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

My paper addresses two issues.

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).

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.

Pondya used US Investment climate report to code how many industries have foreign ownership restriction. First, the raw number of industries being restricted are not equal. Industries are not the same, depending on the nature of the industry and how it fits into the country's development strategy. For example, opening up the country's financial industry is much more of a big deal than allowing furniture companies to join. Second, the omission of foreign industry is construed as a 100% free. This can lead to serious bias as a country's FDI into an industry is so non-existent that it is not worth discussing. So what is a lackluster industry is coded in the data as 100% open.

For example, China 1979 permit FDI only as joint venture in SEZ, 1986 allow wholly owned FDI outside of SEZ, 1990 protection from nationalization, CEO no longer has to be appointed by a Chinese board.

https://www.imf.org/external/pubs/ft/pdp/2002/pdp03.pdf

http://law.wisc.edu/gls/documents/foreign$_{i}nvestment1.pdf - Initially, until the early 1970s, when the le$

- Korea o begin with, there were policies that restricted the areas where TNCs could enter. Until as late as the early 1980s, around 50 per cent of all industries and around 20 per cent of the manufacturing industries were still off-limits to FDI [EPB, 1981: 70 1]. Even when entry was allowed, the government tried to encourage joint ventures, preferably under local majority ownership, in an attempt to facilitate the transfer of core technologies and managerial skills

There is also export requirement, local content requirement. It's very hard to check all of these (cite the paper about non-trade barrier (?) (?)

The second attempt by Pablo Pinto is to measure FDI regime openness. He tries to go for statistical technique instead of measuring something substantive. In the first stage, he estimates country fixed effect in a regression model that uses FDI flow as the dependent variable and a bunch of dyadic variables. In the second stage: he takes the intercept from the first stage, i.e. the fixed effect, and regress it on that year covariates. The residual is considered "FDI regime openness" for that country year. The problems with FDI flows as usual, it is questionable whether it is okay to consider the residual term "FDI regime openness". There are many other factors that can affect FDI flow, anything that is not included go into this residual term. To make this claim, beyond the already strong assumption of no endogeneity, it is actually claiming that the model capture absolutely everything that is not FDI regime openness. This is a very strong claim.

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.[1] For official j, the utility of having firm i investing in his country is:

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

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

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

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

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

where

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:

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

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.[2] 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

[2] 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.

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 $\frac{p(\theta^*)}{p(\theta)}$. 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, $Pr(A_{ij})|S_{ik}$.[3]

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

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

[3]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)

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

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

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

B.2 Updating firms' parameters, α

Target distribution:

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

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),

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

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

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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