1997) and Gravelle (1988) assert that reducing tax evasion is the primary goal of U.S. tax treaties via reduced transfer pricing and Hines (1996) shows that the way in which source countries eliminate double taxation can have different implications for FDI activity.

[15] The Asia-Pacific Economic Community (APEC), the Dollar Currency Unions (DOLLAR), the European Economic Area (EEA), the European Free Trade Area (EFTA), the EU, the Eurozone (Euro), the Latin American Integration Agreement (LAIA), and the North American Free Trade Agreement (NAFTA) have sufficient observations to be included.

juxtapose alternative theories, we seek to include representative regressors that encompass as many of the previous approaches as possible. The number of previous approaches is only superseded by the remarkable diversity of the associated results. Table 1 summarizes the diversity of positive and negative effects that have be obtained for the same regressors in FDI studies; it highlights not only model uncertainty, but also the fragility of the results when model uncertainty is not accounted for as part of the statistical methodology. If different approaches focus only on particular subsets of the FDI model space, it is no surprise that the associated results generate potentially different conclusions for the same regressor. The purpose of HeckitBMA is to resolve this model uncertainty, which requires this comprehensive set of regressors.

5. Data

Our dataset is based on Razin, Sadka, and Tong (2008), which includes data on productivity, GDP per capita, skill differences, common language, distance, population, and host and source country financial risk.[16] Their FDI outflow data was obtained from the OECD *International Direct Investment Database* (OECD) and deflated by the U.S. CPI. We augment the Razin et al. (2008) dataset to allow tests of the alternative theories outlined above. The additional data collected includes additional controls for tax rates, tax treaties, trade agreements, currency unions, institutions, market potential, market size, and exchange rate agreements.

Average effective corporate tax rates are calculated using the definition and information in Altshuler et al. (1998), Blonigen and Davies (2004), and U.S. Treasury Corporate Tax Files. A list of bilateral tax treaties was obtained from Neumeyer and Spess (2005). Trade Agreements (multilateral and bilateral), as well as currency union indicators were obtained from Eicher and Henn (2011). Market potential is constructed according to the definition provided in Blonigen et al. (2007).

For institutional variables we include country risk proxies that are obtained from International Country Risk Guides (ICRG 1985-2000), which also provides the exact variable definitions. Information on economic risk covers the host and source country's

[16] Financial risk is an index of five components: foreign debt as a percentage of GDP, foreign debt service as a percentage of exports of goods and services, current account as a percentage of exports of goods and services, net international liquidity as months of import cover, and exchange rate stability.

Corruption, Bureaucratic Efficiency, and Investment Profile.[17] Political risk is proxied by Democratic Accountability, Ethnic Tension, Internal/External Conflict, Government Stability, Political Violence, Rule of Law, Military Government Participation, Religious Tensions, and a Socio-Economic profile (which includes unemployment, consumer confidence, and poverty measures).[18] Our unbalanced panel finally covers years 1988-2000 and includes 46 countries (21 non-OECD), 803 unique country pairs with 14863 total observations, of which 64 percent indicate zero FDI flows. There are small differences between the 55 regressors in our study compared to the 56 regressors in Blonigen and Piger's (2011) cross section. These differences relate to the differences in time dimensions in the studies. Sources and summary statistics are provided in Table 2, and the frequencies of FDI host/source flows are provided in Table 3.

6. FDI Determinants and Model Uncertainty

To establish a benchmark, we commence with a set of diagnostics comparing OLS to BMA results, abstracting from the issue of selection bias. Table 4 show that the OLS regression suggests a surprising large number of 34 statistically significant FDI determinants. In contrast, BMA produces a much more parsimonious set of 23 regressors that also generates a better BIC (20815 compared to 21016 for OLS). The BMA results also allow somewhat of a comparison to Blonigen and Piger (2011), who also examine model uncertainty and FDI determinants, but who do not address selection bias. Here a cautionary note is order, however, since they examine FDI stocks while we examine the dynamics of FDI flow. In addition they examine a cross section (in 2000) while we use a panel, rendering the true comparison perhaps difficult.

Comparing our preliminary diagnostic BMA results that do not account for sample selection bias with those of Blonigen and Piger (2011), we find similar effects for regressors related to gravity, and similarities/differences in host/source income levels (capital per capita, education difference, skill levels, real GDP, GDP differences). Our BMA results that take advantage of the time/dynamic dimension of FDI also highlights the differential effects of (a) taxation and productivity, (b) regional trade agreements

[17] Investment profile measures government attitude toward inward investment as determined by (i) risk to operations, (ii) taxation, (iii) repatriation, and (iv) labor costs.
[18] ICRG variables are coded such that higher values reflect less risk.

(APEC), currency unions (dollar), and (c) non-economic country characteristics (common heritage language/history, corruption, internal conflict, religious tensions).

6.1 FDI Determinants, Model Uncertainty and Selection Bias

Our central object of interest is, however, to control for selection bias and model uncertainty simultaneously, since a large fraction of the data is either randomly or systematically missing.[19] Tables 4 and 4 reports both Heckit and Heckit BMA results to highlight the impact of model uncertainty on the number and types of reported FDI determinants at the intensive (extensive) FDI margins.[20] The Tables are ranked by the regressors' inclusion probabilities of HECKITBMAs intensive FDI margin. The Tables highlights the importance of model uncertainty in the analysis of FDI determinants: Heckit suggests 35 (27) FDI determinants at the intensive (extensive) margins, which are dramatically higher than the 24 (14) regressors suggested by HeckitBMA.

The substantially greater number of regressors suggested by Heckit indicates the importance of model uncertainty in FDI regressions. Heckit simply reports statistical significance for the full model, but does not account for the existence of alternative models and theories. Table 5 reports that alternative models, which are much more parsimonious, receive far greater support from the data. This is confirmed by the difference between the joint likelihoods in Heckit and the best models in HeckitBMA. The likelihood-ratio test, which does not penalize for the included number of regressors, easily rejects the Heckit model in favor of the best HeckitBMA model, the model that received the greatest weight in the model averaging procedure. Similarly, the Bayesian Information Criterion (BIC), which is used to compare the performance of nested model specifications, clearly favors HeckitBMA. Hence it is no surprise that Heckit overestimates significance levels to generate an excessively large number of FDI

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[19] Strictly speaking the absence of FDI flows between country pairs may be due to (a) the lack of incentives for flows (even if there were no fixed costs), (b) setup costs that do not allow flows to take place, and (c) measurement errors. An alternative approach would be simply include all zeros and ignore the selection equation. To implement the approach we would have to follow Eichengreen and Irwin (1995) and add a "1" to all observations, so that the dependent variable becomes become ln(flow + 1) since ln(0) is not defined. The approach has been discussed extensively in Frankel (1996) and Santos Silva and Tenreyro (2006) and rejected as it leads to inconsistent estimates whose biases depend on the approach and dataset.

[20] As in Razin, Rubenstein, and Sadka (2004) we include a negative FDI lag, to account for negative FDI flows (e.g., the liquidation of foreign subsidiaries).

determinants. HeckitBMA provides not only fewer, but also different FDI determinants. It supports two additional FDI determinants (one each at the intensive and extensive margins) that were not significant in the Heckit methodology. This highlights again that Heckit inference was not based on models that received the strongest support from the data. HeckitBMA reveals not only more parsimonious models, but models that also suggest different regressors, regressors that where shown to have no effect in Heckit.

6.2. Robust FDI Determinants in the Global Sample

In this section we detail robust FDI determinants. We first examine regressors that are associated with the decision to invest. This FDI margin is crucially important given the structure of the data where large segments of observations are either zero because FDI is not profitable, or because the data is systematically missing. Both Heckit and HeckitBMA show that the gravity approach is appropriate and that the Heckman selection methodology is necessary. All gravity regressors exhibit high inclusion probabilities and correct magnitudes at both margins of FDI. In addition, we find that the Inverse Mills Ratio indicates decisive (or highly significant) evidence of selection bias in the HeckitBMA (or Heckit) procedures as reported in Tables 4 and 5. The exclusion restriction (Past_FDI_Dummy) suggested by Razin et al. (2008) is shown to exert a decisive effect on the decision to invest.[21] It is thus clear that a full account of firms' decisions to invest in a selection (or participation) stage is critical to eliminating the omitted variables bias that contaminates parameter estimates in pure OLS approaches.[22]

To simplify the discussion of the effects in Table 5, we group effective FDI determinants into two categories, "economic" and "country characteristics," and consider extensive and intensive FDI determinants in sequence. For the extensive FDI margin, HeckitBMA suggests that country characteristics such as a common colonial background, lacking a common border, the absence of religious tensions (in the host), socio economic tension and corruption (in the source) increase the likelihood of FDI flows. Economic

[21] Razin et al. (2008) propose that FDI setup costs imply a profitability threshold so that past FDI relations can serve as an exclusion restriction.

[22] Goldberger (1972) and Greene (1981) show that in the presence of selection bias, the OLS estimator is biased downward and the degree of the bias is related to the proportion of data censored. Since 64% of the data in the OECD FDI dataset is potentially censored the bias may be substantial. This may be one reason why Blonigen and Piger's (2011) approach does not produce a substantial number of robust FDI determinants.

factors that exert a positive effect on the extensive margin of FDI include a host's market size, market potential, and level of development, while higher taxes and productivity negatively impact a source country's decision to invest. Notably, neither trade nor tax agreements, nor educational differences influence the decision to undertake FDI.

At the intensive margin, HeckitBMA indentifies a significantly greater number of FDI determinants. Robust FDI determinants at the intensive margin pertain not only specifically to the host and source, but also to bilateral characteristics such as common history/language, as well as share membership in an RTA (APEC) or a currency union (Dollar). Country characteristics that increase FDI include the lack of corruption and internal/religious tensions in the host and the absence of corruption, better bureaucratic efficiency and democratic accountability in source countries. Economic characteristics that increase bilateral FDI flows include larger market size and lower taxes (in both source and host), and a higher levels of development, productivity, and growth in the host country. Interestingly large market potential reduces FDI flows to a host and higher levels of development reduce FDI flows from source countries, ceteris paribus. As expected a source's investment profile and bureaucratic efficiency increase FDI flows.

The results are also insightful in terms of the absence of effects that are commonly reported in the literature. No RTA other than APEC influences FDI in either the selection or flow equation, and tax treaties are never found to be effective FDI determinants. In addition, skill differences are also shown to exert no effect on FDI. These results confirm the findings of the previous literature that RTA export platform effects may be weak and that tax treaties may not only facilitate, but also impede FDI when treaties are also designed to reduce tax evasion and transfer pricing. Blonigen and Piger (2011) also do not find that skill differences drive knowledge-capital FDI motives.

6.2 Robust FDI Determinants Across OECD Countries

Our previous results presuppose that a uniform set of FDI determinants exists for our global sample. There exists, however, ample evidence that subsamples of countries follow distinctly different development and FDI patterns. Masanjala and Papageorgiou (2008) highlight the differences in growth determinants in Africa, and Eicher et al. (2007) document differences in growth determinants for OECD countries, even after accounting for model uncertainty. In the specific context of FDI, Blonigen and Wang (2004) emphasize that data on FDI between countries are highly skewed, where the lion's share of activity is observed among developed countries while there is little or no activity for smaller developing nations. One approach to addressing the potential heterogeneity in FDI determinants is to separate developed and developing countries in empirical FDI studies. We proceed by running a simple diagnostic test (not reported here, but available form the authors) that adds a region dummy to our specification. We find that results remain basically unchanged, but that the OECD dummy is an important regressors for determining FDI flows.

With this evidence in hand, we proceed to split the sample and examine the determinants of FDI flows for OECD country-pairs only (A non-OECD subsample is not possible since there are no reported flows for non-OECD country pairs). The results are largely identical, but differ in a number of FDI determinants in rather expected fashion. Among OECD country pairs, the source's market size, corruption, and socio economic factors are no longer relevant in the selection stage; neither are the host's market potential or common colonial history and borders. One can expect the differences in these variables to be rather minor in the OECD dataset. Instead we find a number of additional selection criteria that determine selection for OECD country pairs. OECD country pairs in APEC are more likely to engage in FDI, but while higher taxes, financial risk and ethnic tensions in the host cause increased FDI outflows. Reduced host market size lowers the probability of investment, which is in line with the Razin et al. (2007) FDI fixed costs theory; the same is true for ethnic tensions.

In terms of the determinants of the actual FDI flows, we find the same pattern as in the selection equation. A number of regressors loose their effect while others gain in importance. No longer relevant are the source's market size, investment profile, or level of democracy, along with the host's market potential and level of internal conflict. At the same time, 2SBMA discovers that OECD country pairs exhibit additional FDI determinants that did not exert a sizable effect in the global sample. Military interference in policies, government instability increase FDI outflows from OECD source countries, while lower financial risk, increased bureaucratic efficiency and lower ethnic tensions increase FDI flows to host countries. Overall these results are expected in the sense that market size and potential loose their importance in a sample of rather similar developed nations, while the investment profile gains in importance among OECD countries that share a similar level of development. Notable is also that key parameters in the regression are *not* affected by the sample split. Neither the gravity equation parameters, nor regressors related to any of the FDI theories discussed above (excluding the export platform approach), nor the exclusion restriction experience sizable changes in the magnitudes of their effects.

7. Conclusion

FDI flows increased dramatically in the past 20 years. Over the same time period, the literature produced a dramatic proliferation of FDI theories as well as empirical FDI approaches. The uncertainty surrounding FDI theories and empirical approaches has created the notion that few FDI determinants are truly robust. Numerous empirical studies estimate only subsets of particular FDI theories to produce results that are often either inconclusive or outright contradictory. Statisticians refer to such diversity of theories and results as model uncertainty. When model uncertainty is not addressed comprehensively as part of the empirical strategy, traditional robustness analyses overstate significance levels and confidence intervals.

We extend the FDI literature in two dimensions. First, we construct a large dataset that represents a comprehensive set of FDI determinants that have been proposed by previous theories. Second, since large shares of FDI data are systematically missing from even the most detailed FDI dataset, we introduce HeckitBMA, which extends Bayesian Model Averaging to resolve the model uncertainty and in the presence of selection bias. Our approach allows us to separate and estimate the determinants of two separate aspects of the FDI decision: a) the decision to invest abroad and b) how much to invest in a particular host country.

Our results show that the impact of model uncertainty on FDI estimates is substantial and that the Heckman selection methodology is necessary. Without controlling for model uncertainty, the conventional Heckit procedure suggests nearly twice as many FDI determinants as HeckitBMA at the extensive margin and 12 additional regressors (33%) at the intensive margin. This is not surprising, since Heckit does not consider the models associated with alternative theories. Instead we find that HeckitBMA assigns the greatest weight to more parsimonious models that score dramatically better in terms of joint likelihoods or Bayesian Information Criteria (BIC). The determinants of the intensive and extensive margins of FDI are also shown to differ profoundly.

We find only mixed support for horizontal or export platform FDI theories (Markusen, 1984). Trade agreements and currency unions do not encourage FDI across the board, but only in specific instances (e.g., dollarization and APEC membership). Host country market potential is shown to exert a decisive effect on FDI flows, but the effect runs counter to the predictions of export platform FDI theory. As in Blonigen et al. (2007), we find that a host's proximity to large markets results in *less* FDI – as large, proximate markets divert FDI from a potential small host, perhaps to take advantage of scale economies. Vertical FDI theory (Helpman, 1984) is not strongly supported since FDI is sensitive to higher levels of development and, contrary to the knowledge-capital model, we find no evidence that educational differences exert robust effects on either the intensive or extensive margins. The one exception is that export platform FDI theories, as represented by our measure of market potential, no longer receives support from the data as an FDI flow or selection determinant. Given the market size of OECD countries we thus infer that export platform motivations for FDI are largely driven by differences in levels of development, which is not surprising since export platform FDI exploits not only the proximity to other large markets, but also the cost advantage of a particular producer.

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Table 1: Diversity of FDI Determinants and Their Estimated Effects
(Gravity Approaches Only)

Variable Name		Estimated Effect In Past +	none	-	Variable Description
Gravity	DISTANCEij		1	16	natural log of bilateral distance
	MRKT_SIZEi	8	2		source natural log of real GDP
	MRKT_SIZEi	13	5	2	host natural log of real GDP
Geography / History	BORDERij	2	3		=1 if pair share a common border
	COLONYij	4	2		=1 if pair share colonial relationship
	COM_LANGij	10	3		=1 if pair share common language
Factor Endowment	DEVELOPMENTi	3	4		source natural log of real GDP per capita
	DEVELOPMENTj	7	7		host natural log of real GDP per capita
	EDU_DIFFij	2	4	2	source minus host education level
Growth & Productivity	GDP_GROWTHi				source GDP growth rate
	GDP_GROWTHj	2	3		host GDP growth rate
	MRKT_POTENTIALj	1	1		sum of host's distance-weighted GDP to all other countries
	PRODUCTIVITYj	1	1		host productivity (real GDP per worker)
	PRODUCTIVITYi	1	1	1	source productivity (real GDP per worker)
Fiscal / Monetary Policy	TAXi		1		source corporate effective tax rate
	TAXj		3	5	host corporate effective tax rate
	RERij		4	2	real exchange rate (host/source currency)
RTAs / CUs / Investment	INVEST_TREATYij	1	3		=1 if both countries are in a treaty
	RTAij	0	0	0	
	Bi_RTAij	1	3	1	
	NAFTAij	1	3	1	
	EUij	1	3		
	EFTAij	1	1		
	EEAij				
	LAIAij				
	APECij	1	2		
	EUROij				
	DOLLARij				
Economic Risk	BUREAUj	2			host bureaucratic quality
	BUREAUi				source bureaucratic quality
	CORRUPTj	3	2		host corruption
	CORRUPTi				source corruption
	FIN_RISKj	2	2		host financial risk
	FIN_RISKi	1	2	2	source financial risk
Political Risk	DEMOCRATICj	1			host democratic accountability
	DEMOCRATICi				source democratic accountability
	ETHNIC_TENSIONj		1		host ethnic tentions
	ETHNIC_TENSIONi				source ethnic tentions
	EXTERN_CONFLICTj	1			host external conflict
	EXTERN_CONFLICTi				source external conflict
	GOV_STABILITYj	2			host government stability
	GOV_STABILITYi				source government stability
	INTERN_CONFLICTj		1		host internal conflict
	INTERN_CONFLICTi				source internal conflict
	INV_PROFILEj	2			host investment profile
	INV_PROFILEi				source investment profile
	LAW_ORDERj	2	1		host law and order
	LAW_ORDERi				source law and order
	MILITARYj		1		host military in politics
	MILITARYi				source military in politics
	RELIGIOUS_TENSIONj		1		host religion in politics
	RELIGIOUS_TENSIONi				source religion in politics
	SOCIO_ECONj		1		host socioeconomic conditions
	SOCIO_ECONi				source socioeconomic conditions

Notes: Based on gravity FDI studies. Variables are listed as positive or negative if significant at the 5 percent level.

Table 2: Descriptive Statistics
(Full Sample)

	Mean	StDev	Min	Max	Source
APECij	0.09	0.29	0	1	Eicher & Henn (2011)
BI_RTAij	0.01	0.11	0	1	Eicher & Henn (2011)
BORDERij	0.04	0.19	0	1	Eicher & Henn (2011)
BUREAUi	3.15	0.95	0	4	International Country Risk Guide
BUREAUj	3.18	0.95	0	4	International Country Risk Guide
COLONYij	0.03	0.18	0	1	Eicher & Henn (2011)
COM_LANGij	0.18	0.38	0	1	RST(2008)
CORRUPTi	4.23	1.32	1.08	6	International Country Risk Guide
CORRUPTj	4.25	1.33	1.08	6	International Country Risk Guide
DEMOCRATICi	4.90	1.25	1	6	International Country Risk Guide
DEMOCRATICj	4.96	1.21	1	6	International Country Risk Guide
DISTANCEij	8.24	0.92	4.92	9.42	RST(2008)
DOLLARij	0.00	0.04	0	1	Eicher & Henn (2011)
EDU_DIFFij	-0.06	3.22	-8.50	9.89	RST(2008)
EEAij	0.08	0.26	0	1	Eicher & Henn (2011)
EFTAij	0.01	0.09	0	1	Eicher & Henn (2011)
ETHNIC_TENSIONi	4.82	1.27	1	6	International Country Risk Guide
ETHNIC_TENSIONj	4.81	1.33	1	6	International Country Risk Guide
EUij	0.10	0.29	0	1	Eicher & Henn (2011)
EUROij	0.01	0.10	0	1	Eicher & Henn (2011)
EXTERN_CONFLICTi	10.88	1.50	4.25	12	International Country Risk Guide
EXTERN_CONFLICTj	10.86	1.59	4.25	12	International Country Risk Guide
FDI (log)	9.17	1.17	5.81	10.75	RST(2008)
FIN_RISKi	39.83	7.38	18	50	RST(2008)
FIN_RISKj	39.83	7.28	18	50	RST(2008)
GDP_GROWTHi	0.04	0.04	-0.13	0.14	constructed from RST(2008)
GDP_GROWTHj	0.04	0.05	-0.13	0.45	constructed from RST(2008)
MRKT_SIZEi	5.32	1.37	1.71	9.10	constructed from RST(2008)
MRKT_SIZEj	5.38	1.37	1.71	9.10	constructed from RST(2008)
GOV_STABILITYi	7.61	2.02	1	12	International Country Risk Guide
GOV_STABILITYj	7.57	2.04	1	11	International Country Risk Guide
INTERN_CONFLICTi	10.06	2.21	3	12	International Country Risk Guide
INTERN_CONFLICTj	10.02	2.28	3	12	International Country Risk Guide
INV_PROFILEi	6.97	1.73	2.33	11.17	International Country Risk Guide
INV_PROFILEj	6.97	1.74	2.42	11.17	International Country Risk Guide
INVEST_TREATYij	0.12	0.32	0	1	Neumayer and Spess (2005)
LAIAij	0.02	0.15	0	1	Eicher & Henn (2011)
LAW_ORDERi	4.71	1.40	1	6	International Country Risk Guide
LAW_ORDERj	4.71	1.44	1	6	International Country Risk Guide
MILITARYi	4.82	1.50	1	6	International Country Risk Guide
MILITARYj	4.85	1.52	0	6	International Country Risk Guide
MRKT_POTENTIALj	0.57	0.20	0.34	1.42	constructed see Blonigen et al., 2007)
DEVELOPMENTi	9.24	1.10	6.06	10.75	RST(2008)
DEVELOPMENTj	1.27	2.26	-2.85	11.14	RST(2008)
NAFTAij	0.00	0.06	0	1	Eicher & Henn (2011)
NEG_FDI_LAG	0.05	0.22	0	1	constructed from RST(2008)*
PRODUCTIVITYi	36.32	18.44	2.67	74.66	RST(2008)
PRODUCTIVITYj	37.25	18.00	4.24	74.66	RST(2008)
RELIGIOUS_TENSIONi	5.20	1.07	1	6	International Country Risk Guide
RELIGIOUS_TENSIONj	5.14	1.16	1	6	International Country Risk Guide
RERij	103.51	31.55	16.73	597.64	USDA http://www.ers.usda.gov
SOCIO_ECONi	6.66	1.64	2	11	International Country Risk Guide
SOCIO_ECONj	6.68	1.65	2	11	International Country Risk Guide
TAXi	0.23	0.11	0.00	0.73	1980-92: Altshulter et al. (1998); 1994-02: IRS/SOI, World Tax Database
TAXj	0.22	0.11	0.00	0.73	1980-92: Altshulter et al. (1998); 1994-02: IRS/SOI, World Tax Database

*Note that this estimator is appropriate also in the case where the desired FDI fows were actually negative, as in the case where a foreign subsidiary is liquidated, but were reported as zeros.

Table 3 Frequency of Host/Source Observations, By Country

	FDI Host		FDI Source	
	N Obs	**Obs ≠ 0**	**N Obs**	**Obs ≠ 0**
Argentina	448	132	424	49
Australia	397	221	386	155
Austria	425	133	394	216
Belgium	455	0	441	0
Brazil	336	100	324	45
Canada	418	165	401	160
Chile	437	107	425	22
China	na	na	432	78
Colombia	445	67	430	26
Costa Rica	280	1	274	5
Denmark	416	153	409	212
Egypt	135	21	169	9
Finland	418	127	378	230
France	372	323	401	374
Greece	438	123	415	44
Indonesia	132	38	165	18
Ireland	436	173	414	143
Israel	449	77	421	78
Italy	410	237	394	294
Japan	410	190	437	354
Korea (South)	441	202	432	237
Malaysia	365	94	362	53
Mexico	319	200	356	34
Netherlands	414	226	404	313
New Zealand	384	128	387	104
Norway	421	136	399	183
Pakistan	174	28	na	na
Panama	419	20	400	17
Philippines	441	111	426	33
Portugal	417	208	415	159
Poland	na	na	28	12
Singapore	297	87	289	66
South Africa	171	52	193	30
Spain	420	285	410	284
Sweden	424	186	363	232
Switzerland	411	157	387	278
Thailand	439	121	425	34
Turkey	409	125	432	63
United Kingdom	420	262	396	340
United States	383	294	391	355
Venezuela	437	77	434	48
Total	**14863**	**5387**	**14863**	**5387**

Table 4: FDI Determinants, Model Uncertainty, and Model Selection

Sample	FDI Flow Global OLS		FDI Flow Global BMA			FDI Flow Global Heckit		FDI Selection Global Heckit	
	mean	*stdev*	*incl prob*	*post mean*	*post stedv*	*mean*	*stdev*	*mean*	*stdev*
APECij	**0.956*****	0.087	**1.00**	0.949	0.083	**0.924*****	0.087	0.109	0.068
COLONYij	**1.124*****	0.111	**1.00**	1.143	0.110	**1.056*****	0.110	**0.405*****	0.104
COM_LANGij	**0.621*****	0.073	**1.00**	0.676	0.071	**0.591*****	0.072	**0.119****	0.053
CORRUPTi	**0.183*****	0.038	**1.00**	0.209	0.034	**0.174*****	0.038	**0.074*****	0.025
DISTANCEij	**-0.626*****	0.036	**1.00**	-0.683	0.026	**-0.581*****	0.037	**-0.194*****	0.028
DOLLARij	**4.466*****	0.740	**1.00**	4.388	0.740	**4.595*****	0.732	-0.257	0.363
GDP_GROWTHj	**3.307*****	0.716	**1.00**	2.790	0.663	**3.184*****	0.710	0.415	0.450
DEVELOPMENTi	**0.979*****	0.027	**1.00**	1.016	0.024	**0.926*****	0.028	**0.316*****	0.020
DEVELOPMENTj	**0.854*****	0.028	**1.00**	0.863	0.026	**0.802*****	0.029	**0.295*****	0.021
INTERN_CONFLICTj	**0.063***	0.026	**1.00**	0.096	0.019	**0.060****	0.026	-0.018	0.018
MRKT_POTENTIALj	**-0.777*****	0.131	**1.00**	-0.702	0.118	**-0.816*****	0.131	**0.255*****	0.098
MRKT_SIZEi	**0.555*****	0.081	**1.00**	0.769	0.071	**0.508*****	0.081	**0.279*****	0.051
MRKT_SIZEj	**-1.234*****	0.086	**1.00**	-1.091	0.078	**-1.195*****	0.086	**-0.101***	0.061
PRODUCTIVITYj	**0.040*****	0.004	**1.00**	0.040	0.004	**0.039*****	0.004	-0.002	0.003
RELIGIOUS_TENSIONj	**0.389*****	0.036	**1.00**	0.349	0.033	**0.371*****	0.036	0.041	0.026
TAXi	**-4.360*****	0.287	**1.00**	-4.489	0.275	**-4.154*****	0.287	**-0.824*****	0.197
TAXj	**-4.899*****	0.277	**1.00**	-4.846	0.267	**-4.721*****	0.276	**-0.764*****	0.200
CORRUPTj	**0.104*****	0.037	**1.00**	0.132	0.031	**0.102*****	0.037	0.035	0.026
NEG_FDI_LAG	**-0.227*****	0.071	0.54	-0.112	0.116	**-0.294*****	0.071	**0.826*****	0.078
ETHNIC_TENSIONi	**0.164*****	0.032	**0.99**	0.138	0.035	**0.154*****	0.031	**0.062*****	0.019
INTERN_CONFLICTi	**-0.122*****	0.029	**0.98**	-0.095	0.029	**-0.118*****	0.029	-0.023	0.018
BUREAUi	**0.233*****	0.076	**0.88**	0.221	0.105	**0.246*****	0.075	-0.06	0.042
DEMOCRATICi	**0.104*****	0.039	0.23	0.022	0.044	**0.105*****	0.039	**0.045***	0.024
INV_PROFILEi	0.0167	0.027	**1.00**	0.091	0.017	0.019	0.027	-0.022	0.019
LAIAij	**-0.651****	0.297	0.34	-0.274	0.416	**-0.660****	0.294	**-0.268***	0.146
SOCIO_ECONi	**0.066*****	0.025	0.01	0.000	0.005	**0.064****	0.025	**0.062*****	0.017
SOCIO_ECONj	**0.094*****	0.023	0.11	0.005	0.016	**0.095*****	0.023	0.026	0.016
Bi_RTAij	**0.699*****	0.198	0.05	0.017	0.086	**0.633*****	0.196	**0.487*****	0.135
PRODUCTIVITYi	**0.009****	0.004	0.09	0.001	0.002	**0.009****	0.004	**-0.009*****	0.003
BUREAUj	0.0481	0.059	0.13	0.016	0.047	0.052	0.059	-0.044	0.039
INV_PROFILEj	**-0.114*****	0.026	0.02	-0.001	0.009	**-0.105*****	0.026	**-0.039****	0.019
GOV_STABILITYj	0.0577**	0.023	0.23	0.010	0.020	**0.053****	0.023	0.008	0.016
INVEST_TREATYij	**0.177****	0.082	0.09	0.017	0.058	**0.157***	0.081	**0.125****	0.053
BORDERij	0.163	0.126	0.01	0.001	0.014	**0.244***	0.126	**-0.544*****	0.111
DEMOCRATICj	**0.090****	0.036	0.01	0.001	0.007	**0.092*****	0.036	0.028	0.025
LAW_ORDERj	0.0222	0.040	0.02	0.002	0.013	0.015	0.040	0.043	0.029
RERij	**-0.002***	0.001	0.03	0.000	0.000	**-0.002***	0.001	0.0002	0.001
NAFTAij	0.237	0.274	0.01	0.003	0.041	0.267	0.273	0.135	0.377
EXTERN_CONFLICTj	-0.031	0.025	0.02	-0.001	0.006	-0.035	0.025	0.019	0.016
FIN_RISKj	0.007	0.006	0.00	0.000	0.000	0.007	0.006	0.004	0.004
MILITARYj	0.052	0.039	0.00	0.000	0.002	0.057	0.039	0.002	0.026
EFTAij	-0.157	0.179	0.00	0.000	0.010	-0.224	0.178	0.311	0.192
GOV_STABILITYi	0.032	0.024	0.00	0.000	0.001	0.033	0.024	-0.019	0.016
ETHNIC_TENSIONj	0.01	0.028	0.00	0.000	0.001	0.009	0.028	**0.037***	0.019
EXTERN_CONFLICTi	0.022	0.026	0.00	0.000	0.001	0.026	0.026	**-0.033***	0.017
EDU_DIFFij	0.005	0.013	0.00	0.000	0.000	0.006	0.012	-0.0001	0.009
EEAij	0.056	0.106	0.00	0.000	0.003	0.024	0.106	**0.237****	0.095
EUij	0.104	0.094	0.00	0.000	0.003	0.116	0.093	-0.034	0.083
FIN_RISKi	0.008	0.007	0.01	0.000	0.001	0.006	0.007	**0.012*****	0.004
GDP_GROWTHi	-0.625	0.975	0.01	-0.006	0.103	-0.708	0.966	0.014	0.593
LAW_ORDERi	-0.023	0.046	0.00	0.000	0.002	-0.026	0.045	0.014	0.028
MILITARYi	0.008	0.047	0.00	0.000	0.003	-0.002	0.047	-0.002	0.027
RELIGIOUS_TENSIONi	0.046	0.039	0.00	0.000	0.002	0.033	0.038	-0.034	0.025
EUROij	0.056	0.179	0.00	0.000	0.007	0.045	0.178	-0.032	0.177
PAST_FDI_DUM								**2.183*****	**0.038**
Inv_MILLS						**-0.322*****	0.052		
BIC[1]	21016.78		20814.67			28513.18			
N	5387		5387			5387		14863	

[1] BMA statistic is based on best models in the selection stage. ***/**/* indicate 1, 5, 10 percent frequentist significance levels. Posterior means are conditional on inclusion.

Table 5: Robust FDI Determinants

Sample	FDI Flow Global HeckitBMA			FDI Selection Global HeckitBMA			FDI Flow OECD HeckitBMA			FDI Selection OECD HeckitBMA		
	incl prob	*post mean*	*post stedv*	*incl prob*	*post mean*	*post stedv*	*incl prob*	*post mean*	*post stedv*	*incl prob*	*post mean*	*post stedv*
APECij	**1.00**	0.904	0.133	0.48	0.098	0.112	**1.00**	0.976	0.204	**1.00**	1.330	0.423
COLONYij	**1.00**	1.071	0.178	**1.00**	0.498	0.095	**1.00**	0.852	0.234	0.02	-0.003	0.034
COM_LANGij	**1.00**	0.662	0.113	0.03	0.003	0.019	**1.00**	0.501	0.142	0.01	-0.001	0.010
CORRUPTi	**1.00**	0.196	0.057	**0.65**	0.042	0.034	**1.00**	0.199	0.061	0.03	0.002	0.013
DISTANCEij	**1.00**	-0.651	0.043	**1.00**	-0.199	0.023	**1.00**	-0.739	0.053	**1.00**	-0.121	0.031
DOLLARij	**1.00**	4.437	1.187	0.00	-0.001	0.022	**na**	**na**	**na**	**na**	**na**	**na**
GDP_GROWTHj	**1.00**	3.201	1.053	0.00	0.002	0.036	**1.00**	6.438	2.191	0.01	0.001	0.124
DEVELOPMENTi	**1.00**	0.971	0.040	**1.00**	0.269	0.022	**1.00**	0.955	0.051	**1.00**	0.360	0.036
DEVELOPMENTj	**1.00**	0.827	0.043	**1.00**	0.237	0.023	**1.00**	0.957	0.054	**1.00**	0.337	0.036
INTERN_CONFLICTj	**1.00**	0.108	0.032	0.00	0.000	0.001	0.01	0.000	0.006	0.01	0.000	0.004
MRKT_POTENTIALj	**1.00**	-0.744	0.189	**0.70**	0.205	0.154	0.01	0.000	0.043	0.01	0.001	0.027
MRKT_SIZEi	**1.00**	0.680	0.106	**1.00**	0.295	0.067	0.01	0.001	0.023	0.01	0.000	0.013
MRKT_SIZEj	**1.00**	-1.087	0.122	0.03	-0.001	0.009	**1.00**	-2.121	0.252	**0.82**	-0.439	0.233
PRODUCTIVITYj	**1.00**	0.039	0.006	0.07	0.000	0.001	**1.00**	0.045	0.007	0.25	-0.004	0.008
RELIGIOUS_TENSIONj	**1.00**	0.335	0.053	**0.79**	0.050	0.031	**1.00**	0.306	0.091	**0.66**	0.122	0.098
TAXi	**1.00**	-4.353	0.445	0.31	-0.169	0.271	**1.00**	-3.603	0.532	**1.00**	-2.147	0.329
TAXj	**1.00**	-4.721	0.428	**0.55**	-0.326	0.325	**1.00**	-4.902	0.541	**1.00**	-2.189	0.336
CORRUPTj	**1.00**	0.143	0.049	0.00	0.000	0.001	**1.00**	0.248	0.070	0.09	0.009	0.034
NEG_FDI_LAG	**0.99**	-0.291	0.118	**1.00**	0.826	0.077	**0.99**	-0.339	0.132	**1.00**	0.773	0.120
ETHNIC_TENSIONi	**0.88**	0.114	0.064	0.03	0.001	0.006	**1.00**	0.292	0.065	**1.00**	0.200	0.031
INTERN_CONFLICTi	**0.82**	-0.078	0.051	0.00	0.000	0.001	**1.00**	-0.178	0.062	0.01	0.000	0.004
BUREAUi	**0.67**	0.159	0.147	0.00	0.000	0.002	**1.00**	1.621	0.163	0.01	0.000	0.011
DEMOCRATICi	**0.67**	0.081	0.076	0.01	0.000	0.005	0.01	0.001	0.014	0.09	0.010	0.036
INV_PROFILEi	**0.65**	0.048	0.044	0.00	0.000	0.001	0.03	0.001	0.010	0.02	0.000	0.005
LAIAij	0.48	-0.401	0.531	0.01	-0.001	0.015	**na**	**na**	**na**	**na**	**na**	**na**
SOCIO_ECONi	0.37	0.029	0.044	**0.83**	0.038	0.021	0.01	0.000	0.006	0.40	0.035	0.048
SOCIO_ECONj	0.17	0.009	0.024	0.00	0.000	0.001	0.01	0.001	0.008	0.14	0.011	0.030
Bi_RTAij	0.14	0.066	0.201	0.07	0.020	0.082	0.27	0.172	0.343	0.10	0.047	0.156
PRODUCTIVITYi	0.10	0.001	0.003	**0.83**	-0.007	0.004	0.14	0.001	0.004	**1.00**	-0.019	0.004
BUREAUj	0.10	0.011	0.044	0.01	0.000	0.003	**1.00**	0.922	0.152	0.01	0.001	0.015
INV_PROFILEj	0.05	-0.003	0.016	0.00	0.000	0.000	**0.96**	-0.096	0.045	0.06	-0.004	0.018
GOV_STABILITYj	0.05	0.002	0.011	0.00	0.000	0.001	0.01	0.000	0.005	0.01	0.000	0.003
INVEST_TREATYij	0.04	0.007	0.041	0.40	0.062	0.082	0.04	0.016	0.101	0.03	0.008	0.054
BORDERij	0.04	0.008	0.054	**1.00**	-0.496	0.104	0.04	0.009	0.057	0.02	-0.004	0.032
DEMOCRATICj	0.04	0.002	0.016	0.00	0.000	0.001	0.02	0.001	0.017	0.01	0.000	0.005
LAW_ORDERj	0.03	0.002	0.016	0.01	0.000	0.003	0.13	0.019	0.059	0.02	0.001	0.013
RERij	0.03	0.000	0.000	0.00	0.000	0.000	0.01	0.000	0.000	0.02	0.000	0.000
NAFTAij	0.02	0.009	0.089	0.00	0.000	0.016	**na**	**na**	**na**	**na**	**na**	**na**
EXTERN_CONFLICTj	0.02	-0.001	0.006	0.03	0.001	0.005	0.10	-0.008	0.029	0.01	0.000	0.004
FIN_RISKj	0.02	0.000	0.002	0.00	0.000	0.000	**0.83**	0.025	0.017	0.03	0.000	0.003
MILITARYj	0.01	0.000	0.006	0.00	0.000	0.001	0.01	-0.001	0.012	0.01	0.000	0.006
EFTAij	0.01	-0.001	0.028	0.02	0.005	0.046	0.02	0.003	0.042	0.02	0.004	0.040
GOV_STABILITYi	0.01	0.000	0.004	0.00	0.000	0.001	**0.52**	-0.043	0.053	0.01	0.000	0.004
ETHNIC_TENSIONj	0.01	0.000	0.004	0.09	0.004	0.013	**1.00**	0.202	0.060	**1.00**	0.205	0.038
EXTERN_CONFLICTi	0.01	0.000	0.003	0.01	0.000	0.003	0.12	-0.010	0.034	0.01	0.000	0.004
EDU_DIFFij	0.01	0.000	0.001	0.00	0.000	0.001	0.01	0.000	0.002	0.01	0.000	0.001
EEAij	0.01	0.000	0.011	0.00	0.000	0.008	0.24	-0.060	0.129	0.01	0.001	0.019
EUij	0.01	0.000	0.010	0.00	0.000	0.003	0.04	-0.006	0.039	0.05	-0.008	0.039
FIN_RISKi	0.01	0.000	0.001	0.04	0.000	0.002	0.01	0.000	0.002	**0.86**	0.026	0.014
GDP_GROWTHi	0.01	-0.001	0.117	0.00	0.002	0.052	0.31	1.188	2.145	0.01	0.013	0.183
LAW_ORDERi	0.01	0.000	0.006	0.01	0.000	0.003	0.01	0.001	0.013	0.01	0.000	0.006
MILITARYi	0.01	0.000	0.006	0.00	0.000	0.002	**0.75**	-0.193	0.151	0.02	-0.002	0.016
RELIGIOUS_TENSIONi	0.01	0.000	0.005	0.00	0.000	0.001	0.01	0.000	0.011	0.01	0.000	0.006
EUROij	0.01	0.000	0.021	0.00	0.000	0.008	0.01	-0.002	0.033	0.01	-0.001	0.021
PAST_FDI_DUM				**1.00**	2.232	0.037				**1.00**	2.271	0.063
Inv_MILLS		**-0.315[a]**	0.084					**-0.505[a]**	0.128			
BIC[1]		28095.43										
N		5387			14863			3162			4841	

[1] HeckitBMA statistics are based on best models in the selection and flow equations.

[a] The 95% Credible Interval for the Inverse Mills Ratio does not contain zero. Posterior means are conditional on inclusion.