The political determinants of FDI spillover

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1 Introduction

We introduce a model that can estimate the utility of both sides, building from their utility function up.

2 Literature

The IPE literature on the relationship between politics and FDI has focused largely on how political factors shape and direct the flow of FDI across countries. Among the considered factors include: corruption, regime type, political violence, expropriation, etc. The dominant theoretical insight in this literature is the "obsolescing bargain" power of foreign firms. Once foreign firms sink their illiquid investment into the host countries, they no longer have a bargaining power and may be vulnerable to the caprice and avarice of the host. All of the political factors are a variant on what characteristics of the state mitigate or exacerbate this obsolescing bargaining problem. Later analyses extend the framework to dyadic framework, examining the interplaying effect of both the host and the home country characteristics.

Is this interesting? Presumably it is interesting because we care about the role of the nation states in the international economy, which in turn it is important because the flow of FDI has welfare implications for millions of citizens in the host countries. A frequent policy conclusion from this body of research is echoed widely in the policy sphere is that countries need to improve the investment climate, reduce corruption, or maintain political stability to attract FDI.

But do countries want to? This causally prior question, and arguably more pregnant with politics, it has been understudied.

On the one hand, some scholars have looked at the demand for FDI. However, these efforts have been stymied by recalcitrant issues with data and methods.

One the other hand, I also want to raise the issue of the quality of FDI.

Implicit in this phrase are two under-examined ideas: one is that country always want to attract FDI. Two is that it does not differentiate between the type of FDI that a country would want.

2.1 Countries' demand for FDI

Recognizing the need to theorize about the demand for FDI, scholars have recently paid more attention to this area (Pinto 2013; Pandya 2016). Similar to the rich IPE literature in trade and exchange rate (Broz and Frieden 2001; Milner and Kubota 2005), these studies argue that countries' demand for FDI varies according to FDI's distributive effect on their domestic constituencies.[1] 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 with them for labor, local 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, serious empirical issues prevent their statistical analyses from truly validating their theoretical arguments. The bottleneck is measuring country's demand for FDI.

For example, consider Pinto and Pinto (2008); Pinto (2013)'s approach, which controls for economic and institutional factors that affect bilateral FDI flow into a country. The author then claims that the country's demand for 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 still do not know whether it is because the country welcomes FDI or because foreign firms find something attractive in the country.[3]

In contrast to Pinto (2013)'s statistical approach, Pandya (2014, 2016) aimed to substantively measure countries' demand for FDI, using the annual US Investment Climate Reports to code how many industries have foreign ownership restriction or face investment screening. This measurement is easier to interpret and available 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

[1] The alternative to preference as the explanan of FDI flow is institutional characteristics.

[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 of 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).

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 ignoring the varying effect of FDI across sectoral constituencies. Second, given the coding rules, an industry is coded as free if there is no mention of restriction. If the industry in a FDI receives little FDI, it may not be worth mentioning, and yet still coded as open. Thus, where there is little FDI it may look like the country is extremely friendly. This concern is not hypothetical. Figure 1 shows that, following the coding of the US Investment Climate Reports, China seemed to be 100% open to FDI up until 1986, when it started imposing restrictions. The reality is opposite. When China first opened up for FDI in 1979, only limited FDI is 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.

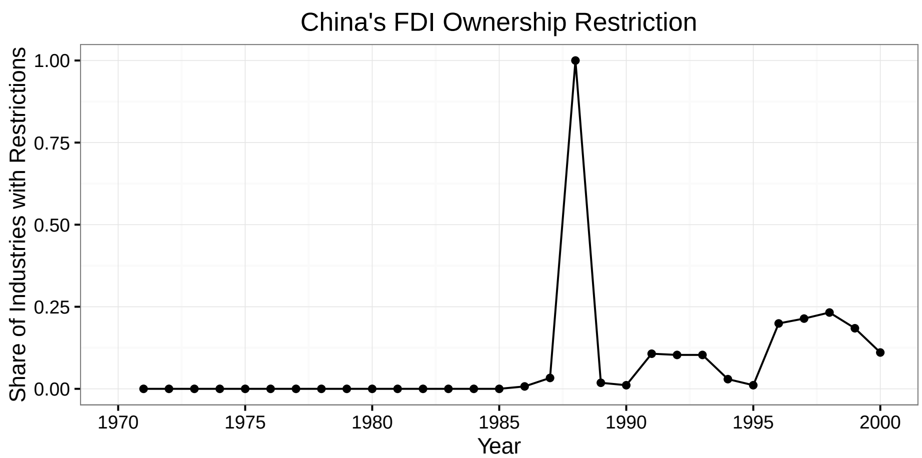

Figure 1: China's FDI Ownership Restriction, as coded in Pandya (2010). The sharp spike in 1988 also does not seem to correspond to any actual change in policy, and thus likely an artifact of reporting. See Zebregs and Tseng (2002) for a historical overview of China's FDI policy.

2.2 The measurement of FDI

From Kerner, "I suggest that most of what we claim requires FDI data does not. Instead, we are asking questions about employment, payrolls, capital inputs, and output from FDI. We should measure these instead."

First is the aggregate nature of FDI data used by political science research.

FDI flow exclude locally raised finance data. This is appropriate for the purpose of measuring balance of payment, but not so much when we care about the actual size of the foreign firms in the country (808). The IMF has admitted to this problem, even suggesting in 2005 that FDI inflows data has become hardly applicable to sound economic analyses due to this (Ouddeken 2005)

FDI stock at market value fluctuates based on market price as well, something unrelated to the FDI firm behavior. FDI stock at historical value is simply the accumulation of FDI flow (as other countries calculate it).

Most of FDI literature has used FDI flow (Jensen 2003; Ahlquist 2006; Beazer and Blake 2011; Graham 2010). Some debate on measuring FDI, but it's on outliers and FDI or FDI/GDP (Li 2009)

Second, it allows us to get at the preferences of country. Previously, most of the research is on the preference of firms. Only two works by Pondya and Pablo Pinto looks at the other side.

The theoretical interest is there as scholars start to fill in the other side of the equation. However, the empirics left wanting.

All of these models also cannot investigate countries' preference for specific firms' characteristics. Pondya's look at cross industry, but because of data issue she can only do cross-sectional at the industry level instead of country-industry level. This level of aggregation is dubious: the same industry in one country is different from another country. For example, automobile value chain is vastly different across countries (example here)

All of the industry estimates are based on US firms, which really cannot be realized to others. (It can for some basic industry characteristics / technology level, not for whether an industry is market oriented or not.)

My data use capital size, which is great because that's exactly what countries look for.

(Yamawaki 1991, 295) says that the data "list virtually all the foreign subsidiaries of Japanese companies"

3 The Utility Model

3.1 Officials' Utility

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

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

where

$$\begin{aligned} \beta_j &\text{ is a vector of official } j\text{'s preference for relevant characteristics of firms} \\ x_i &\text{ is a vector of firm } i\text{'s measured values on those characteristics} \\ \epsilon_{1ij} &\text{ is the unobserved component that influences official } j\text{'s utility} \end{aligned}$$

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

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

where

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

b_j is the baseline utility of official j without any firm investing

ϵ_{0ij} is the component that influences official j's utility

For each firm i, official j will make an offer to invest if $U_j(i) > U_j(\neg i)$. Some relevant firm characteristics (i.e. X_i) that the official may consider are: technological intensity, jobs, and 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.

The opportunity set of firm i is the set of all countries that have made firm i an offer. 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. This is the gist of the statistical challenge. TO overcome this issue, we will use Markov chain Monte Carlo to sample from and approximate $p(O_i|\boldsymbol{\beta})$.

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 make an offer and chooses the one that brings the highest utility. In our model, the relevant country characteristics are: 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 is

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

4 Model Estimation

While Logan (1996, 1998) successfully reformulated standard discrete choice models 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 deal with this problem, Logan (1996) used the Expectation-Maximization (EM) algorithm.[5] However, an important downside of the EM algorithm is its lack of 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.

To overcome this difficulty, I use a Bayesian approach that provides the posterior distribution of the parameters. Firms' opportunity sets, firms' preferences, and countries' preferences are all considered random variables. I estimate their posterior distributions using the Metropolis-Hastings algorithm, which samples from the desired distribution by proposing new values and decide whether to those values.

For example, suppose we want to sample from the posterior distribution $p(\theta)$ and we already had a working collection of values $\{\theta^1, \ldots, \theta^{(s)}\}$. To add new values to this collection, we would propose a new value θ^*, then decide whether to keep it with the probability $\frac{p(\theta^*)}{p(\theta)}$.

[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 maximize the likelihood.

The intuition is that if $\frac{p(\theta^*)}{p(\theta)}$ is large, then θ^* is very likely compared to θ given $p(\theta)$. Thus, we should keep θ^* and add it to the collection. In other words, we decide to keep newly proposed values of θ at a rate proportional to how often they should appear according to $p(\theta)$. Repeating this step many times, at the end we will have a collection of θ values that approximates $p(\theta)$ as desired.

Appendix B describes the details of our Bayesian model and derives the Metropolis-Hastings acceptance ratio. The key points are that we use flat priors so that our results are driven entirely by the data. The joint distribution of the data and parameters, including the opportunity sets, the firms' and countries' preferences, factor out nicely:

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

5 Results

Host GDP is negative, host GDP per capita is positive, host democracy is positive, agree with (Eicher et al. 2012)

A EM algorithm

Our data contains a random sample of firms and the countries in which they invest. We want to find the parameters that maximize the likelihood of this observed data. This likelihood is:

$$L = \prod_{i,j\text{:i is matched with j}} Pr(A_{ij})$$

where $Pr(A_{ij})$ is the probability of a specific match between firm i and country j. $Pr(A_{ij})$ can be calculated as follows:

$$
\begin{aligned}
& Pr(A_{ij}) && (10)\\
& = \sum_{k=1}^{R} Pr(A_{ij}|S_{ik})Pr(S_{ik}) && (11)\\
& = \sum_{k=1}^{R} Pr(A_{ij}|S_{ik}) \prod_{m\in O_k} Pr(o_{im}=1) \prod_{n\in \bar{O}_k} Pr(o_{in}=0) && (12)\\
& = \sum_{k:j\in O_k} \frac{\exp(\alpha w_{ij})}{\sum_{h\in O_k}\exp(\alpha w_{ih})} \prod_{m\in O_k, m>0} \frac{\exp(\beta x_i)}{1+\exp(\beta x_i)} && (13)\\
& \times \prod_{n\in \bar{O}_k, n>0} \frac{1}{1+\exp(\beta x_i)} && (14)
\end{aligned}
$$

Here, the term $Pr(o_{ij}=1)$ represents the probability that country j makes an offer to firm i, through which the official's preference enters our estimation. On the other side, $Pr(A_{ij})|S_{ik}$ is the probability that firm i will accept the offer from official j, given the offering set O_k. The firm's preference is reflected in our estimation through this term, $Pr(A_{ij})|S_{ik}$.[6]

It is important to note that the offering set O_k contains *all* offers that firm i receives, only one of which is the observed match between firm i and country j. The intuition is that if we observe the full set of offers that all officials make to all firms, then by looking at the final match we can see how firms and officials reject inferior offers and thus deduce their preferences.

B Deriving the Metropolis Hasting acceptance ratio

B.1 Updating the opportunity set

Target distribution for a firm i

$$p(O_i|A_i,\alpha,\boldsymbol{\beta}) = \frac{p(O_i,A_i,\alpha,\boldsymbol{\beta})}{p(A_i,\alpha,\boldsymbol{\beta})} \tag{15}$$

[6]The appendix shows how these terms are derived.

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:

$$
\begin{aligned}
MH_O = \frac{p(O_i^*|A_i,\alpha,\boldsymbol{\beta})}{p(O_i|A_i,\alpha,\boldsymbol{\beta})} &= \frac{p(O_i^*,A_i,\alpha,\boldsymbol{\beta})}{p(A_i,\alpha,\boldsymbol{\beta})} \times \frac{p(A_i,\alpha,\boldsymbol{\beta})}{p(O_i,A_i,\alpha,\boldsymbol{\beta})} && (16)\\
&= \frac{p(O_i^*,A_i,\alpha,\boldsymbol{\beta})}{p(O_i,A_i,\alpha,\boldsymbol{\beta})} && (17)\\
&= \frac{p(A_i|O_i^*,\alpha)p(O_i^*|\boldsymbol{\beta})}{p(A_i|O_i,\alpha)p(O_i|\boldsymbol{\beta})} && (18)\\
& && (19)
\end{aligned}
$$

where the factorization of the likelihood in Equation (18) 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)

$$
\frac{p(O_i^*|A_i,\alpha,\boldsymbol{\beta})}{p(O_i|A_i,\alpha,\boldsymbol{\beta})} = \frac{\sum\limits_{j:j\in O_i} \exp(\alpha' W_j)}{\sum\limits_{j:j\in O_i} \exp(\alpha' W_j) + \exp(\alpha' W_{j^*})} \times \exp(\boldsymbol{\beta}'_{j^*} X_i) \quad (20)
$$

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

$$
\frac{p(O_i^*|A_i,\alpha,\boldsymbol{\beta})}{p(O_i|A_i,\alpha,\boldsymbol{\beta})} = \frac{\sum\limits_{j:j\in O_i} \exp(\alpha' W_j)}{\sum\limits_{j:j\in O_i} \exp(\alpha' W_j) - \exp(\alpha' W_{j^*})} \times - \exp(\boldsymbol{\beta}'_{j^*} X_i) \quad (21)
$$

B.2 Updating firms' parameters, α

Target distribution:

$$
p(\alpha|A,O,\boldsymbol{\beta}) = \frac{p(O,A,\alpha,\boldsymbol{\beta})}{p(A,O,\boldsymbol{\beta})} \quad (22)
$$

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:

$$MH_\alpha = \frac{p(\alpha^*|A,O,\boldsymbol{\beta})}{p(\alpha|A,O,\boldsymbol{\beta})} = \frac{p(A_i|O_i,\alpha^*)p(O_i|\boldsymbol{\beta})}{p(A_i|O_i,\alpha)p(O_i|\boldsymbol{\beta})} \tag{23}$$

$$= \frac{p(A_i|O_i,\alpha^*)}{p(A_i|O_i,\alpha)} \tag{24}$$

where Equation (24) 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),

$$MH_\alpha = \prod_i \left[\frac{\exp(\alpha^{*\prime} W_{a_i})}{\exp(\alpha' W_{a_i})} \times \frac{\sum\limits_{j:j\in O_i} \exp(\alpha' W_j)}{\sum\limits_{j:j\in O_i} \exp(\alpha^{*\prime} W_j)} \right] \tag{25}$$

$$= \prod_i \left[\exp(\epsilon'_\alpha W_{a_i}) \times \frac{\sum\limits_{j:j\in O_i} \exp(\alpha' W_j)}{\sum\limits_{j:j\in O_i} \exp(\alpha^{*\prime} W_j)} \right] \tag{26}$$

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

$$\log MH_\alpha = \sum_i \left[\epsilon'_\alpha W_{a_i} + \log\left(\sum_{j:j\in O_i} \exp(\alpha' W_j) \right) - \log\left(\sum_{j:j\in O_i} \exp(\alpha^{*\prime} W_j) \right) \right] \tag{27}$$

B.3 Updating countries' parameters, β

Target distribution:

$$p(\boldsymbol{\beta}|A,O,\alpha) = \frac{p(O,A,\alpha,\boldsymbol{\beta})}{p(A,O,\alpha)} \tag{28}$$

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:

$$MH_\beta = \frac{p(\beta^*|A,O,\alpha)}{p(\beta|A,O,\alpha)} = \frac{p(A_i|O_i,\alpha)p(O_i|\boldsymbol{\beta}^*)}{p(A_i|O_i,\alpha)p(O_i|\boldsymbol{\beta})} \tag{29}$$

$$= \frac{p(O_i|\boldsymbol{\beta}^*)}{p(O_i|\boldsymbol{\beta})} \tag{30}$$

where Equation (29) is due to the flat prior on β and the symmetric proposal distribution.

We plug in Equation (7),

$$MH_{\beta} = \prod_{i} \left[\prod_{j \in O_j} \frac{\exp(\beta_j^{*\prime} X_i)}{\exp(\beta_j^{\prime} X_i)} \times \prod_{j} \frac{1 + \exp(\beta_j^{*\prime} X_i)}{1 + \exp(\beta_j^{\prime} X_i)} \right] \tag{31}$$

$$\log MH_{\beta} = \sum_{i} \left[\sum_{j \in O_i} \beta_j^{*\prime} X_i - \beta_j^{\prime} X_i + \sum_{j} \log(1 + \exp(\beta_j^{*\prime} X_i)) - \log(1 + \exp(\beta_j^{\prime} X_i)) \right] \tag{32}$$

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

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