Two-Sided Matching Model of FDI Investment Location: Estimating Both Firms' and Countries' Preferences*

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Abstract

In this paper, I address three long-standing issues in the literature on the political determinants of Foreign Direct Investment (FDI). First, the majority of works use FDI stock and flow as the outcome of interest even though these aggregate statistics are poor measures of multinational corporations' (MNCs) activities. Second, while recent scholarship starts theorizing about countries' demand for FDI, there has not been a satisfactory way to measure countries' preferences. Third, even though policy makers pay much attention to the quality of FDI, the academic literature has mainly focused with its quantity. I propose a new empirical approach—the two-sided matching model—that addresses these three concerns. The model derives its functional form explicitly from actors' utility functions, then uses firm-level data to estimate both firms' and countries' preferences in a matching process. Applying the two-sided model on a dataset of Japanese foreign affiliates, I find that MNCs do not prefer democracies, contradicting the prevailing theory. On the side of countries' preferences, I find tentative evidence that a government's long time horizon increases its preference for high-tech FDI.

1 Introduction

The political science literature on Foreign Direct Investment (FDI) has focused largely on how politics shapes the flow of FDI across countries. The central insight of this literature is that multinational corporations (MNCs) face an "obsolescing bargain" against the host government. Once the MNC has sunk its investment, it is vulnerable to the host government's changing regulations, backtracking on deals, or even expropriating its properties (Li 2009; Sawant 2010). Certain institutional and political characteristics, such as numerous veto players, executive constraint, or strong property rights, allow the host government to make a credible commitment and thus ameliorate the severity of the "obsolescing bargain" problem (Busse and Hefeker 2007; Jensen et al. 2014; Li and Resnick 2003). According to the literature, MNCs should invest more in countries with these characteristics.

*The Metropolis-Hastings approach in this paper draws heavily upon conversations with Professor Michael Newton. I also thank Professor Michael Ward for introducing the two-sided matching model, and Professor Andrew Delios for sharing the Japanese FDI data.

This dominant approach in the literature has three long-standing issues that my paper will address. First, the majority of the literature relies on FDI stock and flow data as the outcome of interest even though they are often not an appropriate measure for the scale of MNCs' activities (Kerner 2014). While it would be ideal to use firm-level data instead, both the lack of cross-national firm-level data and a suitable statistical model have posed a challenge.

Second, while there has been much focus on MNCs choosing host countries, the literature has largely neglected the other side of the investment decision: what are countries' preferences regarding MNCs? Consider the established finding that democracies receive more FDI. Without controlling for countries' preferences, it is difficult to interpret this fact as democracies actively pursuing MNCs or as MNCs finding democracies attractive. Not only are countries' preferences central to the modeling of investment decision, arguably it is also more steeped with politics and deserves more attention. Pinto (2013) and Pandya (2016) are two pioneering works in this area of research, proposing partisan politics and regime types as factors shaping countries' preferences for FDI. However, while their theories are ground-breaking, the empirical estimation of countries' preferences remains difficult.

Third, in addition to empirical issues raised above, I propose that we need to theorize about countries' preferences for FDI quality. While the political science literature has largely focused on the quantity of FDI, national policies and discourses pay much attention to the quality of FDI, using various incentives and restrictions to target certain types of FDI. Indeed, MNCs come with varying capital, demand for labor, and technology, all of which have different effects on the host country's economy. For example, policy makers and scholars have highlighted high-tech MNCs as a source of technological transfer for developing host countries, allowing them to upgrade their technical capacity and improve their productivity (Findlay 1978; Nunnenkamp and Spatz 2004). While such high-quality FDI has been enthusiastically endorsed by the development community, I argue that only governments with a long time horizon want to attract high-tech FDI because technological transfer takes time to pay off.

In sum, the current literature would benefit from an analysis that is capable of using firm-level data to estimate both firms' and countries' preferences for each other's characteristics. To accomplish this goal, I adapt the two-sided matching model originally designed for the labor market and the marriage market. In this model, both firms and countries evaluate their available options and choose the best according to their utility functions. As in many social science contexts, we only observe the final firm-country matches and not the full set of available options (also known as the opportunity set). I solve this problem by using the Metropolis Hastings algorithm, a Markov chain Monte Carlo (MCMC) approach that repeatedly samples new opportunity sets and rejects them at an appropriate rate to approximate their true distribution. Since the two-sided matching model is derived explicitly from actors' utility functions, their parameters also enjoy a straightforward interpretation in the utility space instead of some aggregate outcomes.

The paper proceeds as follows. Section 2 discusses the three long-standing issues with the literature and how they can be improved. Section 3 lays out the utility structure in the two-sided matching model and describes the matching process. Section 4 shows how the model can be estimated with the Metropolis-Hastings algorithm. Section 5 shows an application of the model on a census of Japanese firms overseas. Section 6 presents the result. Section 7 concludes.

2 Three Issues in the Literature of FDI's Political Determinants

2.1 Measuring MNCs' Activities

For the majority of political science theory regarding FDI, the quantity of interest is the scale of MNCs' activities in a country, and not necessarily how much FDI crosses its border. Indeed, we theorize about how MNCs may reduce their activities for fear of expropriation, and how the host country's political factors can induce MNCs to invest more with a credible commitment not to expropriate. It is also the scale of MNCs' activities that determines how many jobs are created or how much of the domestic market is competed away, engendering labor's support and local business' lament.

However, to measure the scale of MNCs' activities, the vast majority of works uses how much FDI crosses the border, specifically FDI stock and flow (Jensen 2003; Ahlquist 2006; Beazer and Blake 2011; Graham 2010). As Kerner (2014) points out, these measures, whose original purpose is to monitor balance of payments, are often misleading about MNCs' activities. FDI flow does not count locally raised capital and reinvested earnings since they do not cross any border. FDI stock calculated at market value fluctuates based on market price, unrelated to firms' behavior. FDI stock calculated at historical value, which records asset value at the time it was acquired, is more stable and appropriate to measure the scale of MNCs' activities. Unfortunately, due to onerous data requirements, most countries measures FDI stock by simply adding up FDI flow across years.

Given the interest of political science theory in MNCs' activities, Kerner (2014) suggests less use of FDI stock and flow and more use of firm-level statistics. For example, consider the hypothesis that countries with more veto players have more stable policies and are thus more attractive to FDI (Li 2009). Instead of using FDI stock and flow into a country to measure its attractiveness, we can study whether more MNCs are located there.

While firm-level data has become more abundant in recent years,[1] it is not clear how to analyze this type of data appropriately. Given the data structure of a set of firms interacting with a set of countries, one may consider a dyadic-based analysis, frequently used in the International Relations literature. In such analysis, the unit of observation is a firm-country dyad, and the model used is typically OLS regression. Each dyad is assumed to be independent of each other, and any bias caused by interdependency is fixed via post-estimation procedures, such as clustered standard errors (Dorff and Ward 2013).

Unfortunately, this dyadic approach is inappropriate to analyze MNCs' investment location. Once a firm chooses to invest in a country, it is by definition not investing in another. Therefore, the values of firm-country dyads deterministically constrain one another and cannot be modeled as independent draws from a common distribution.

[1] Examples of firm-level data include the US Bureau of Economic Analysis (BEA)'s survey of all US firms abroad, Tokyo Keizai's Overseas Japanese companies database (*Kaigai Sinshutsu Kigyou Souran*), World Bank's Enterprise Survey, and Orbis database of companies worldwide.

The two sided matching model solves this problem by considering one firm-country match as the unit of observation. The intuition is as follows. If we observe that a firm is welcome to invest in countries $j_1, j_2, \ldots, j_n$ but ends up investing in country j^*, it must mean country j^* offers the highest utility to firms. Continuing the previous example, if country j^* has more veto players than average, we can infer that MNCs indeed prefer countries with more veto players.

2.2 Estimating Countries' Demand for FDI

Recognizing that our model of investment location has not taken into account countries' demand for FDI, Pinto (2013) and Pandya (2016) recently broke ground in this area. Similar to the rich IPE literature in trade and exchange rate, these studies argue that countries' demand for FDI varies according to FDI's distributive effect on their domestic constituencies (Broz and Frieden 2001; Milner and Kubota 2005). In this theoretical framework, labor supports FDI because foreign firms bring capital that increases the demand for labor and raises productivity, both of which lead to higher wage. On the other hand, domestic firms oppose FDI because foreign firms compete for local labor, inputs, and markets. Both Pinto (2013) and Pandya (2016) formulate their theories as a variant of this labor-vs-business tension, which surfaces in the former work as left-vs-right governments, and in the latter as democratic-vs-authoritarian regimes.

While these pioneering works have enriched our understanding of the relationship between politics and FDI, their empirical approaches do not satisfactorily measure countries' demand for FDI, leaving their theoretical arguments untested.

Consider Pinto (2013)'s approach, which controls for economic and institutional factors that affect FDI flow into a country. The author then claims that the country's openness towards FDI is what's left in the residual.[2] For this approach to be valid, every economic, institutional, and endowment factors that affect FDI flow have to be controlled for, leaving only the country's demand in the error term. This claim is much stronger than the regular assumption of exogenous and normally distributed error, which is valid as long as the omitted factors are uncorrelated with the independent variable of interest. Framed substantively, since the residual is likely to contain more than just the country's demand for FDI, if we observe an abnormally high level of FDI, we do not know whether it is because the country welcomes FDI or because MNCs find something attractive in the country.[3]

In contrast to Pinto (2013)'s statistical approach, Pandya (2014, 2016) substantively measures countries' demand for FDI, using the annual US Investment Climate Reports to code the number of industries that have foreign ownership restrictions or face investment screen-

[2]Specifically, the estimation of FDI openness involves two steps. First, the author runs a gravity model explaining bilateral FDI flows, estimating the intercept as the host country-year fixed effect. Second, this fixed effect is then regressed on several economic and endowment factors of that country-year (i.e. GDP, GDP per capita, average school years, arable land). The residual in the second stage is considered the country's "FDI openness" in that year.

[3]In addition, the data requirement of bilateral FDI flows, ideally disaggregated by sectors, is very demanding. Therefore, this approach is limited to OECD countries only (Pinto and Pinto 2008). During the period the authors study, 1980-2000, OECD countries accounted for 95% of global FDI outflow and 90% of inflow. However, since then the role of the developed world in global FDI has declined sharply, reduced to 60.8% of outflow and 40.6% of inflow in 2014 (UNCTAD 2015).

ing. The advantages of this measurement are its ease of interpretation and its availability for many countries. However, two problems remain. First, adding up the raw count of restricted industries is not appropriate because industries are not all the same. For example, given the reach of the banking sector into all corners of the economy, a country's opening up its financial industry indicates much more FDI-friendliness than, say, allowing foreign furniture makers to set up shops. Since the theoretical argument is driven by FDI's distributive effect, it is suspect to ignore the varying impact of FDI across sectoral constituencies.

Second, according to the coding rules, an industry is coded as free if there is no mention of restriction. If an industry receives little FDI, it may not be worth mentioning as being restrictive and yet still coded as open. Therefore, "zero restriction" in the dataset can either mean that a country is very closed or very open to FDI. This concern is not hypothetical. Figure 1 shows that, following the coding of the US Investment Climate Reports, China seemed 100% open to FDI up until 1986 when it started imposing restrictions. The reality is the opposite. Prior to 1986, only limited FDI was allowed as joint-venture in Special Economic Zones (SEZ). The year of 1986 was, in fact, the first time China allowed any wholly owned FDI outside of SEZs.

Figure 1: China's FDI Ownership Restriction, as coded in Pandya (2010). Prior to 1986, FDI in China was limited to few experimental Special Economic Zones, and thus not mentioned in US Investment Reports. The sharp spike in 1988 also does not seem to correspond to any actual change in policy, and likely another artifact of reporting. (See Zebregs and Tseng (2002) for a historical overview of China's FDI policy.)

The two-sided matching model circumvents these thorny measurement issues by incorporating countries' utility function directly into the model. If we observe that country j welcomes firms $i_1, i_2, \ldots, i_n$ to invest but not others, we can compare the characteristics of firms $i_1, i_2, \ldots i_n$ with the others to infer country j's preference.

2.3 Estimating Countries' Preferences for FDI's Technological Intensity

While the political science literature has focused almost exclusively on the quantity of FDI, treating all FDI as one homogeneous flow of capital, policy makers seem to pay much more attention to distinguishing types of FDI. Commenting on the role of International Investment Agreements (IIAs), UNCTAD (2015) says, "Today, increasing the quantity of investment is not enough. What matters is its quality, i.e. the extent to which investment delivers concrete sustainable development benefits." Governments in developing countries, from Ghana to China, all offer various forms of tax incentives and fee waivers to attract FDI that invests in a remote region, brings new technology, or focuses on exporting (Ricupero 2000). Since 2006, China's official FDI policy has been "quality over quantity," promoting FDI with intense R&D in high-productivity sectors (Guangzhou 2011). Indeed, for developing countries, the hope is that MNCs will transfer their technologies to the domestic economy by training workers or partnering with local suppliers.

Despite the importance of disaggregating FDI by its quality, data unavailability remains the bottleneck. The few existing attempts use detailed data from only one country or limit the sample to OECD countries (Alfaro 2003; Alfaro and Charlton 2007; Javorcik 2004). With cross-country firm level data now available, we often have information on the firms' industry or even research and development (R&D) expenditure. With the two-sided matching model, I will be able to estimate countries' preferences for firms' technological intensity. I hypothesize that, since MNCs' technologies takes time to diffuse to local businesses, a country' preference of high-tech FDI is shaped by its time horizon.

3 The Two-Sided Matching Model

This section lays out the set-up of the two-sided matching model, including the utilities of countries' officials and of MNCs. Then, the matching process is a natural consequence of actors' choosing the best option available to them.

3.1 Officials' Utility

Following Logan (1998), we consider the utility function of two actors, the official and the firm.[4] For official j, the utility of having firm i invest in his country is:

$$U_j(i) = \boldsymbol{\beta}_j' X_i + \epsilon_{1ij} \tag{1}$$

where

β_j is a vector of official j's preference for relevant characteristics of firms

x_i is a vector of firm i's measured values on those characteristics

ϵ_{1ij} is the unobserved component that influences official j's utility

[4] For ease of exposition, in this section I will refer to country j and official j interchangeably.

On the other hand, the utility of not having firm i investing is:

$$U_j(\neg i) = b_j + \epsilon_{0ij} \tag{2}$$

where

$$\begin{aligned} b_j & \text{ is the baseline utility of official } j \text{ without any firm investing} \\ \epsilon_{0ij} & \text{ is the component that influences official } j\text{'s utility} \end{aligned}$$

For each firm i, official j will make an offer to invest if $U_j(i) > U_j(\neg i)$. Relevant firm characteristics (i.e. X_i) that the official may consider are: technological intensity, number of jobs, and size of capital. The corresponding β's represent the official's preference for these characteristics.

Following the discrete choice literature, we model $\epsilon_{1ij}, \epsilon_{0ij}$ as having the Gumbel distribution. Then, the probability of official j making an offer to firm i takes the familiar binomial logit form:

$$\begin{aligned} Pr(o_{ij} = 1) &= Pr(U_j(i) > U_j(\neg i)) && (3) \\ &= Pr(\epsilon_{0ij} - \epsilon_{1ij} < \boldsymbol{\beta}_j' X_i - b_j) && (4) \\ &= \frac{\exp(\boldsymbol{\beta}_j' X_i)}{1 + \exp(\boldsymbol{\beta}_j' X_i)} && (5) \end{aligned}$$

where Equation (5) is due to the fact that the difference between two Gumbel-distributed random variables has a logistic distribution. We make the constant term b_j disappear into $\boldsymbol{\beta}_j$ by adding an intercept column to the matrix of firm characteristics X_i.

We call the set of all countries that welcome firm i to invest the opportunity set of firm i. If we know the preferences of all countries, we can calculate the probability that firm i gets an opportunity set O_i as follows:

$$\begin{aligned} p(O_i|\boldsymbol{\beta}) &= \prod_{j \in O_i} p(o_{ij} = 1|\boldsymbol{\beta}) \prod_{j \notin O_i} p(o_{ij} = 0|\boldsymbol{\beta}) && (6) \\ &= \prod_{j \in O_i} \frac{\exp(\boldsymbol{\beta_j'} X_i)}{1 + \exp(\boldsymbol{\beta_j'} X_i)} \prod_{j \notin O_i} \frac{\exp(\boldsymbol{\beta_j'} X_i)}{1 + \exp(\boldsymbol{\beta_j'} X_i)} && (7) \end{aligned}$$

In our observed data, since we only observe the final matching of firms and countries, this opportunity set is unobserved. As Section 4 will discuss, we use the Metropolis-Hastings algorithm to approximate the posterior distribution of the opportunity set.

3.2 Firms' utility

On the other side, for firm i, the utility of investing in country j is:

$$V_i(j) = \alpha' W_j + v_{ij} \tag{8}$$

where

α is a vector of firms' preference for relevant characteristics of countries
W_j is a vector of country j measured values on those characteristics
v_{ij} is the unobserved component that influences firm i's utility

Firm i evaluates all the countries that welcome it to invest and chooses the country that brings the highest utility. This choice of firms concludes the matching process, resulting in the observed final match between a firm and a country in our data.

In our model, relevant country characteristics can be: labor quality, level of development, and market size. Since all firms are considered having homogeneous preferences, α does not have a subscript i. The model can be easily extended so that there is heterogeneous preference among firms.

If v_{ij} is modeled as having a Gumbel distribution, then the probability that firm i will accept the offer of official j out of all the offers in its opportunity set O_i takes the multinomial logit form (Cameron and Trivedi 2005):

$$p(A_i = a_i | O_i, \alpha_i) = \frac{\exp(\alpha' W_{a_i})}{\sum_{j:j \in O_i} \exp(\alpha' W_j)} \tag{9}$$

4 Model Estimation

While Logan (1996, 1998) successfully reformulate the random utility mode in the discrete choice literature to a two-sided setting, the estimation of the two-sided model remains challenging. The key difficulty lies in the fact that we do not know the full sets of offers that firms receive from countries. Therefore, the likelihood function is incomplete, missing the data on firms' opportunity sets. With an incomplete likelihood function, we cannot use Maximum Likelihood Estimation to estimate firms' and countries' preferences.

To solve this problem, Logan (1996) uses the Expectation-Maximization (EM) algorithm.[5] However, an important downside of the EM algorithm is its lack of a standard error. Therefore, while the algorithm is capable of producing the best estimate for the parameters of interest, it is difficult to know how good our best guess really is.

[5]The EM algorithm finds the best parameter estimates by iterating between two steps. First, given the current best guess of firms' and countries' preferences, pick values for the unobserved opportunity sets so that we maximize the likelihood. Second, given the current best guess of the unobserved opportunity sets, taken from step 1, pick values for firms' and countries' preferences so that we maximize the likelihood. By iterating between these two steps, the algorithm constantly searches for parameters values that push the likelihood higher.

To overcome this difficulty, I use the Metropolis-Hastings algorithm, a MCMC approach that can approximate the posterior distribution of the opportunity sets, firms', and countries' preferences.

To illustrate the Metropolis-Hastings algorithm, consider our need to sample from the posterior distribution of the opportunity sets, $p(O|\text{data})$, which can take any complicated form. Suppose we already had a working collection of values $\{O^{(1)}, \ldots, O^{(s)}\}$. To add new values to this collection, we would propose a new value O^*, then decide whether to keep it with the probability $\frac{p(O^*|\text{data})}{p(O|\text{data})}$. The intuition is that if $\frac{p(O^*|\text{data})}{p(O|\text{data})}$ is large, then O^* is very likely compared to O given $p(O|\text{data})$. Thus, we should keep O^* and add it to the collection. In other words, we decide to keep newly proposed values of O at a rate proportional to how often they should appear according to $p(O|\text{data})$. Repeating this step many times, at the end we will have a collection of O values that approximates $p(O|\text{data})$ as desired.

Appendix A describes the details of our model estimation and derives the Metropolis-Hastings acceptance ratio. I use flat priors so that the results are driven entirely by the data. In deriving the joint distribution of the data and parameters, there are two important ideas. First, the opportunity sets are determined solely by countries' preferences, not firms'. Second, given the opportunity sets, the final matches are determined solely by firms' preferences, not countries'. Thus, the joint distribution of data and parameters factorizes nicely as follows:

$$p(A_i, O_i, \alpha, \boldsymbol{\beta}) = p(A_i|O_i, \alpha)p(O_i|\boldsymbol{\beta})$$

where our observed match data is A_i, which denotes the country that firm i accepts to invest in.

5 Applying the Two-Sided Matching Model to Japanese MNCs

In this section, I apply the two-sided matching model to study the investment location of Japanese firms overseas. The data comes from the *Kaigai Shinshutsu Kigyou Souran*, an annual publication that contains information about the foreign affiliates of Japanese firms, including their location, industry, capital, and labor size.[6] This database is reputed to include all Japanese firms overseas (Yamawaki 1991). The final sample includes 6474 Japanese foreign affiliates in 2003, spreading across 37 countries, with China and the US leading as the two top destinations for Japanese MNCs (Table 2).

For countries' characteristics that firms consider, I include:

- Market size: MNCs are expected to prefer countries with a large market size, which present MNCs with many potential customers. Indeed, this has been often cited as the allure of China to MNCs (Luo et al. 2010). I follow the standards in the literature and include log GDP (constant 2005 US$), taken from the World Bank's World Development Indicators.

[6] I thank Professor Andrew Delios for generously sharing the data.

- Level of development: MNCs are expected to prefer countries with a high level of development. A developed economy has consumers with high purchasing power and better infrastructure. To measure development, I use log GDP per capita (constant 2005 US$) from World Development Indicators.

- Labor quality: As one primary factor of production, labor matters greatly to firms' productivity and profit. To measure labor quality, I use the average years of schooling of adult, taken from the UNDP's Human Development Report.[7]

- Democracy: Democracy has been a mainstay in the political science literature on FDI. Scholars have argued that MNCs want to invest in democratic regimes for various reasons, including stable policy, credible commitment, and strong property rights (Ahlquist 2006; Li and Resnick 2003; Jensen 2003). On the other hand, recent works have also argued that democratic regimes want FDI more than autocratic regimes (Pandya 2016). Thus, it is unclear whether the observed high level of FDI in democracies is due to the push or the pull factors. By controlling for countries' preference in the two-sided matching model, I can better estimate the effect of democracies on firms' utility. I measure democracy using the binary Demoracy & Dictatorship, developed by Cheibub et al. (2009).

For firms' characteristics that countries consider, I include:

- Capital size (in US$): A main argument for the benefit of FDI is that it brings capital to the country, improving labor productivity. MNCs' capital is especially important for developing countries, which cannot muster much domestic capital from their poor population. The capital size of a firm is included in the Japanese Overseas Business dataset.

- Labor size: Similarly, a reputed benefit of FDI is that it creates jobs, generating not just economic growth but also increasing the government's popularity among the populace. The total number of employees of a firm is included in the Japanese Overseas Business dataset.

- Technology intensity: I proxy for a firm's technology intensity by the industry to which it belongs. OECD (2009) categorizes ISIC industries into four levels of technology intensity—low, medium low, medium high, and high—according to the level of R&D expenditure divided by sales. I convert the industry classification of firms in my data from SIC 3 to ISIC and categorize their technology intensity from 1 to 4, with 1 being low and 4 being high. On several occasions, one industry in SIC 3 matches to multiple ISIC (rev 3) industries or none at all. In the former case, I take the average across matched ISIC industries. In the latter case, the data is missing and later removed from the analysis.

[7] Since Taiwan is not included in UNDP's and World Bank's data, I collected its statistics from the Taiwanese Statistical Website.

6 Results

I run a Metropolis-Hastings algorithm for 2,000,000 iterations, choosing the proposal step size so that the acceptance rate falls within 20% and 50% (Hoff 2009). To reduce autocorrelation between iterations, I thin the sample and only keep the sampled values every 100 steps, resulting in a final posterior sample of 20,000.

6.1 Results on Firms' Preferences

Figure 2 show the trace plots of α, firms' preference parameters for countries' log GDP, log GDP per capita, democracy, and labor quality. The plots show that the MCMC chains converge after the 10000$^{\text{th}}$ iterations, except for the average years of schooling. Thus, our interpretation for this variable has to be more cautious.

Table 1 report the posterior means and quantiles of firms' preference parameters. The posterior means can be interpreted naturally in the utility space as the relative weights that firms assign to countries' characteristics.[8] For example, since the value of firms' preference for democracy is 0.02 and for log GDP per capita is 2.5, it means that being a democracy is worth 0.02 / 2.5 = 0.008 of 1 unit increase in log GDP. Interpreting on the level scale, it means that being a democracy is worth 0.305 / 0.025 = 12.2 times a 1% increase in GDP.

However, looking at the posterior quantiles, we find that only GDP per capita is a statistically significant factor in MNCs' utilities. While this finding contradicts existing theories on the determinants of FDI, it comports with the latest empirical evidence. After correcting for selection bias and using Bayesian model averaging to select robust determinants of FDI, Eicher et al. (2012) also finds that host country's size, regime type, and educational attainment do not play an important role in attracting FDI.

	2.5%	25%	50%	75%	97.5%
log GDP	-0.05	0.07	0.12	0.19	0.29
log GDP per cap	1.53	2.15	2.50	2.84	3.44
Average Years of Schooling	-0.23	-0.13	-0.06	0.06	0.23
Democracy	-0.24	-0.08	0.02	0.14	0.40

Table 1: The posterior quantiles of firms' preferences for countries' characteristics.

6.2 Results on Countries' Preferences

Due to the small number of Japanese firms locating in certain countries, the MCMC chains for their parameters converge much slowly, if at all. For example, Myanmar has only seven Japanese firms. Its traceplots show that the MCMC chains do not seem to converge even after 20,000 iterations (Figure 3). Given the lack of convergence, the results in this section remain speculative.

[8] In the utility space, the scale of the parameters do not matter. Consider two scenarios: 1) country A offers 10 "utilities" while country B offers 50; 2) country A offers 1 "utility" while country B offers 5. These two scenarios are identical since the firm will choose country B over country A. For this reason, we focus on interpreting preference parameters as relative weights.

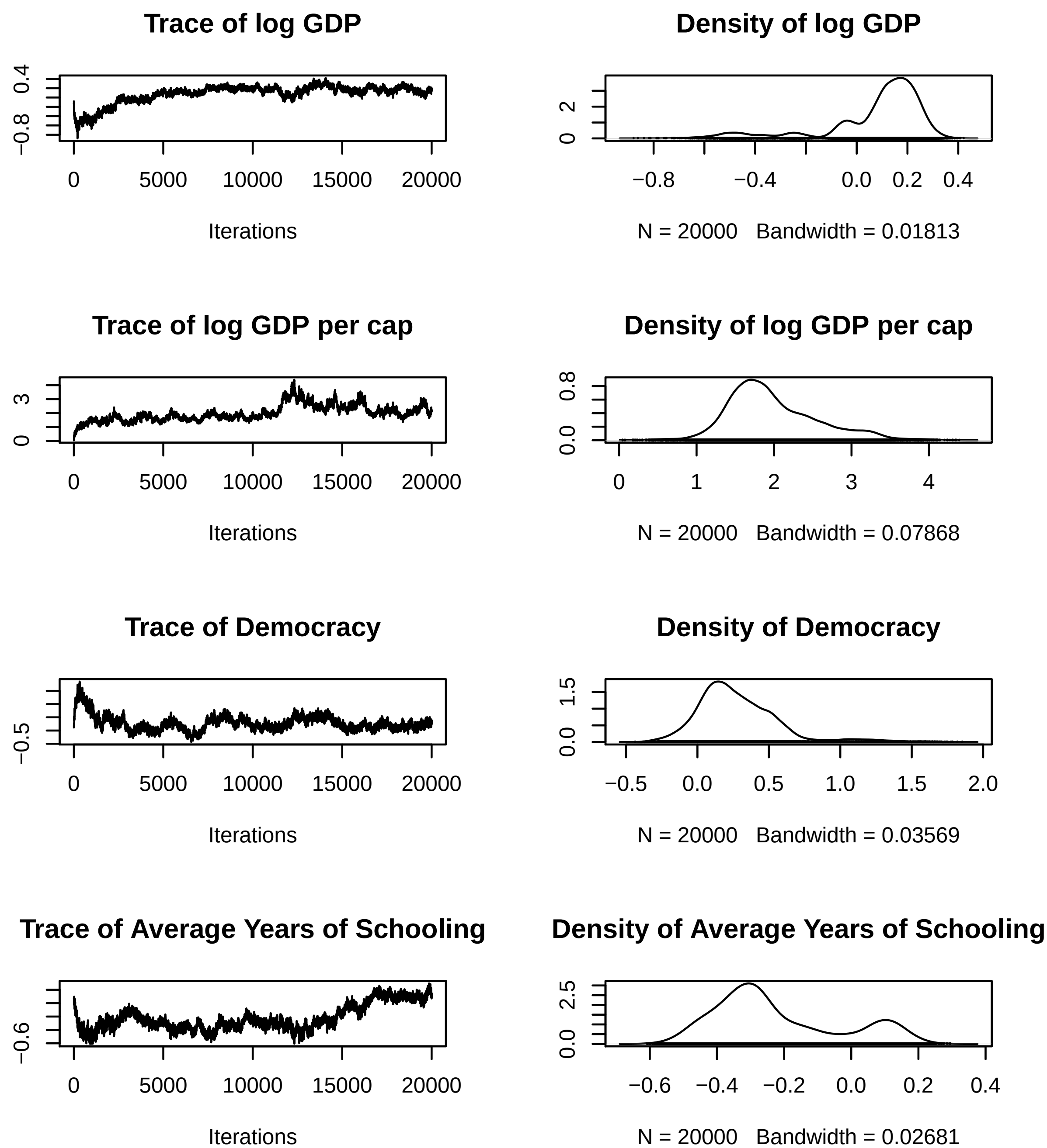

Figure 2: Traceplot of firms' preferences for countries' characteristics.

To test the hypothesis that only governments with a long time horizon actively seeks high tech MNCs, I proxy time horizon with the age of the executive's party. A long-running party has an extended time horizon for two reasons. First, given its longevity, it is possible for the party to come back to power in the future, reaping the benefits of its investment in attracting high-tech FDI. Second, given that a long-running party has a persistent, identifiable brand, it can more easily claim the credit for attracting high-tech MNCs even if the benefit only

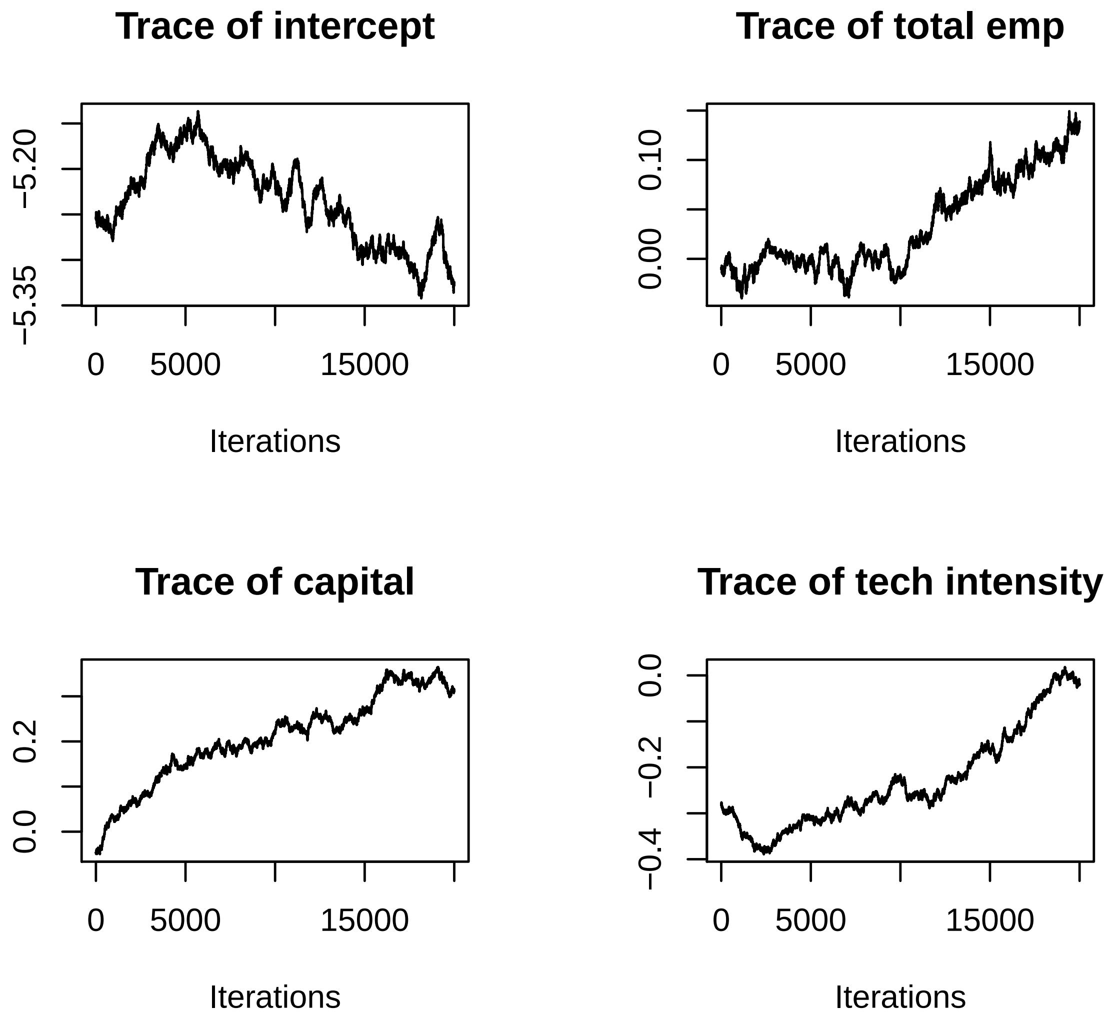

Figure 3: Traceplot of Myanmar's preferences for MNCs' characteristics.

materializes many years later.

Figure 4 attempts to show the positive relationship between a government's time horizon and its preference for high-tech MNCs. While there is a positive slope, the sample size of countries is too small to make any definitive claim.

7 Conclusion

In this paper, I propose the two-sided matching model to estimate firms' and countries' preferences, solving three persistent issues in the literature of FDI's political determinants. The results indicate that, for Japanese MNCs, only a country's level of development matters and not its market size, labor quality, or regime type. This finding suggests that we should take a closer look at the relationship between democracies and MNCs. Since previous works

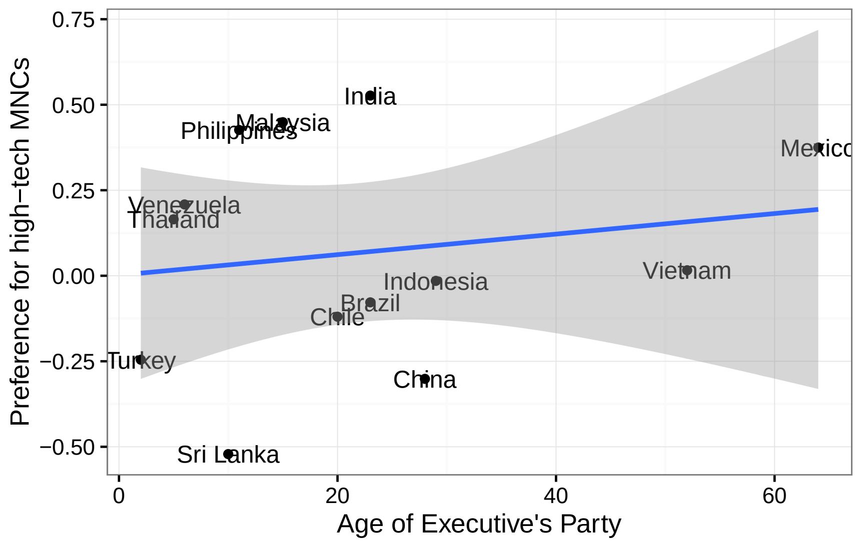

Figure 4: The relationship between a government' time horizon and its preference for high-tech MNCs.

in the literature have not controlled for countries' preferences, they may have mistaken democracies' love for FDI as FDI's fondness for democracies.

On the other hand, the model's estimation of countries' preference remains lacking. Since each country has its own set of parameters, the parameter space seems too large for the current implementation of the Metropolis-Hastings algorithm to fully explore. Several solutions are possible. First, we can collapse countries into categories of interest, e.g. regime types, (categorical) time horizon length. Second, we can build a hierarchical model, modeling countries' preferences as draws from a common distribution. Such model will allow us to pool information across countries and reduce the parameter space.

A Deriving the Metropolis Hasting acceptance ratio

A.1 Updating the opportunity set

Target distribution for a firm i

$$p(O_i|A_i, \alpha, \boldsymbol{\beta}) = \frac{p(O_i, A_i, \alpha, \boldsymbol{\beta})}{p(A_i, \alpha, \boldsymbol{\beta})} \tag{10}$$

We propose a new O_i^* by randomly sample a new offer, j^* for each firm. If the new offer is not already in the current opportunity set, we add the offer to the set. If it already is in the opportunity set, we remove it from the set.

We then calculate the Metropolis-Hasting acceptance ratio:

$$\begin{aligned}
MH_O = \frac{p(O_i^*|A_i, \alpha, \boldsymbol{\beta})}{p(O_i|A_i, \alpha, \boldsymbol{\beta})} &= \frac{p(O_i^*, A_i, \alpha, \boldsymbol{\beta})}{p(A_i, \alpha, \boldsymbol{\beta})} \times \frac{p(A_i, \alpha, \boldsymbol{\beta})}{p(O_i, A_i, \alpha, \boldsymbol{\beta})} && (11)\\
&= \frac{p(O_i^*, A_i, \alpha, \boldsymbol{\beta})}{p(O_i, A_i, \alpha, \boldsymbol{\beta})} && (12)\\
&= \frac{p(A_i|O_i^*, \alpha)p(O_i^*|\boldsymbol{\beta})}{p(A_i|O_i, \alpha)p(O_i|\boldsymbol{\beta})} && (13)\\
& && (14)
\end{aligned}$$

where the factorization of the likelihood in Equation (13) is due to the fact that the acceptance of firm i only depends on what is offered to it and what is its preference, $p(A_i|O_i^*, \alpha)$; what is offered to i depends on the preferences of all countries, $p(O_i^*\ \boldsymbol{\beta})$.

If we plug in Equation (9) and Equation (7)

$$\frac{p(O_i^*|A_i, \alpha, \boldsymbol{\beta})}{p(O_i|A_i, \alpha, \boldsymbol{\beta})} = \frac{\sum\limits_{j:j\in O_i} \exp(\alpha' W_j)}{\sum\limits_{j:j\in O_i} \exp(\alpha' W_j) + \exp(\alpha' W_{j^*})} \times \exp(\boldsymbol{\beta}'_{j^*} X_i) \tag{15}$$

where j^* is the index of the newly sampled job. This is the case when the newly proposed job is not already offered, so it's added to the opportunity set.

When the newly proposed job is already offered, so it's removed from the opportunity set, we have

$$\frac{p(O_i^*|A_i, \alpha, \boldsymbol{\beta})}{p(O_i|A_i, \alpha, \boldsymbol{\beta})} = \frac{\sum\limits_{j:j\in O_i} \exp(\alpha' W_j)}{\sum\limits_{j:j\in O_i} \exp(\alpha' W_j) - \exp(\alpha' W_{j^*})} \times - \exp(\boldsymbol{\beta}'_{j^*} X_i) \tag{16}$$

A.2 Updating firms' parameters, α

Target distribution:

$$p(\alpha|A,O,\boldsymbol{\beta}) = \frac{p(O,A,\alpha,\boldsymbol{\beta})}{p(A,O,\boldsymbol{\beta})} \tag{17}$$

We propose a new α^* using a symmetric proposal distribution that sample α^* in a box whose boundary is $\alpha^* \pm \epsilon_\alpha$

Metropolis-Hasting acceptance ratio:

$$\begin{aligned} MH_\alpha = \frac{p(\alpha^*|A,O,\boldsymbol{\beta})}{p(\alpha|A,O,\boldsymbol{\beta})} &= \frac{p(A_i|O_i,\alpha^*)p(O_i|\boldsymbol{\beta})}{p(A_i|O_i,\alpha)p(O_i|\boldsymbol{\beta})} && (18)\\ &= \frac{p(A_i|O_i,\alpha^*)}{p(A_i|O_i,\alpha)} && (19)\end{aligned}$$

where Equation (19) is due to the flat prior (so $\frac{p(\alpha^*)}{p(\alpha)} = 1$) and the symmetric proposal distribution (so $\frac{p(\alpha^*|\alpha)}{p(\alpha|\alpha^*)} = 1$)

If we plug in Equation (9),

$$\begin{aligned} MH_\alpha &= \prod_i \left[\frac{\exp(\alpha^{*\prime}W_{a_i})}{\exp(\alpha' W_{a_i})} \times \frac{\sum\limits_{j:j\in O_i}\exp(\alpha' W_j)}{\sum\limits_{j:j\in O_i}\exp(\alpha^{*\prime}W_j)}\right] && (20)\\ &= \prod_i \left[\exp(\epsilon'_\alpha W_{a_i}) \times \frac{\sum\limits_{j:j\in O_i}\exp(\alpha' W_j)}{\sum\limits_{j:j\in O_i}\exp(\alpha^{*\prime}W_j)}\right] && (21)\end{aligned}$$

Finally, we log transform the MH acceptance ratio for numerical stability.

$$\log MH_\alpha = \sum_i \left[\epsilon'_\alpha W_{a_i} + \log\left(\sum_{j:j\in O_i}\exp(\alpha' W_j)\right) - \log\left(\sum_{j:j\in O_i}\exp(\alpha^{*\prime}W_j)\right)\right] \tag{22}$$

A.3 Updating countries' parameters, β

Target distribution:

$$p(\boldsymbol{\beta}|A,O,\alpha) = \frac{p(O,A,\alpha,\boldsymbol{\beta})}{p(A,O,\alpha)} \tag{23}$$

We propose a new $\boldsymbol{\beta}^*$ using a symmetric proposal distribution that sample $\boldsymbol{\beta}^*$ in a box with side length ϵ_β

Metropolis-Hasting acceptance ratio:

$$MH_\beta = \frac{p(\beta^*|A, O, \alpha)}{p(\beta|A, O, \alpha)} = \frac{p(A_i|O_i, \alpha)p(O_i|\boldsymbol{\beta}^*)}{p(A_i|O_i, \alpha)p(O_i|\boldsymbol{\beta})} \tag{24}$$

$$= \frac{p(O_i|\boldsymbol{\beta}^*)}{p(O_i|\boldsymbol{\beta})} \tag{25}$$

where Equation (24) is due to the flat prior on β and the symmetric proposal distribution. We plug in Equation (7),

$$MH_\beta = \prod_i \left[\prod_{j \in O_j} \frac{\exp(\beta_j^{*\prime} X_i)}{\exp(\beta_j^\prime X_i)} \times \prod_j \frac{1 + \exp(\beta_j^{*\prime} X_i)}{1 + \exp(\beta_j^\prime X_i)} \right] \tag{26}$$

$$\log MH_\beta = \sum_i \left[\sum_{j \in O_i} \beta_j^{*\prime} X_i - \beta_j^\prime X_i + \sum_j \log(1 + \exp(\beta_j^{*\prime} X_i)) - \log(1 + \exp(\beta_j^\prime X_i)) \right] \tag{27}$$

In the MCMC implementation, since $\boldsymbol{\beta}$ is high dimensional, we conduct multiple block Metropolis Hastings, updating several β's at one time.

B Summary Statistiscs

Australia	62	New Zealand	15
Belgium	26	Pakistan	11
Brazil	103	Philippines	199
Canada	64	Poland	8
Chile	8	Portugal	14
China	1709	Saudi Arabia	7
Colombia	8	Singapore	222
France	76	Spain	35
Germany	72	Sri Lanka	10
Hong Kong	179	Sweden	15
Hungary	15	Taiwan	372
India	99	Thailand	696
Indonesia	391	Turkey	8
Ireland	8	United Kingdom	179
Italy	36	USA	909
Korea	275	Venezuela	7
Malaysia	416	Vietnam	100
Mexico	85		
Myanmar	7		
Netherlands	28		

Table 2: The list of countries included in the sample and the number of Japanese firms located in each country.

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