Two-Sided Matching Model

by

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Dissertation submitted in partial fulfillment of the requirements for the degree of
Doctor of Philosophy in the Department of Department of Political Science
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Abstract

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Abbreviations

EM	Expectation Maximization.
FDI	Foreign Direct Investment.
IPA	Investment Promotion Agency.
IPE	International Political Economy.
LDA	Latent Dirichlet Allocation.
MCMC	Markov Chain Monte Carlo.
MH	Metropolis-Hastings.
MLE	Maximum Likelihood Estimation.
MNC	Multinational Corporation.
MVN	Multivariate Normal.

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Introduction

In recent decades, the global flow of Foreign Direct Investment (FDI) has risen from almost nothing in the 1970s to over $2.3 trillion dollars in 2016, becoming an important source of global capital (Figure 1.1). For developing countries especially, capital from multinational corporations (MNCs) is robust to global economic downturns, prompting major international organizations to endorse FDI as a key factor to economic development and poverty reduction (Mallampally and Sauvant, 1999; World Economic Forum, 2013). Within International Political Economy (IPE), much of the literature also starts with the view that these countries will always seek FDI for its various benefits (Jensen, 2008a). These works focus on *how* countries can attract FDI, and do not question *whether* they want to do so (Jensen, 2003; Li and Resnick, 2003; Li, 2006; Ahlquist, 2006).[1]

At first glance, the benefits of FDI seem obvious. Not only does FDI bring capital to and create jobs in the host economy, it also holds the promise of technological spillover from foreign to domestic firms. As Findlay (1978) theorizes, technological

[1] Two recent exceptions are Pinto (2013); Pandya (2016), who are the first to examine variation in countries' demand for FDI.

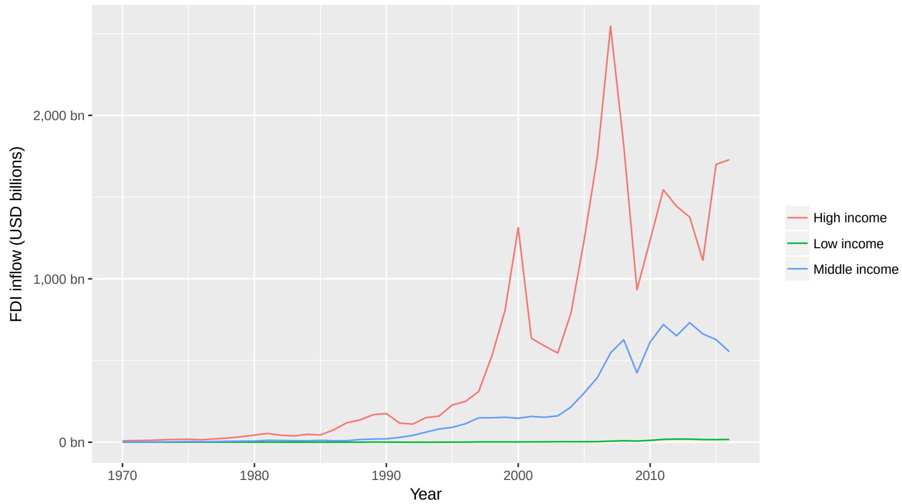

FIGURE 1.1: FDI global inflow, 1970-2006. The last four decades witness the growth of FDI into the most important source of global capital. Source: World Bank's World Development Indicators.

spillover from FDI shifts the domestic factor-price frontier to the right, resulting in a continually increasing capital stock and sustained economic growth. With FDI playing such a key role to development, it seems reasonable to assume that countries always want FDI.

And yet, despite the theoretical argument, recent empirical evidence shows that not all FDI are the same and that its effects are highly conditional. For example, there is no conclusive evidence of FDI having a positive effect on growth (Nair-Reichert and Weinhold, 2001; Carkovic and Levine, 2002) or poverty reduction (Guerra et al., 2009). This puzzle opens a substantial literature on how the growth-enhancing and spillover effect of FDI is conditional on the absorptive capacity of the host economies, i.e. its level of human capital, technological sophistication, and financial market development (Durham, 2004; Nunnenkamp and Spatz, 2004; Fu, 2008; Willem, 2004). In addition, while the capital brought and jobs created by FDI may be unconditionally good for the overall economy, its distributional effects cut across constituencies in the host economy, creating political cleavage across both sectoral and geographical divides (Chintrakarn et al., 2012; Goldberg and Pavcnik, 2007; Nunnenkamp et al., 2007).

Given the evidence on the conditional effect of FDI, it is no longer tenable to assume that countries' preference for FDI is homogeneous. By holding this assumption, we neglect the role of the state in shaping global capital flow, falling prey to the discredited "race to the bottom" thesis of globalization (Mosley, 2005). Arguably, examining countries' preference for FDI should be of more interest to political scientists than the current focus on determinants of MNCs' location, which often amounts to adding a political variable to an existing economic model of FDI flow. In addition, even if we only care about MNCs' preference, to get an accurate estimate we must still take into account countries' preference. For example, consider the received wisdom that democracies receive more FDI (Jensen, 2008b). Without controlling for countries' preferences, it is difficult to interpret this finding as democracies actively pursuing MNCs or as MNCs finding democracies attractive.

1.1 Goal of the dissertation

This dissertation aims to estimate the preference of countries and MNCs for each other. I develop an empirical strategy that takes into account the two-sided nature of the FDI market, i.e. a subsidiary can only materialize if both the MNC and the host government agree. Recognizing that this two-sided matching dynamics can also be found in the labor or the marriage markets, I adapt the statistical models first developed in Sociology for labor and marriage markets and apply them to the study of FDI (Logan, 1996; Logan et al., 2008).

In doing so, I simultaneously address three long-standing issues in the FDI literature.

First, I bring the state back in, filling the gap in the literature on the variation of countries' preference for FDI. Two notable exceptions are Pinto (2013) and Pandya

(2016), whose pioneering works propose partisan politics and regime types as factors shaping preferences for FDI. However, while their theories are ground-breaking, the empirical estimation of countries' preference remains inadequate. In addition, these researchers have not used their findings to re-estimate the preference of MNCs and disentangle the "push" and "pull" factors of FDI flow.[2] Using a two-sided matching model, I will naturally be able to estimate both sides' preference.

Second, I propose that we need to pay more attention to countries' preference for different types of FDI. While the IPE literature has largely focused on the quantity of FDI flow, countries pay much attention to the its type, using various incentives and restrictions to target certain types of FDI. Indeed, MNCs come with varying amount of capital, labor demand, and technological sophistication, all of which have different effects on the host country's economy. Just as the two-sided matching model can estimate MNCs' utility function for countries' characteristics (e.g. market size, level of development), it can also estimate countries' utility function for MNCs' characteristics (e.g. technological sophistication, export strategy).

Third, while the majority of the literature uses FDI flow data, these statistics are accounting constructs created to keep track of countries' balance of payment and thus map poorly to concepts in Political Science theories. Very often, the variable of interest in our theories is the scale of MNCs' activities in the host country, which can be very different from the amount of border-crossing capital thanks to MNCs' complex financial and tax strategies (Kerner, 2014). Therefore, we would do much better testing our theories with firm-level operational data. Because the two-sided matching model is a behavioral model in which each actor's decision is a unit of observation, and we can naturally use it to analyze firm-level data.

These three issues are related and represent the status quo in the FDI literature.

[2] "Push factors" refer to characteristics of the home country and of the MNC, pushing capital out from its origin. "Pull factors" refer to the characteristics of the host country, pulling capital towards its destination.

Data limitation forces scholars to look at country-level aggregate FDI flow, making it difficult to study countries' preference for FDI types. And without studying countries' preference, our current models of MNCs' location choice are also suspect.

In sum, my dissertation benefits the field by using firm-level data to estimate both firms' and countries' preference for each other's characteristics. In this two-sided matching model, MNCs and countries evaluate their available options according to their utility functions, choose the best alternative, culminating in an MNC's subsidiary located in a host country.

Estimating this model would be straightforward if we observed not only subsidiaries' locations but also their set of options (called their "opportunity set" in the matching literature).[3] Unfortunately, while data on subsidiaries' location are available, the opportunity set is generally unobserved as researchers cannot peek into the negotiation process between countries and MNCs. The two-sided matching model solves this problem by using the Metropolis-Hastings (MH) 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. In addition, the estimated preference parameters in the two-sided model have a convenient interpretation as the relative weight of different variables on MNCs' and countries' utility. This allows us to make statements such as: "In evaluating MNCs, China values a 2% increase in the firm's capital as much as a 1% increase in labor demand."

[3] Discrete choice models can be used to estimate the utility function when both the choice and the set of options are observed. Indeed, discrete choice models remain the dominant empirical approach in the industrial location literature, effectively ignoring the fact that not all MNCs have the same set of location options (Arauzo-Carod et al., 2010).

1.2 Roadmap

In the rest of this introductory chapter, I review in-depth the three issues in the literature of FDI's political determinants, outlining the current attempts to address them and how my approach can contribute to the solution.

In Chapter 2, I describe the two-sided matching model, including both its game-theoretic origin and its statistical estimation. Chapter 3 uses simulations to demonstrate the correctness of the model and explore its characteristics. Chapter 4 applies the model on US labor market data, the original domain of the two-sided matching approach, in order to compare with and expand upon previous results. Chapter 5 brings us back to the study of FDI, applying the model on firm-level data of Japanese MNCs in East and Southeast Asia. Chapter 6 concludes and explores potential applications of the two-sided matching model in other areas of Political Science.

1.3 Three issues in the FDI literature

1.3.1 Estimating countries' demand for FDI

Despite earlier pessimism about countries engaging in a race to the bottom to attract footloose global capital, empirical evidence shows that countries' policies still vary substantially (Drezner, 2001). While the broader IPE literature has recognized the variation in countries' trade, welfare, environmental, and fiscal policies in the face of globalization, we have surprisingly done less work to explain variation in countries' FDI policies. Recognizing this gap in the literature, Pinto (2013) and Pandya (2016) recently broke ground in this area. Similar to the rich IPE literature in international trade, 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. The author controls for economic and institutional factors that affect FDI flow into a country, then claims that what's left in the residual is the country's demand for FDI.[4] For this approach to be valid, every economic, institutional, and endowment factors that affect FDI flow has to be controlled for, leaving only the country's demand in the error term. This claim is much stronger than the common assumption of exogenous 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.[5]

In contrast to Pinto (2013)'s statistical approach, Pandya (2014, 2016) attempts to find a proxy for countries' demand for FDI. The author uses the annual US In-

[4] 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.

[5] In addition, this approach requires data on bilateral FDI flow, ideally disaggregated by sectors. Therefore, this approach is limited to OECD countries only (Pinto and Pinto, 2008). During the period the authors study, 1980-2000, OECD countries account 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, reducing to 60.8% of outflow and 40.6% of inflow in 2014 (UNCTAD, 2015).

vestment Climate Reports to construct the number of industries that have foreign ownership restrictions or face investment screening. 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 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, we must not ignore the varying impact of FDI across sectoral constituencies.

Second, according to the coding rule, an industry is coded as free if there is no mention of restriction. However, when there is little FDI, US Investment Climate Report may find it not worth mentioning and does not report the restrictions. 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 1.2 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.

The two-sided matching model circumvents these thorny measurement issues by modeling countries' demand for FDI directly. Intuitively, if we observe that a country welcomes certain firms to invest but not others, we can compare the characteristics of the invited and the uninvited firms to infer that country's preference for FDI.

1.3.2 Estimating countries' preference for types of FDI

In addition to estimating countries' demand for FDI, we should also examine countries' preference for different types of FDI. Indeed, while the Political Science lit-

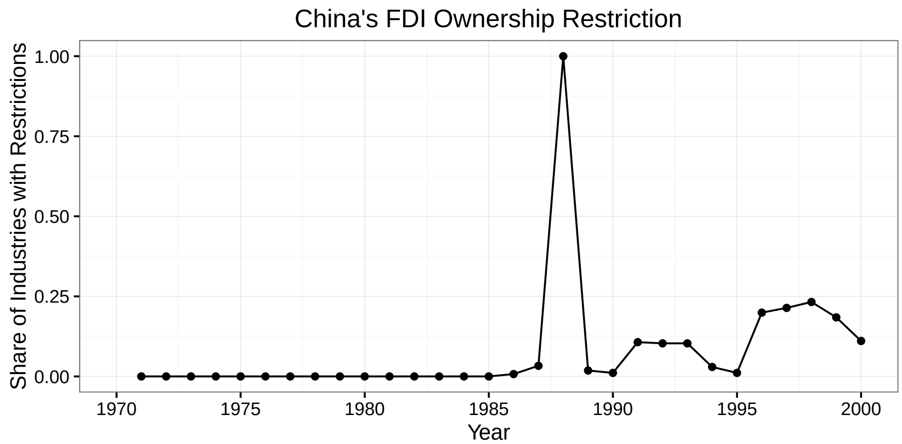

FIGURE 1.2: China's FDI ownership restriction, as coded in Pandya (2010). Prior to 1986, FDI in China was limited to few experimental Special Economic Zones, and thus not mentioned in US Investment Reports. The sharp spike in 1988 also does not seem to correspond to any actual change in policy, and likely another artifact of reporting. (See Zebregs and Tseng (2002) for a historical overview of China's FDI policy.)

erature 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 its types. Commenting on the role of International Investment Agreements, 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 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). For example, since 2006, China's official FDI policy has been "quality over quantity," promoting FDI with intense R&D in high-productivity sectors (Guangzhou, 2011).

Despite the importance of disaggregating FDI by its type, two data limitations prevent researchers from doing so. First, FDI flow data typically does not disaggregate into types of FDI. Alfaro and Charlton (2007) attempt to get around this problem by using Germany's sectoral skill intensity as the proxy for the FDI quality from each sector in the OECD. To do so is to assume that 1) Germany's sectoral variation is the same as everyone else's in the OECD, and 2) there is little variation in skill intensity within a sector. Both assumptions are untenable, especially since the authors divide all manufacturing industries into only two categories: low skill and high skill.

Second, even if we can differentiate types of FDI, it remains an open question how to estimate countries' preference for them. Alfaro and Charlton (2007) use information from IPAs' website and survey response as a proxy for their countries' preference—if an IPA lists an industry as a "target industry," the authors say that the country wants to attract that type of FDI. While this approach seems reasonable at first glance, Figure 1.3 shows that there is little variation in what IPAs claim to be their target industries. Because investment promotion is mainly a marketing and aspirational exercise, almost everyone claims that they target manufacturing, advanced manufacturing, and infrastructure. In addition, if we use IPAs as a proxy for countries' preferences, we should also model the selection process in which the countries that decide to establish an IPA may not be the same as those who do not. Both of these issues are not addressed by Alfaro and Charlton (2007), and we are still in need of a way to estimate countries' preference for different types of FDI.

In sum, differentiating FDI by sectors only gives us a crude typology of FDI. We can address this challenge using firm-level data, giving us information on not only a firm's sector but also its operational characteristics, such as research and development (R&D) expenditure or export intensity. These measures are firm-specific and get closer to what countries are looking for in FDI projects. Using R&D expenditure or export intensity as firms' characteristics in the two-sided matching model, I will be able to estimate countries' preferences for these traits.

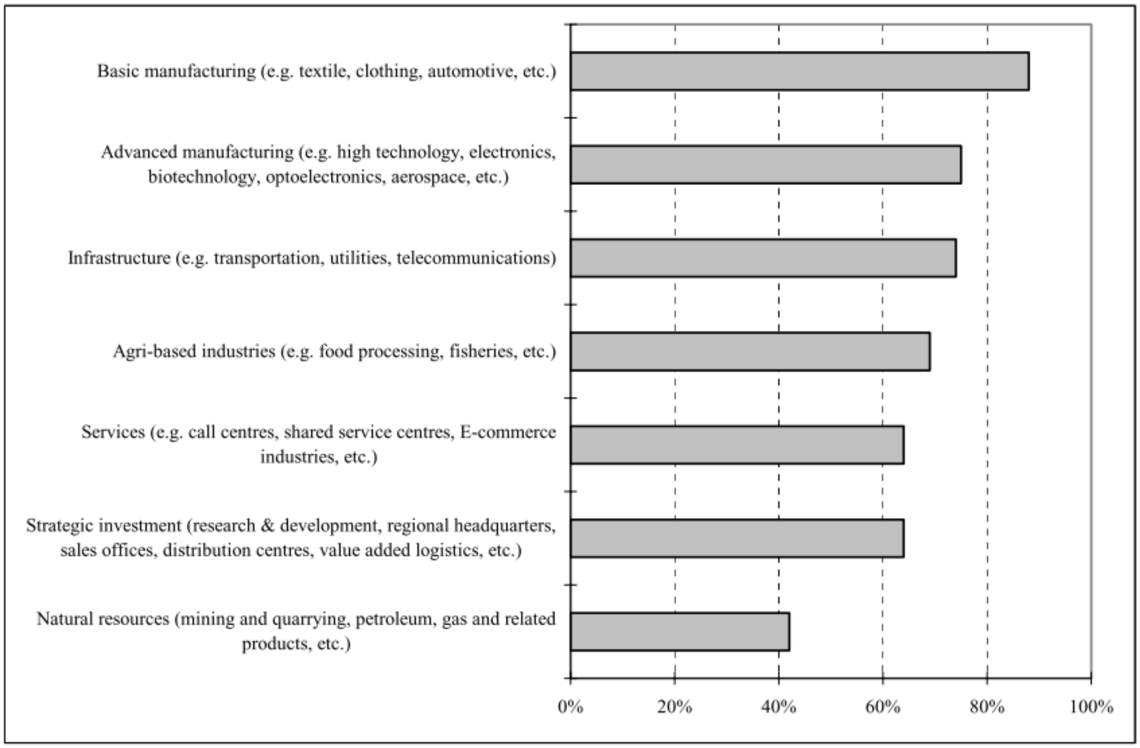

FIGURE 1.3: Target industries by IPAs around the world. Because of the image building aspect of investment promotion, almost all IPAs say that they want to attract "manufacturing," "advanced manufacturing," and "infrastructure." Therefore, using what is listed as investment priorities may not be a reliable way to measure countries' preference for FDI. Source: UNCTAD (2001)

1.3.3 Measuring MNCs' activities

As Kerner (2014) argues, the IPE literature on FDI is a bit of a misnomer. Political scientists are rarely interested in FDI *per se*—rather, they are interested in the activities of MNCs, which in turn, affect other important issues such as nation-state autonomy (Mosley, 2005), economic development (Moran, 1998), labor standards (Mosley and Uno, 2007), and environmental policies (Prakash, 2007). However, while the theory involves MNCs as the central actor in the causal mechanism, the empirics often uses FDI flow as the variable of interest. These two concepts—the level of MNCs' affiliate activities in a country and FDI inflow into a country—are not the same.

Consider the definition of FDI from UNCTAD, the main producer of FDI data widely used by researchers:

> FDI has three components: equity capital, reinvested earnings and intra-company loans.
>
> - Equity capital, i.e. the foreign investors purchase of shares of an enterprise [in the host country].
> - Reinvested earnings, i.e. the foreign investors share ... of earnings not distributed as dividends by affiliates, or earnings not remitted to the foreign investor.
> - Intra-company loans between direct investors and affiliate enterprises.
>
> (UNCTAD, 2007, 245)

In essence, FDI data captures the amount of capital that crosses border. It is a poor proxy for the scale of MNCs' activities in the host country because it overlooks important components of MNCs' activities while including components that are only relevant for balance of payment statistics (Beugelsdijk et al., 2010).

Consider the argument that FDI is the driver for the diffusion of labor standards across countries. Mosley and Uno (2007) theorizes that FDI can have this effect through three channels. First, MNCs may pressure the host government for better rule of law and social programs. For MNCs to be able to effectively exert this pressure, they must prove themselves valuable to the government by providing jobs or tax revenue. Both of these factors are tenuously related to the amount of foreign capital inside the host country. Indeed, an MNC can employ thousands of employees, pay millions in tax, but show up as a net 0 on FDI flow data because the profit is repatriated to the foreign investor or through intra-company loans.[6] The scale of MNCs' operation is further understated because FDI statistics does not take into account capital raised locally. Also not included is the superior productivity of MNCs, which acts as an important multiplier when translating the amount of capital to the amount of output.

Second, scholars argue that MNCs may bring along best practices for workers' rights and spread it to local firms. If this spillover effect happens via competition, i.e. MNCs providing better working condition and forcing local firms to compete, then MNCs must employ a lot of labor for this effect to be noticeable. Or if the spillover happens via demonstration, then MNCs must form a lot of linkages with local firms, as suppliers and buyers, for the diffusion of norms to happen. Both the size of the labor force and the type of linkages with the local economy are not captured by FDI flow statistics.

Third, scholars argue that MNCs may care more about labor quality than its cost, and thus may invest in higher wages, better benefits, or more training. Once again, for this effect to be noticeable, the MNC's industry, size of labor force, and investment in productivity all matter a lot more than how much capital it brings in and out of the country. In addition, non-equity transactions between the parent company and the subsidiary, such as transfer of knowledge, technology, and management practices, are not counted in FDI flow statistics, thus excluding another component that is arguably much more important to labor quality than the amount of capital.[7]

This mismatch between theory and empirics may also be a reason behind the

[6] The issue of intra-company loans is particularly fraught with issues because companies very frequently use intra-company loans to get out of paying tax in a country. These loans will be recorded on the book as a massive outflow, even though the MNC still has a large presence on the ground.

[7] These issues are not isolated to studies of FDI and labor standards, but are common to the whole IPE literature of the effect of FDI on policy convergence, such as environmental policies (Prakash, 2007).

unsettled debate on the effect of FDI on poverty reduction. Scholars have theorized that FDI can lead to economic development through three channels: cheaper goods, technology transfer, and tax revenue. Once again, the causal variable in the second and third channels is the scale and the type of MNCs' activities in the host country, not necessarily the amount of capital crossing the border. Indeed, productivity spillover is highly conditional on the technological capability of the MNC and whether it forms thick linkages with the local suppliers. The effect of FDI via tax revenue is also fraught with issues, as MNCs frequently use intra-company transactions to artificially reduce book profit and get out of paying tax (Malesky, 2015).[8] Since FDI flow statistics do not record these intra-company transactions, it is not surprising that researchers reach the confusing conclusion that FDI does not generate tax revenue.

What about studies that use FDI as the dependent variable, and are thus perhaps interested in the flow of capital in and of itself?[9] The vast majority of these studies on the determinants of FDI flow rely on the "obsolescing bargain" model. Originally developed by Vernon (1971), the model is so named because the bargaining dynamics between the MNC and the host government changes over time, initially favoring the MNC and gradually tips towards the host government as the MNC commits more fixed capital on the ground. Indeed, knowing that it is costly for the MNC to uproot its increasingly large and immobile operation, the host government can unilaterally alter the original bargain, most egregiously by expropriating the MNC's asset and profit, but more often via "creeping expropriation," e.g. increased tax or tougher regulation (Li, 2009). Political economists argue that MNCs are acutely aware of the "obsolescing bargain," and thus prefer to invest in countries whose governments

[8] These tactics are called "transfer pricing," and can include tactics such as charging for internal intellectual properties and services whose price can be set arbitrarily by the firm

[9] Arguably, political scientists are not interested in the flow of capital in and of itself, but because of its implications for development, state autonomy, and other effects on policy. The discussion above has shown how problematic it is to study these effect of FDI using FDI flow data.

can make a credible commitment that they will not alter the original deal. This argument translates into a large literature claiming that MNCs prefer countries with democratic accountability (Jensen, 2003), a federal system (Jensen and McGillivray, 2005), membership in international trade agreements (Büthe and Milner, 2008), less political risk (Beazer and Blake, 2011; Graham, 2010), or more veto points (Choi and Samy, 2008).

The linchpin of this argument is the assumption that FDI capital is illiquid and cannot be quickly removed from the host country at will. This assumption is not fully warranted. According to the US Bureau of Economic Analysis (BEA)'s 2004 survey, 43% of US MNCs' balance sheet comprises of liquid assets that can be liquidated within one year under normal operating situations. Among the 57% of the balance sheet that are illiquid, 24% are "other non-current assets," which include non-tangible assets like brand names, trademarks, and patents—some of which are not expected to be liquidated but can be easily removed from host countries. Only another 24% of the balance sheet is made up of physical capital, i.e. Plant, Property, and Equipment (PPE), which cannot be easily moved and match most closely to what we have in mind as the "illiquid capital" in the obsolescing bargain model (Kerner and Lawrence, 2014, 113). Since FDI flow data does not distinguish between liquid and illiquid capital, it is suspect to use FDI flow data to test the "obsolescing bargain" argument, calling into questions the entire literature on the political determinants of FDI.

Besides the conceptual mismatch between FDI flow and MNCs' activities, from a statistical standpoint, this measurement error may also be a contributing factor to why there is little consensus in the FDI literature. Even if the measurement error is random, it will inflate the standard error of our estimate when FDI is the dependent variable, and bias our estimate towards 0 when FDI is the independent variable. These effects may explain Jensen (2012)'s surprising finding that lower corporate tax rate does not lead to more FDI flow, or the mixed empirical evidence for the relationship between FDI and development (Mold, 2004, 108).

Even more worryingly, the measurement error is unlikely to be random.[10] For example, the amount of locally raised capital—an important source of capital for MNCs yet not captured in FDI flow data—is likely to correlate with how developed the local capital market is or how wildly the exchange rate fluctuates. Similarly, repatriated earnings, which does not necessarily indicate reduced MNCs' activities but is recorded as an outflow in FDI flow data, is likely to correlate with the tax rate of not only the host country but also other tax havens that the MNC may have an affiliate in.

To deal with this measurement error problem, scholars have attempted to use measurements that are closer to the theory than FDI flow. Given that political scientists are often interested in MNCs' activities, recent work emphasizes using MNCs' operational data directly. These firm-level datasets allow researchers to measure directly the quantities of interest. For example, re-visiting Li (2009)'s hypothesis that democracies are more attractive to MNCs, Kerner (2014) uses data on US MNCs' fixed capital expenditure to more precisely test the relationship between democratic institutions and FDI *illiquid* capital, not just FDI in general. The author finds that there is no relationship between democratic institutions and FDI flow, but there is a positive relationship between democracy and MNCs' fixed capital expenditure, confirming the theoretical expectation. Similarly, when Jensen (2008b) re-examines whether MNCs favor democratic regimes because they pose less political risk, the author avoids using FDI flow and relies on price data of political risk insurance agencies instead.[11]

[10] See Gallop and Weschle (2017) for a recent and more comprehensive discussion of measurement error in political science research.

[11] Scholars in other areas of IPE are also paying more attention to the issue of measurement error and the mismatch between empirics and theory, e.g. (Karcher and Steinberg, 2013).

1.4 Next steps

In sum, the current FDI literature would benefit from focusing on countries' preference for FDI, distinguishing types of FDI, and using firm-level operational data instead of aggregate FDI flow statistics. While the theoretical needs are clear and firm-level data has become more abundant in recent years, political scientists have not developed a model to estimate this data structure appropriately.[12]

Very often, given the data structure of a set of firms interacting with a set of countries, scholars resort to a dyadic-based analysis perhaps due to its being a familiar tool. 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 patently inappropriate to analyze MNCs' investment location. Indeed, 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.[13]

I propose using the two sided matching model to simultaneously address all of these three issues in the literature. This approach models the matching process explicitly, thus taking into account the dependency across dyads. The matching process is made up of actors maximizing their utility functions—therefore, we gain

[12] 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.

[13] As a recent example, Arel-Bundock (2017) uses Orbis, a global dataset of firms, to study the location decision of MNCs. The author uses random forest, a non-parametric machine learning approach, to predict whether an investment materializes for each of MNC-country dyad. However, because the predictors in the random forest model are dyad-specific, this approach cannot model interactions between dyads. In addition, since random forest does not produce interpretable coefficients, this black-box approach does not allow us to understand the preference of actors, how these preference are correlated with other characteristics, and how they may evolve over time.

direct insight into what countries and MNCs value the most. Finally, the model uses firm-level operational data, circumventing the measurement error problem of aggregate FDI flow statistics. In the next chapter, I describe in details how the two-sided matching model is set up and estimated.

2

Two-sided matching model

As discussed in Chapter 1, our goal is to develop a two-sided matching model for the FDI market. To do so, I draw insights from studies of matching markets in other domains. Marriage is a prominent example of such a market—others include the matching between firms and workers, federal judges and law clerks, the *formateur* of a coalition government and other minority parties, or countries and multinational corporations (MNCs) that are looking for a location to invest. In all of these matching markets, actors from two disjoint sets evaluate the characteristics of the other side and voluntarily form a match only if both deem each other satisfactory.[1]

This chapter will proceed as follows. First, I discuss the game theory literature of two-sided matching models, where much of the terminology and insight originate. I will highlight key results that are relevant to our goal of estimating actors' preference in matching markets. Second, I describe the two-sided logit model, first developed by Logan (1996) to study the labor market, and how I use a Bayesian MCMC approach to estimate it.

[1] Throughout the dissertation, I use "two-sided matching market" and "matching market" interchangeably. On the other hand, note that a two-sided market is not necessarily a matching market (Rysman, 2009).

2.1 Game theory models of matching markets

Gale and Shapley (1962) are the first to study the matching market, using marriage as an example. In this market, there are two finite and disjoint sets of actors: men and women. Each man has preferences over the women, and vice versa. Each man's preference can be represented as an ordered list, ranking each woman based on how much he likes her.

The outcome of this market is a set of marriages, with none or some of people prefer to remain single. We call such a set of marriages a *matching* μ, which is a one-to-one function that matches a man with a woman. We refer to $\mu(x)$ as the *mate* of x. For convenience, we say that if an individual decides to remain single, they are matched with themselves.

We define a matching μ as *stable* if it cannot be improved by any individual or any pair of agents. A matching can be improved in two ways. First, an individual may prefer to remain single than to be matched with his or her mate $\mu(x)$ under the current matching μ. Second, a man and a woman may prefer to be with one another rather than whom they are currently matched with. Therefore, if a matching is stable, no one has a better option than their current situation.

The first key result from the game theory literature is that for any set of preference, there always exists a stable matching (Gale and Shapley, 1962). The proof is constructive, describing the "deferred acceptance" procedure that is guaranteed to produce a stable matching.[2] This result provides some justifications for the as-

[2] The "deferred acceptance" procedure works as follows. In the first stage, every man proposes to his preferred mate. Every woman rejects all of her suitors except the one that she most prefers. However, she does not yet accept her (so far) favorite suitor, but keeps him along. In the second stage, every man that was rejected in the previous round proposes to his second choice. Every woman then picks her favorite from the set of new proposers and the man she keeps along from the previous round. The procedure continues until there is no longer any woman that is unmatched, at which point women finally accept their current favorite choices. (This procedure is called *deferred acceptance* to capture the fact that women defer accepting her favorite choice until the last round in case better options become available.) The resulting match is stable because, throughout the

sumption that the observed matching in real matching market is stable, and that the agents' utility has already been maximized. Our empirical model of two-sided matching markets thus needs to describe a process that produces a stable matching.

While a central coordinator employing the *deferred acceptance* algorithm is guaranteed to come up with a stable matching, it is unclear whether decentralized markets, such as the labor market or the FDI market, would be able to reach this outcome by themselves.[3] The second key result from the game theory literature is that stable matching in decentralized matching market is indeed possible, even likely. For example, Roth and Vate (1990) show that, starting from an arbitrary matching, the market can converge to a stable matching with probability 1 if we allow random blocking pairs, i.e. two individuals that are not matched but prefer each other to their current match, to break off and form their own match. In addition, Adachi (2003) shows that a random search process, in which pairs of man and woman randomly meet and decide whether each other is better than their current mates, will converge towards a stable matching if the search cost is negligible.[4] These results further suggest that the matching we observe in decentralized markets is likely stable and that our empirical model ought to describe a process that produces a stable matching.

The third key result is that all conclusions regarding the one-to-one matching market (e.g. marriage) generalize to the many-to-one matching market (e.g. labor market). However, there is an additional assumption: firms treat workers as substi-

procedure, every woman has received all the offers that would have been made to her, and she has chosen her favorite among all of those offers. If there were any other man that she would prefer to her current match, that man would not have been available to her. Therefore, the final match cannot be further improved by any man or woman.

[3] The deferred acceptance procedure was used in the market for US medical residency with enthusiastic participation from medical students and hospitals. The high participation rate indicates that the matching produced is stable enough to entice students and hospitals away from arranging their own matches outside of the centralized market.

[4] In this model, searching has a time cost. Thus, negligible search cost is modeled as agents having a time discount close to 1.

tutes, not complements (Roth and Sotomayor, 1992). In other words, firms never regret hiring a worker even if another worker is no longer available. Therefore, when we conduct empirical analysis of many-to-one markets, we should focus on markets where agents have such "substitutable preference." (For the FDI market, this means that a country's offer to an MNC is not conditional on its offer to another.) Otherwise, a stable matching is not guaranteed, and it becomes unclear what kind of matching process our empirical model should approximate.

2.2 Empirical models of matching markets

The game theory literature takes agents' preference as given and proves the existence of a stable matching. In contrast, empirical models of matching markets takes the observed matching as given and attempt to estimate agents' preference.

Unfortunately, most extant empirical models fail to adequately account for the structure of a two-sided matching market. Often, researchers simply analyze the market from one side, e.g. estimating a firm's preference by looking at the type of workers it hires. This approach does not take into account the fact that a match depends not only on an agent's preference but also his opportunity. For example, a farm may want to hire highly-educated workers but cannot do so because highly-educated workers do not want to work on farms. Modeling this interaction between preference and opportunity is a key contribution of this dissertation.

Alternatively, some researchers measure agents' preferences by surveying them directly (Posner, 2001; Sprecher et al., 1994). While this approach circumvents the need to disentangle preference and opportunity, surveys can only measure agents' *stated* preference. In addition, such surveys require a high data collection effort while data on final matching (e.g. married couples, workers' current job, country location of MNCs) are widely available. This dissertation aims to make use of such matching data to estimate agents' *revealed* preference.

In addition to academic research in two-sided markets, companies have also developed a commercial interest in studying them as the Internet witnesses a proliferation of two-sided matching markets, e.g. online marketplaces (AirBnB), dating sites (eHarmony), or job board (Elance). To help their users discover a match quicker, these sites often build a recommender system that suggests potential matches.[5] To maximize user engagement and profitability, these sites are incentivized to make recommendations that resemble a stable matching so that their users get the best match possible. And to find the stable matching, they are also interested in estimating the preferences of their users.

While most of these algorithms are proprietary, some works in this area are published. An interesting approach is the paper by Tu et al. (2014), which uses the latent Dirichlet allocation (LDA) model to uncover the latent types of users based on their activities on an online dating platform.[6] In the original application of LDA model in topic modeling, each document is a mixture of latent topics, and each topic is a distribution over words. In this application of online dating, each user is a mixture of latent "types," and each type is a distribution signifying relative preference over various mates' features. For example, the "outdoor type" may have higher preference for athleticism or dog ownership over other traits.

While the LDA model works well for the online dating market, it is not applicable to most social science problems for two reasons. First, this model requires data of users reaching out to multiple partners rather than just the final match. Second, the LDA model only clusters users' into latent types without describing what these types may mean, leaving it up to the analyst to attach substantive labels to these types. In

[5] To clarify, the term "recommender system" typically refers to systems that recommend items to users based on the reviews of users like them. That is not what we are discussing here. Instead, we focus on matching markets where the recommender system recommends users to one another.

[6] Besides Tu et al. (2014), Hitsch et al. (2010); Goswami et al. (2014) are two other attempts to estimate users' preference in online matching markets. However, these papers take a simple one-sided approach, ignoring the interplay between preference and opportunity.

contrast, social scientists likely want to estimate the preference of pre-defined types such as men vs women or young vs old. Therefore, while the LDA model is suitable for exploratory and predictive purposes, it does not have the interpretability that social scientists desire.

2.3 Two-sided logit model

In this section, I present a statistical model of the two-sided matching market, focusing on the case of many-to-one matching, first proposed by Logan (1996). For easier exposition, throughout the chapter I will use the familiar example of the labor market, where many workers can be matched to one firm.

We assume that the matching process in the labor market happens in two stages. In the first stage, each firm evaluates each worker in the sample, deciding whether to hire that worker or not. At the end of this stage, each worker will have received a set of offers from firms, which we call his *opportunity set*. In the second stage, each worker evaluates the firms in his opportunity set and chooses the firm that he likes best. This constitutes the final, observed match between a worker and a firm. This is a many-to-one matching problem because a firm can make offers to multiple workers, none, some, or all of which can be accepted by workers.

In this model, firms and workers decide sequentially, with firms making offers first in order for workers to have opportunity sets to choose from. While firms and workers in real life certainly do not act in this sequential manner, the idea of the opportunity set is still applicable. Workers in the real labor market may not know their exact set of offers, but they can certainly guess which firms are within their reach based on their characteristics and on guesses about firms' preference.

Our model only needs data on 1) the covariates of firms and workers, and 2) the job that workers accept. Such data is widely available in many social science surveys of the job market. Importantly, we do not need to observe the opportunity set.

Therefore, our model obviates the need to follow the matching process and record who makes offer to whom, which is rarely possible for researchers.

If we assume that firms and workers are utility-maximizing agents, at the end of the matching process, no firm or worker would voluntarily change their final matches. As discussed in Section 2.1, this property is called *stability* in the game theoretic two-sided matching literature. We want our model to have this property because matching markets tend to produce stable matching.

This stability property does not imply that the matches will never change. Indeed, if actors' preference shifts, their characteristics change, or new actors enter the market, the matches will also change as a result of actors' recalculating their utility and adjusting their decisions. Therefore, since we are estimating actors' preference using only a snapshot of matching market, we are making the assumption that on a systemic level, the average characteristics of the actors and their preference remain sufficiently static for our estimates to be meaningful.

This section will proceed as follows. First, I discuss the utility model for how firms make offers to workers. Second, I discuss the utility model for how workers choose the best offer among those extended by firms. Third, I show how we can use a Bayesian MCMC approach to estimate the model.

2.3.1 Modeling firms' decision making

A firm j's decision on whether to hire worker i rests on two utility functions. First, firm j's utility for hiring worker i is:

$$U_j(i) = \boldsymbol{\beta}_j' X_i + \epsilon_{1ij} \tag{2.1}$$

where β_j is a vector of firm j's preference for worker characteristics, x_i is a vector of worker i's measured values on those characteristics, and ϵ_{1ij} is the unobserved component that influences firm j's utility.

On the other hand, the utility of not hiring worker i is:

$$U_j(\neg i) = b_j + \epsilon_{0ij} \tag{2.2}$$

where b_j is the baseline utility of firm j, and ϵ_{0ij} is the unobserved component that influences firm j's utility.

Firm j will make an offer to hire worker i if $U_j(i) > U_j(\neg i)$. Relevant worker characteristics (i.e. X_i) that a firm may consider are age, education, or experience. The corresponding β's represent the firm's preference for these characteristics.

This model makes two important assumptions about firms' hiring process. First, whether a firm decides to hire worker A depends on the characteristics of worker A alone, i.e. it will continue to hire worker A regardless of whether another worker B is available. In other words, firms regard workers as substitutes rather than complements.[7] This assumption is not universally true. A Hollywood producer may want to hire two specific lead actors for their chemistry, and if one is unavailable, the other also has to be replaced. However, for large firms where workers are closer to swappable cogs than unique superstars, this assumption is reasonable.

Second, the model assumes that the utility of hiring a worker does not depend on how many other workers accept the offer. In other words, the firm is large enough to employ all the workers to whom it extends offer without feeling the effect of diminishing marginal productivity of labor. This assumption is less restrictive than it may seem. Indeed, we can model the fact that the workers under consideration are less productive than the previous batch of workers by allowing firm j to have a high baseline utility b_j. Therefore, we are not assuming that there is never any diminishing marginal productivity of labor, only that there is negligible diminishing effect

[7] In the terminology of Roth and Sotomayor (1992), firms are assumed to have "substitutable preference," or firms' preference is assumed to have the property of substitutability. As discussed in Section 2.1, this assumption is necessary to prove the existence of stable matching in the case of many-to-one matching.

between the first and the last of the workers under consideration. This assumption is a reasonable approximation if the firm's labor force is large compared to the number of workers being considered.[8]

In addition to the two above assumptions about the process of firm's decision making, we make three parametric assumptions that are standard in the discrete choice literature. First, we assume a linear utility function. Second, we assume that the error terms $\epsilon_{1ij}, \epsilon_{0ij}$ are uncorrelated with one another and across firms. Third, we assume that the as error terms $\epsilon_{1ij}, \epsilon_{0ij}$ follow the Gumbel distribution.[9] The choice of the Gumbel distribution is largely motivated by convenience since it allows us to derive the probability of firm j making an offer to worker i as the familiar binomial logit form:

$$
\begin{aligned}
Pr(o_{ij} = 1) &= Pr(U_j(i) > U_j(\neg i)) && (2.3)\\
&= Pr(\epsilon_{0ij} - \epsilon_{1ij} < \boldsymbol{\beta}_j' X_i - b_j) && (2.4)\\
&= \frac{\exp(\boldsymbol{\beta}_j' X_i)}{1 + \exp(\boldsymbol{\beta}_j' X_i)} && (2.5)
\end{aligned}
$$

$$
Pr(o_{ij} = 0) = 1 - Pr(o_{ij} = 1) = \frac{1}{1 + \exp(\boldsymbol{\beta}_j' X_i)} \qquad (2.6)
$$

In Equation (2.5), the term b_j is absorbed into $\boldsymbol{\beta}$ when we add an intercept term to the covariate matrix X.

Once firms have made their offers, each worker i will have a set of offers from which to pick her favorite. We call this set of offers the *opportunity set* of worker i,

[8] While not concerned with diminishing marginal productivity, Roth and Sotomayor (1992) also assume that firms' quota, i.e. the number of workers they can accept, is sufficiently large to hire everyone in the set of workers under consideration. This assumption simplifies the proof that a stable match always exists in the case of many-to-one matching.

[9] The Gumbel distribution is very similar to the normal, only with a slightly fatter tail that allows for slightly more extreme variation in the unobserved utility. Its density function is $\exp^{-(x+\exp^{-x})}$, with mode 0, mean 0.5772, and fixed variance $\frac{\pi^2}{6}$. In practice, the difference between using Gumbel and independent normal error terms is small (Train, 2009).

denoted O_i. Since unemployment is always an available option, every opportunity set includes unemployment as an "offer."

The probability of worker i obtaining the opportunity set O_i is:

$$p(O_i|\boldsymbol{\beta}) = \prod_{j \in O_i} p(o_{ij} = 1|\boldsymbol{\beta}) \prod_{j \notin O_i} p(o_{ij} = 0|\boldsymbol{\beta}) \tag{2.7}$$

$$= \prod_{j \in O_i} \frac{\exp(\boldsymbol{\beta_j'} X_i)}{1 + \exp(\boldsymbol{\beta_j'} X_i)} \prod_{j \notin O_i} \frac{1}{1 + \exp(\boldsymbol{\beta_j'} X_i)} \tag{2.8}$$

2.3.2 Modeling workers' decision making

Worker i's utility for the accepting an offer from firm j is:

$$V_i(j) = \alpha' W_j + v_{ij} \tag{2.9}$$

where α is a vector of workers' preference for relevant characteristics of firms, W_j is a vector of firm j's measured values on those characteristics, and v_{ij} is the unobserved component that influences worker i's utility.

Worker i evaluates all the firms in her opportunity set and selects the offer that brings the highest utility. This decision of worker i concludes the matching process, resulting in the observed final match between a worker and her chosen firm in our data.

We make two assumptions in modeling the worker's decision making. First, for simplicity, we assume that all workers share the same set of preferences—hence α does not have a subscript i. The model can be extended so that there is heterogeneous preference among workers, either by estimating a separate model for each worker type (i.e. no pooling) or by building a hierarchical model for worker preference (i.e. partial pooling).

Second, we assume that the error term v_{ij} are uncorrelated across j. In other words, the unobserved factors in the utility of one job offer is uncorrelated to the unobserved factors in the utility of another job offer.[10] This assumption is most likely not true: if worker i values some unobserved factors of an offer, she is likely to consider those same factors in another offer as well. The hope is that we have modeled the observed portion sufficiently well that the remaining unobserved factors are close to white noise. In any case, this issue afflicts any application of discrete choice models and is not unique to our setup.[11]

Similar to our model of firm's utility, our model of worker's utility has three additional parametric assumptions that are standard in the discrete choice literature. First, we assume that utility is linear. Second, the error term v_{ij} are uncorrelated across i. Third, we model v_{ij} having a Gumbel distribution so that the probability that worker i will accept the offer of firm j out of all the offers in its opportunity set O_i takes the conditional logit form (Cameron and Trivedi, 2005):

$$p(A_i = a_i | O_i, \alpha_i) = \frac{\exp(\alpha' W_{a_i})}{\sum\limits_{j:j \in O_i} \exp(\alpha' W_j)} \tag{2.10}$$

where a_i is the index of the firm that i accepts to to work for, and Unemployment is indexed as 0.

2.3.3 Model estimation

Our goal is to estimate the preference of firms and workers, i.e. β_j and α. The key insight is that, conditional on the opportunity set being observed, the model of firms' and workers' decision making is a straightforward application of the binary logit and

[10] This assumption also gives rise to the Independence of the Irrelevant Alternatives (IIA) property. IIA implies that the relative odds of choosing between two alternatives depend only on the two alternatives under consideration. It does not depend on whether other alternatives are available or what their characteristics may be. Hence, other alternatives are considered "irrelevant."

[11] The discrete choice literature has developed solutions for such correlated error structure, such as nested logit, probit, and mixed logit, that can be applied here if we suspect that the unobserved portion is strongly correlated.

conditional logit models. Both models can be estimated with familiar tools such as Maximum Likelihood Estimation (MLE).

However, in most social science research problems, the researcher only observes the final match A and not the opportunity set O. For example, labor market data typically does not include the set of offers a worker received (or would have received if she had applied), while data on her current job is widely available. Similarly in the marriage market or the FDI market, researchers often do not have the data on the offers being made, and only observe the final matching between men and women (i.e. who is married to whom) and between MNCs and countries (i.e. which subsidiary is located where).

Logan (1998)'s solution to this problem is to use the Expectation-Maximization (EM) algorithm, an iterative method capable of finding the maximum likelihood estimates when the model depends on unobserved latent variables (i.e. the unobserved opportunity set in this case) (Dempster et al., 1977). Our innovation is to estimate the model using a Bayesian MCMC approach, which offers several advantages. First, our MCMC approach produces the full posterior distribution, making inference and prediction easy. In contrast, EM only produces point estimates out of the box.[12] Second, our MCMC approach can be faster than EM when the latent variable, i.e. the opportunity set, is high dimensional (Rydén, 2008).[13] Third, within the Bayesian framework, we can naturally put a hierarchical structure on firms' preference. This allows us to borrow information across firms, producing more precise estimates even when there is not a lot of data for a specific firm.

[12] Jamshidian and Jennrich (2000) propose a method for estimating the standard error of EM estimates. However, for hypothesis testing, we need further assumptions about the distribution of the EM estimates.

[13] Indeed, our opportunity set O is a $(I \times J)$ matrix of 0s and 1s, where I is the number of workers and J is the number of firms. Thus, there are 2^{IJ} potential values for the opportunity set, which quickly becomes untenable even for a small number of I and J. The high dimension of O forces Logan (1998) to reduce the data dimension by aggregating 17 employers in the data into 5 employer types, e.g. professional or blue collar jobs.

The rest of this section describes the details of the MCMC approach.

2.3.4 Estimating the model using MCMC

We are interested in the posterior distribution of workers' and firms' preference given the observed final match, i.e. $p(\alpha, \beta|A)$. Unconditioned on the opportunity set, this posterior is difficult to derive or sample from. Therefore, we sample from the augmented posterior $p(\alpha, \beta, O|A)$, whose density is much simpler to derive.[14] Specifically,

$$p(\alpha, \beta, O|A) = \frac{p(A|\alpha, \beta, O)p(\alpha, \beta, O)}{p(A)} \tag{2.11}$$

$$\propto p(A|O, \alpha)p(O|\beta)p(\alpha)p(\beta) \tag{2.12}$$

where $p(A|O, \alpha)$ is derived in (2.10), $p(O|\beta)$ is derived in (2.8), $p(\alpha)$ and $p(\beta)$ are prior distributions for α and β. A key insight of this equation is that the acceptance of offers, i.e. $p(A|O, \alpha)$, depends only on the opportunity set and on the workers' preference. Similarly, the opportunity sets, i.e. $p(O|\beta)$, depend only on firms' preference.

Because the opportunity set O is a discrete matrix of 0's and 1's, there is not any convenient conjugate model for (2.12), making Gibbs sampling impossible. Therefore, we use Metropolis-Hastings instead, a technique to sample from an arbitrary distribution $p(\theta)$ using the following steps:

1. Start from an arbitrary value of θ
2. Generate a proposal value θ^* from the proposal distribution $q(\theta^*|\theta)$
3. Calculate the acceptance ratio $MH_\theta = \frac{p(\theta^*)q(\theta|\theta*)}{p(\theta)q(\theta^*|\theta)}$
4. Accept the proposed value θ^* with probability $\max(1, MH_\theta)$

[14] See Tanner and Wong (1987) for a discussion of such data augmentation techniques.

5. Repeat step 2-4 until convergence

In our case, we will use symmetric proposal distributions, i.e. $p(\theta^*|\theta) = p(\theta|\theta^*) \forall \theta, \theta^*$, so that the MH acceptance ratio simplifies to $MH_\theta = \frac{p(\theta^*)}{p(\theta)}$.

Below we describe how to sample from the posterior of each parameter in the model using the Metropolis-Hastings (MH) algorithm. More detailed derivation of the MH acceptance ratio is included in Appendix A. We ensure that our derivation and implementation of the acceptance ratio is correct using the unit-testing approach suggested by Grosse and Duvenaud (2014).

Sampling from the posterior of the opportunity set $p(O|A, \alpha, \beta)$

For each worker i, we propose a new value O_i^* by flipping random cells in the current opportunity set O_i from 0 to 1 and 1 to 0. Substantively, this is equivalent to perturbing the opportunity set by randomly making new offers or withdrawing existing offers. Note that this proposal distribution is indeed symmetric because proposing O_i^* from O_i and proposing O_i from O_i^* both involve flipping the same cells in the opportunity set. Hence, $p(O_i^*|O_i) = p(O_i|O_i^*) =$ the probability of selecting these particular cells out of the opportunity set.

The MH acceptance ratio for the proposed opportunity set O_i^* is

$$MH_O = \frac{p(O_i^*|A_i, \alpha, \boldsymbol{\beta})}{p(O_i|A_i, \alpha, \boldsymbol{\beta})} \tag{2.13}$$

$$= \frac{\sum_{j:j \in O_i} \exp(\alpha' W_j)}{\sum_{j:j \in O_i} \exp(\alpha' W_j) \pm \exp(\alpha' W_{j*})} \times \exp(\pm \boldsymbol{\beta}'_{j*} X_i) \tag{2.14}$$

where $\pm$ evaluates to $+$ if j^* is a new offer being added to the current opportunity set, and evaluates to $-$ if j^* is an existing offer being withdrawn from the current opportunity set.

To understand the intuition behind this formula for MH_O, consider the scenario in which we propose a new opportunity set for worker i by adding an offer from firm j. Since worker i now has one more choice to choose from, it becomes less likely that worker i's accepted job is the best choice. This makes the proposed opportunity set less consistent with the observed data than the current opportunity set, and MH_O should decrease accordingly. This is reflected in the formula for MH_O by the $\exp(\alpha' W_{j*})$ term in the denominator.

On the other hand, whether we should add the offer to the opportunity set also depends on firm j's preference for worker i. If hiring worker i brings firm j net positive utility (i.e. $\boldsymbol{\beta}'_{j*} X_i > 0$), we should add the offer. This is reflected in the formula for MH_O by the multiplier $\exp(\boldsymbol{\beta}'_{j*} X_i)$, which is larger than 1 when $\boldsymbol{\beta}'_{j*} X_i > 0$.

Sampling from the posterior of workers' preference $p(\alpha|A, O, \beta)$

We propose a new α^* using a Normal proposal distribution centered on the current value α with a hand-tuned diagonal covariance matrix. The MH acceptance ratio for the proposed α^* is:[15]

$$MH_\alpha = \frac{\alpha^*|A, O, \beta)}{p(\alpha|A, O, \beta)} \tag{2.15}$$

$$\begin{aligned} \log MH_\alpha = \sum_i \Big[& (\alpha^* - \alpha)' W_{a_i} + \\ & \log \left(\sum_{j:j \in O_i} \exp(\alpha' W_j) \right) - \log \left(\sum_{j:j \in O_i} \exp(\alpha^{*\prime} W_j) \right) \Big] + \\ & \log p(\alpha^*) - \log p(\alpha) \end{aligned} \tag{2.16}$$

Sampling from the posterior of firms' preference $p(\beta|A, O, \alpha)$

We propose a new $\boldsymbol{\beta}^*$ using a Normal adaptive proposal distribution similar to α. The MH acceptance ratio for the proposed β is:

[15] We log-transform the MH acceptance ratio for better numerics.

$$MH_\beta = \frac{p(\beta * |A, O, \alpha)}{p(\beta|A, O, \alpha)} \tag{2.17}$$

$$\log MH_\beta = \sum_i \left[\sum_{j \in O_i} \left(\beta_j^{*\prime} X_i - \beta_j' X_i \right) + \sum_j \left(\log(1 + \exp(\beta_j' X_i)) - \log(1 + \exp(\beta_j^{*\prime} X_i)) \right) \right]$$
$$+ \log p(\boldsymbol{\beta}^*) - \log p(\boldsymbol{\beta}) \tag{2.18}$$

Sampling from the posterior of β's hyperparameters μ_β, τ_β

As discussed above, the Bayesian approach to estimating our two-sided model allows us to put a hierarchical structure on the preference parameter. Here, we model firms' preference $\boldsymbol{\beta}$ as being drawn from the multivariate normal distribution $MVN(\mu_\beta, \tau_\beta)$, where μ_β is the mean and τ_β is the precision.

When the prior $p(\beta)$ is also normal, we have a conjugate multivariate normal model, where μ_β and τ_β are the parameters while β is considered the "data."

Since the model is conjugate, we can sample from the posterior of μ_β and τ_β with Gibbs sampling. Their full conditional distribution of μ_β is:

$$p(\mu_\beta) \sim MVN(\mu_0, \Sigma_0) \tag{2.19}$$

$$p(\mu_\beta|\beta, \tau_\beta) \sim MVN(m, V) \text{ where} \tag{2.20}$$

$$V = (\Sigma_0^{-1} + n\tau_\beta)^{-1} \tag{2.21}$$

$$m = (\Sigma_0^{-1} + n\tau_\beta)^{-1}(\Sigma_0^{-1}\mu_0 + n\tau_\beta\bar{\beta}) \tag{2.22}$$

The full conditional distribution of τ_β is:

$$p(\tau_\beta) \sim \text{Wishart}(\nu_0, S_0^{-1}) \tag{2.23}$$

$$p(\tau_\beta|\beta, \mu_\beta) \sim \text{Wishart}(\nu, S^{-1}) \text{ where} \tag{2.24}$$

$$\nu = \nu_0 + n \tag{2.25}$$

$$S^{-1} = \left(S_0 + \sum(\beta - \mu_\beta)(\beta - \mu_\beta)'\right)^{-1} \tag{2.26}$$

2.4 Conclusion

This chapter has reviewed the game theoretic two-sided matching models, identifying key assumptions and properties that empirical model of two-sided matching market can take advantage of. A key property of matching market is that the final matching is likely to be *stable*, with no agents being able to form a better match. Therefore, our two-sided logit model also aims to describe a process that would result in a stable matching.

In addition to setting up the model, I have also discussed how to estimate it using Bayesian MCMC, specifically the Metropolis-Hastings algorithm. This approach provides us with several advantages over the current approach of EM estimation. First, once we have the posterior distribution of preference parameters, inference and prediction are very flexible and straightforward. Second, the MCMC approach can be more computationally tractable in high dimensions. Finally, we can use a hierarchical modeling approach to partially pool information and better estimate firms' preference even if some firms have a small sample size.

In the next chapter, I show simulation results to demonstrate the correctness of my estimation and to explore other properties of the model.

3

Simulation results

In this chapter, I simulate the matching process of a labor market, using real data on workers' and firms' characteristics and assigned model parameters. I then apply the two-sided logit model to show that the model is able to recover the underlying parameters and to diagnose the properties of the MCMC sampling. I compare the results of the two-sided logit model with the one-sided conditional logit model, showing that the one-sided approach produces biased estimates of workers' and firms' preference. This result demonstrates how the one-sided approach, despite being the default method for analyzing two-sided markets, can be misleading and unable to disentangle the effect of one side's preference from the other's.

In addition, I explore the implications of the fact that, our FDI data does not include the "reservation choice," i.e. the choice that is always available. Indeed, while labor market data often include unemployment as the reservation choice, FDI data does not include firms who consider investing abroad but end up staying home. Simulation results show that some of our estimates will be biased, and I discuss potential remedies.

3.1 Labor market data

To ensure that my simulation result generalizes to real situations, I use real data on workers' and firms' characteristics from the US General Social Survey (GSS), 1982-1990.[1] On one side of the matching market is 2149 workers, a representative sample of US male workers between 25 and 44 years old. Table 3.1 shows the summary statistics for these workers. On average, a worker is 33 (± 5.7) years old and has 13 years (± 3.1) of education. 11% of workers in our sample are non-white.

Table 3.1: Summary statistics of workers' education, age, and race. The data come from the GSS, 1982-1990, for male workers in the US between 25 and 44 years old.

Statistic	N	Mean	St. Dev.	Min	Max
Years of education	2,149	13.103	3.111	2	20
Age	2,149	33.524	5.716	25	44
Non-white	2,149	0.113	0.316	0	1

On the other side of the matching market are five firms, representing five job categories: professional, managerial, sales-clerical-services, manufacturing blue collar, and other blue collar. Table 3.2 shows their characteristics and the sub-categories from which they are aggregated. *Prestige* is the Hodge-Seigel-Rossi score, used in the GSS to measure the prestige of a job (Hodge et al., 1964; NORC, 2014). *Autonomy* is calculated as the odds of having a supervisor, multiplied by -1 so that a higher score is associated with a higher level of autonomy.[2] The prestige and the autonomy scores of a firm in our dataset are the average scores reported by workers who currently work in that job categories. Unemployment by itself does not have a score. Following Logan (1996)'s study on the labor market, I set unemployment's prestige score to 50% of the prestige of the last job held and its autonomy score as

[1] I thank Professor Michael Newton and Professor John Allen Logan for sharing the dataset.

[2] In other words, autonomy $= -\frac{P(\text{having a supervisor})}{P(\text{not having a supervisor})}$

Table 3.2: Characteristics of five firm types in the US, 1982-1990.

Firm category	Prestige	Pr(Supervisor)	Autonomy
Unemployment	18	0.204	-0.256
Professional	59.670	0.163	-0.483
Managerial	48.141	0.442	-3.237
Sales, Clerical, Services	34.545	0.100	-0.112
Manufacturing Blue Collar	34.330	0.071	-0.077
Other Blue Collar	34.035	0.175	-0.214

the average autonomy scores of all workers.

3.2 Simulated matching process

I assign values to workers' and firms' preference parameters, choosing values to achieve some level of realism and to have some workers in each job. Table 3.3 describes the utility functions. I normalize firms' utility of not hiring to 0 so that firm j will extend an offer to worker i if the utility of hiring is positive (i.e. $U_j(i) > 0$). The magnitude of the intercept can thus be interpreted as how selective a firm is in making an offer. For example, professional and managerial firms are highly selective with intercepts of -24 and -22, while the other firms are less so with intercepts of $-9, -8$ and -6. The coefficients represent how much a firm values a worker's trait. For example, managerial and professional firms have a similar preference for a worker's education, with coefficients of 1 and 1.3. On the other hand, managerial firm values a worker's age twice as much as professional firm does, with coefficients of 0.2 and 0.1.

While the two-sided logit model can be extended to accommodate different worker types as well, for this simulation I assume that workers have homogeneous preference, sharing one utility function.

Each utility function has a random component, represented by the Gumbel-distributed error term ϵ. While normally distributed error is more common in simulations, justified by the claim that the error term is the sum of many independent unobserved variables, here I use the Gumbel distribution so that the coefficient estimates from the two-sided logit model can be directly compared with the true preference parameter values.[3] Practically the Gumbel distribution is very similar to the normal distribution, and I discussed the implication of using the Gumbel distribution in further depth in Section 2.3.1.

Table 3.3: Utility functions of firms and workers used in labor market simulation. x_{i1}, x_{i2}, x_{i3} are worker i's education, age, and race (nonwhite is coded as 1). w_{j1}, w_{j2} are firm j's prestige and autonomy, with $j \in \{1, \ldots, 5\}$. The ϵ's are Gumbel-distributed error terms.

Firms' utility functions	
Professional	$U_1(i) = -24 + 1.3x_{i1} + 0.1x_{i2} + 1x_{i3} + \epsilon$
Managerial	$U_2(i) = -22 + 1x_{i1} + 0.2x_{i2} + 1x_{i3} + \epsilon$
Sales, Clerical, Services	$U_3(i) = -9 + 0.75x_{i1} + -0.05x_{i2} + 0x_{i3} + \epsilon$
Manufacturing blue collar	$U_4(i) = -8 + 0.5x_{i1} + 0.02x_{i2} + 0x_{i3} + \epsilon$
Other blue collar	$U_5(i) = -6 + 0.5x_{i1} - 0.01x_{i2} + 1x_{i3} + \epsilon$
Workers' utility function	$V_i(j) = 0.01w_{j1} + 0.1w_{j2} + \epsilon$

With these utility functions, I simulate the matching process as follows:

- First stage: Each firm j evaluates each worker i, calculating the utility of hiring. If the utility of hiring is positive, it will extend an offer. Unemployment is always an option for workers, and is thought of as a "firm" that extends an offer to every worker. After this stage, we generate an opportunity set O that is a 2149×6 matrix. In this matrix, cell O_{ij} is 1 if worker i receives an offer from firm j, and 0 if not. We typically do not observe this opportunity set matrix in real datasets.

- Second stage: Worker i evaluates each firm that extends him an offer in the first stage, calculating the utility of working for that firm. Worker i then chooses

[3] If I use normally distributed error terms, the coefficient estimates have to be divided by $\frac{\pi^2}{3}$ to be comparable with the true values. See Train (2009, chap 2) for a more in-depth discussion of scaling and normalization in discrete choice models.

a firm (or unemployment) if it offers the highest utility. After this stage, we generate a choice vector that is a 2149×1 vector. In this choice vector, cell i equals j if worker i decides to work at firm j. This choice vector is what we observe in real datasets such as the GSS.

3.3 Simulation results

I estimate the two-sided logit model using the MCMC approach described in Chapter 2. For all preference parameters, I use a diffuse prior that is a Normal distribution with mean 0 and variance 100. To propose new samples in the Metropolis-Hastings algorithm, I use Normal distributions with a scale hand-picked by examining the trace plots of discarded runs. The results below are from a MCMC chain of 50,000 iterations with a thinning interval of 5, resulting in 10,000 saved iterations.

Figure 3.1 shows the trace plots of the MCMC samples for workers' preference. We see that the MCMC chain mixes well and quickly converge to the true value indicated by the red line. This result gives us confidence that the MCMC algorithm is implemented correctly and can achieve convergence within a reasonable time frame.

Figure 3.2 shows the trace plots of the MCMC samples for professional firm's preference. We see that the MCMC chain is also able to converge to the true parameter values, albeit slower and with more autocorrelation between iterations.[4] There are several reasons for this poorer mixing.

First, while we can use the entire sample to estimate the preference of workers, only a subset of the sample works at a particular firm, resulting in a smaller sample that we can use to estimate each firm's preference. This problem is clearest in the trace plots for the managerial employer, which only has a sample of 40 workers, or

[4] To improve the mixing of the MCMC chain, I standardize workers' characteristics so that they have mean 0. Therefore, the intercept term has to be changed accordingly. The true intercept values displayed in the plots are the standardized intercepts, which is different from those reported in Table 3.3.

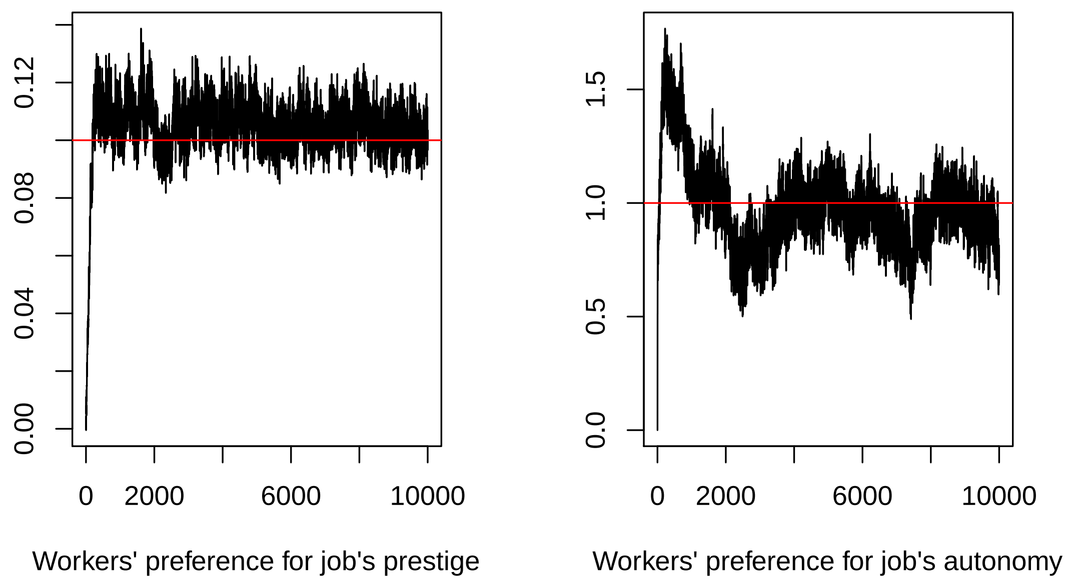

Figure 3.1: Two-sided logit estimates for workers' preference. The black line plots are the trace plots of the MCMC samplers, and the red line indicates the true parameter values. The trace plots show that the MCMC chain is able to converge to the true value after 10,000 iterations (2,000 saved iterations ×5 thinning interval).

1.9% of the total sample To partially combat this issue, I use a hierarchical model in which firms' preference parameters are drawn from a common distribution. By doing so, I "partially pool" the sample across firms, pulling the estimate for firms with small sample sizes towards the common mean, and thus producing estimates that have more predictive power (Gelman and Hill, 2006). For a similar reason, the MCMC chain of the preference parameter for *non-white* has a particularly poor mixing, likely because *non-white* is a binary variable, having less variation and thus information that our model can use.

Second, while workers only have two preference parameters (for firm's prestige and autonomy), each firm has four preference parameters (for worker's education, age, race, and an intercept term), resulting in a total of 24 parameters. Updating the

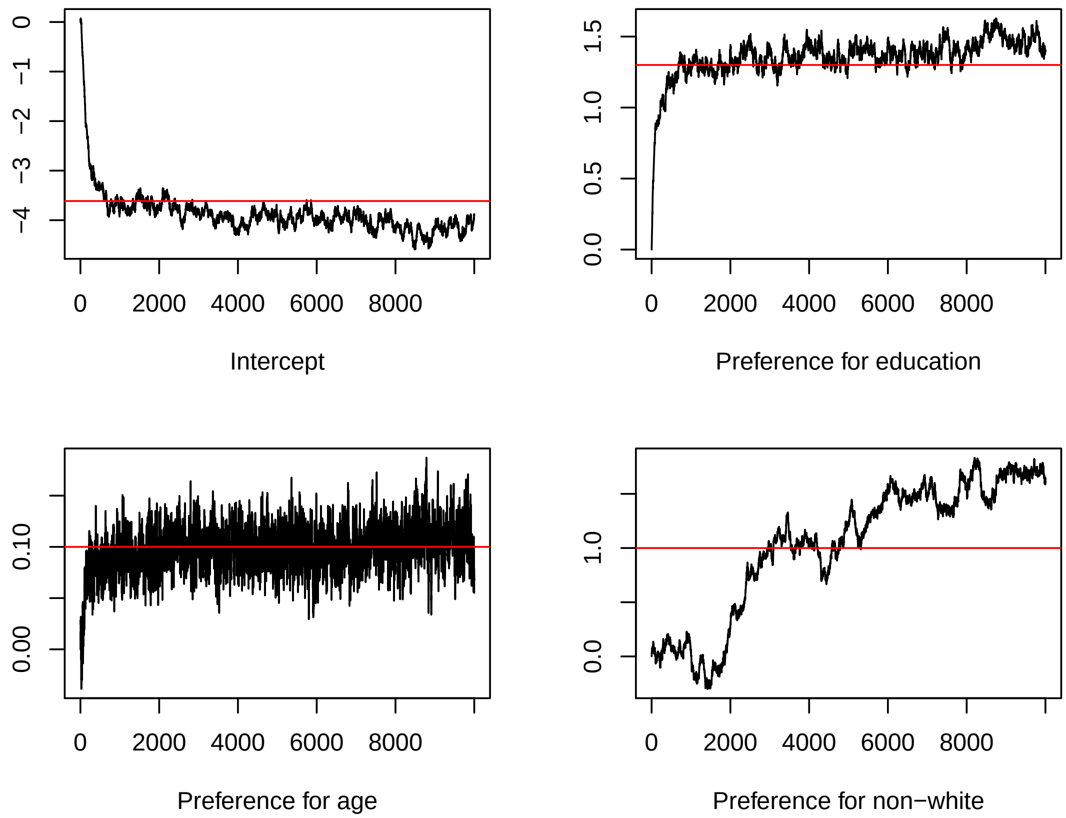

FIGURE 3.2: Two-sided logit estimates for professional firm's preference. The MCMC chain is able to converge to the true parameter value, indicated by the red line, albeit with more autocorrelation than the MCMC chain for worker's preference in Figure 3.1.

MCMC chain in such high dimension is inherently difficult—to update one parameter we only need to come up with one good proposal, but to update 24 parameters we need to come up with good proposals for each of them.

Third, while firms' preference and the opportunity set are highly correlated, our proposals for these parameters are independent, not take into their correlation, and thus causing the MCMC to get stuck at local modes. Section 3.5 will discuss this issue and potential remedies in more details.

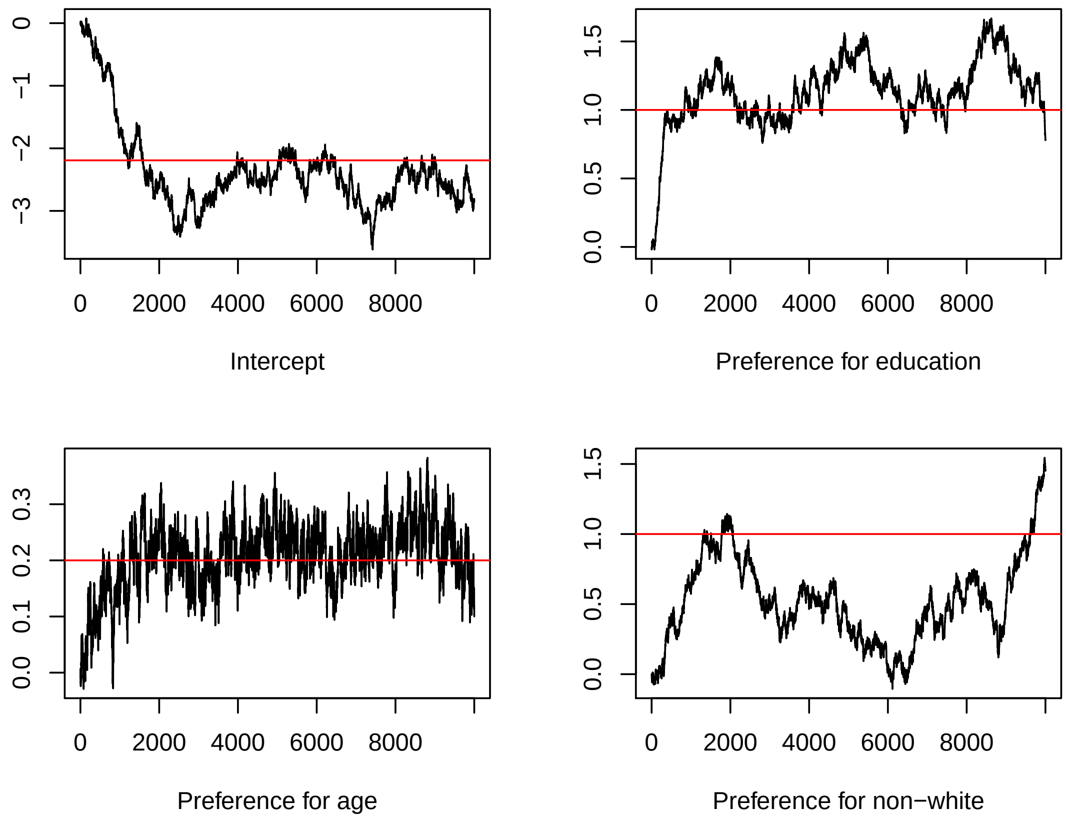

FIGURE 3.3: Two-sided logit estimates for managerial firm's preference. Because the managerial firm only has a small sample size of 40 workers, or 1.9% of the total sample, its preference is estimated more poorly than other's.

3.4 Comparing two-sided logit model and one-sided models

In this section, I demonstrate that, without taking into account the two-sided nature of the matching market, one-sided models produce biased estimates of the actors' preference. While it may be unsurprising that one-sided models fail when the data generating process is so different from their assumptions, this is a worthwhile exercise given that many empirical researches rely on these models. For example, using discrete choice models (multinomial logit, conditional logit), Cheng and Stough (2006) models Japanese MNCs' location choice across Chinese provinces, Aw and Lee (2008) models Taiwanese firms' decision to stay home or to open a factory in China and the

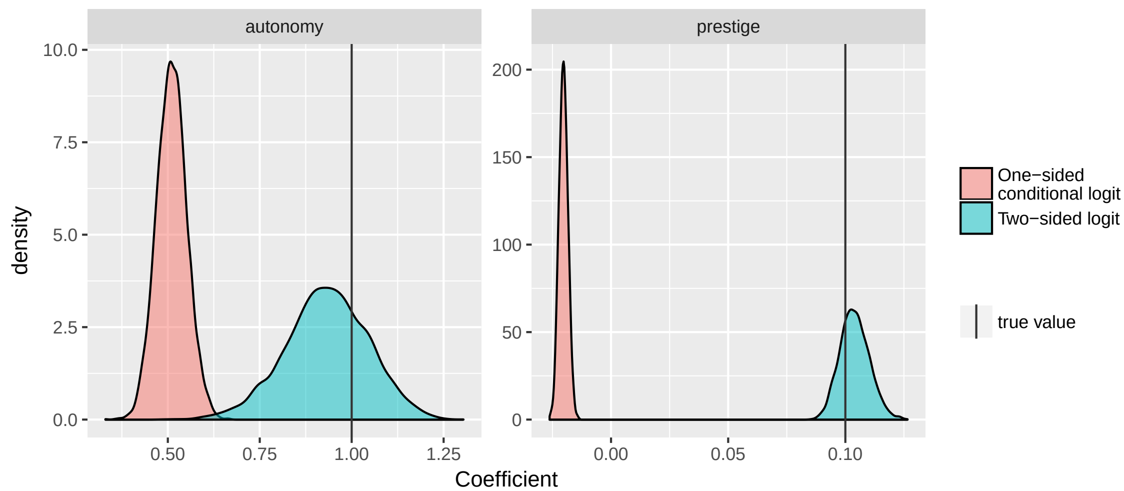

FIGURE 3.4: Estimates of workers' preference, produced by two-sided logit and conditional logit. The density plots show that the two-sided logit's 95% credible interval includes the true value, indicated by the black line, while the conditional logit's 95% confidence interval is far from it.

US.[5] Using count models (Poisson, negative binomial), Wu (1999) models MNCs' location choice in Guangzhou, China. Arauzo-Carod et al. (2010) provides a literature review of how these one-sided models are used in studying the location choice of firms.

Imitating these approaches in the literature, I estimate a conditional logit model in which workers choose the best firm to work for as if all firms were available in their opportunity set. Figure 3.4 shows that the one-sided conditional logit model produces biased estimates of workers' preference. Worse yet, its estimate has little uncertainty and can cause researchers to be overly confident in the wrong result.[6]

It is informative to examine the big difference between the two-sided and one-

[5] In the empirical literature, researchers often use the term "multinomial logit" and "conditional logit" interchangeably to refer to a discrete choice model of unordered choices. In this discussion, I follow the terminology in McFadden (1974)'s seminal paper on discrete choice models, distinguishing "multinomial logit" as the model whose independent variables are the choosers' characteristics, and "conditional logit" as the model whose independent variables are the choices' characteristics.

[6] This conditional logit model is equivalent to a Poisson model in which the dependent variable is the count of workers at each firm, as shown in Guimaraes et al. (2003). Both models, estimated with MLE, would produce exactly the same estimates for the coefficients and their covariance matrix. Therefore, the argument against one-sided conditional logit applies fully to Poisson.

sided estimates for *prestige*. The reason for the large bias is because the one-sided approach confounds the effect of one side's preference with the other's. Figure 3.5 (left) shows the binary heat map for the true opportunity set—a dark blue cell indicates that an offer is made by firm in column j to worker in row i. The columns for professional and managerial firms (2^{nd} and 3^{rd} columns) are quite similar, reflecting the fact that they have similar utility functions and make offers to the same kind of workers. In contrast, in the observed choice (Figure 3.5, right), the columns for professional and managerial firms are very different, reflecting the fact that the professional firm is slightly more desirable, causing workers that receive offers from both firms to overwhelmingly choose to work for the professional firm over the managerial firm. Therefore, there are very few workers at the managerial firm. To the one-sided conditional logit model, it looks as if the managerial firm—a highly prestigious job—were less desirable than even the services and blue collar firms. Therefore, it severely underestimate workers' preference for *prestige* to such an extent that *prestige* is considered a negative trait.

This example shows how misleading it can be to estimate workers' preference by assuming that all the choices are available. Indeed, the managerial firm is rarely chosen not because it is undesirable, but because it has to compete with the professional firm for the same pool of highly educated and experienced workers.

3.5 Issues with MCMC convergence

A big reason for the poor mixing of firms' preference parameters β is the high correlation between β and the opportunity set (Figure 3.6). Intuitively, at any point during the MCMC chain, we cannot propose a new opportunity set that is very different from the current one because it would be too unlikely given the current value of β. Likewise, we cannot propose too different a value for β because it would be rejected given the current opportunity set.

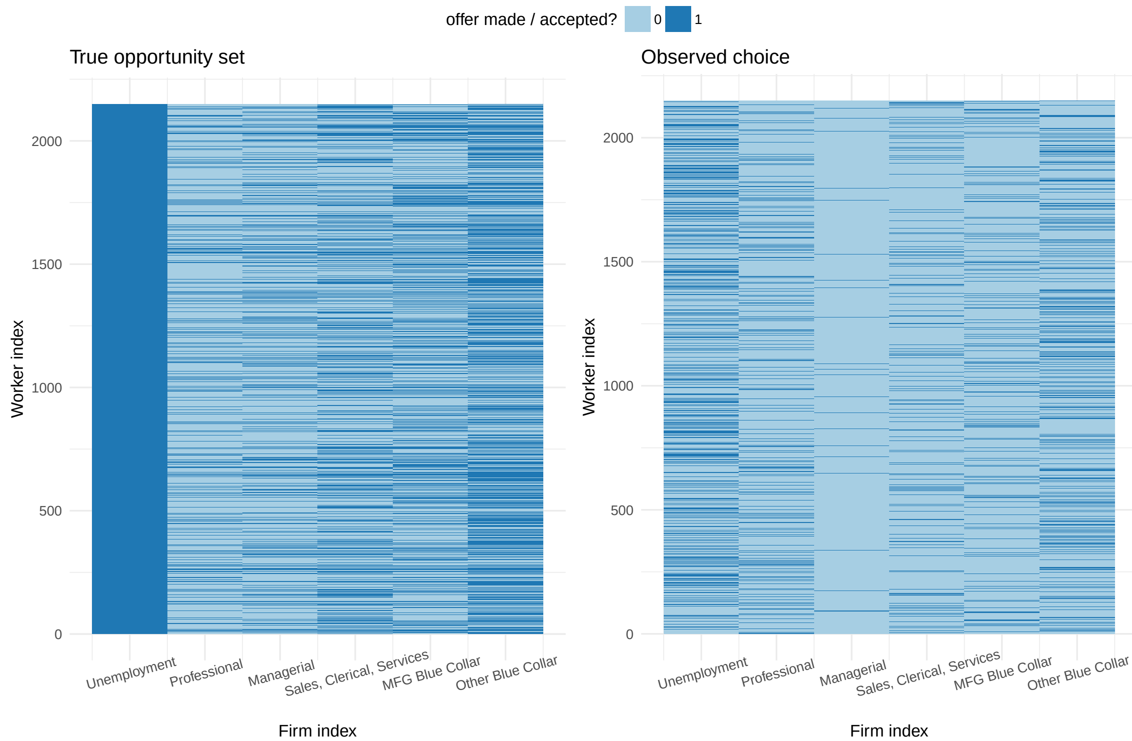

FIGURE 3.5: Binary heat map for the true opportunity set (left) and observed choice (right). A dark blue cell indicates that an offer was made (or accepted) between the firm in the corresponding column and the worker in the corresponding row.

This problem is especially severe for a firm with only a few workers. If we propose a new opportunity set in which this firm extends the offer to a new worker and this worker is very different from the current workers, then this new offer will heavily affect the estimate for β. In contrast, for firms with a large sample size, there is already a lot of information to precisely estimate their preference. Making one new offer in these cases will not substantially change the estimate.

Currently, I make random-walk proposals for β and the opportunity set, which insufficiently takes into account this correlation, causing poor mixing. A potential solution to this problem is to make a correlated proposal for β and for the opportunity set: if we propose a new β that puts a high emphasis on workers' education, then we should also perturb the opportunity set to make more offers to highly-educated

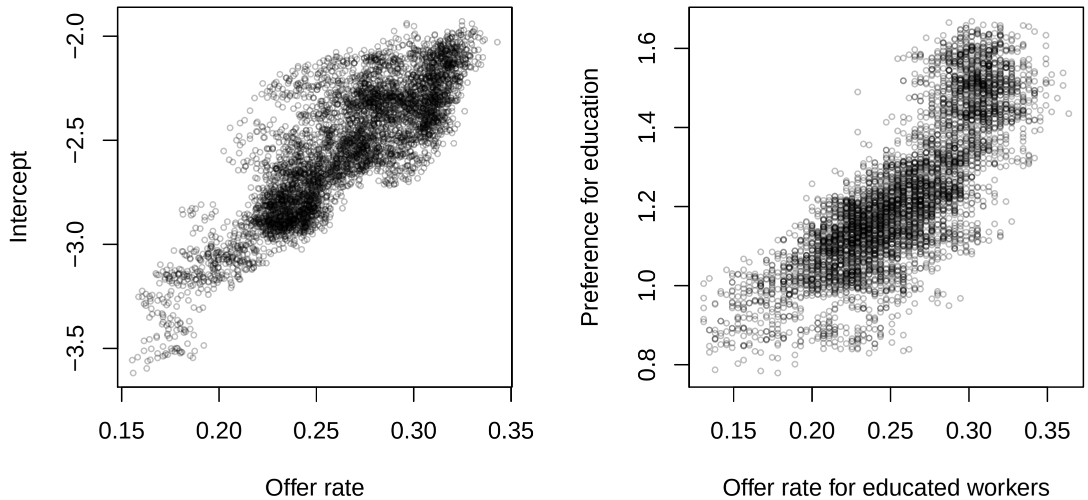

FIGURE 3.6: Correlation between the opportunity set and β. The left panel shows the correlation between the β intercept and the offer rate of a firm. When the intercept is high, the firm is also much more likely to extend an offer. The right panel shows the correlation between the β for education and the offer rate for highly educated workers (top 25% percentile). Once again, we see that if the β for education is high, the firm is much more likely to extend an offer to educated workers.

worker. While the concept is simple, this approach is not straightforward to engineer, and is left for future research.[7]

3.6 Estimation issues when the reservation choice is unobservable

In Chapter 5, I will apply this two-sided matching model to the FDI matching market, where countries extend offers to MNCs, and MNCs choose the best country to invest among their set of options. However, an important difference between the labor market and the FDI market is that in the latter we often will not observe the "reservation choice," i.e. the choice that will always be available regardless of what

[7] Alternatively, we may reparameterize the model entirely and eliminate the opportunity set, whose binary nature makes it impossible to use more modern MCMC approaches such as Hamiltonian Monte Carlo. A potential alternative parameterization is Logan et al. (2008)'s, which samples directly from the utility space.

the other side offers.[8] In the labor market, this "reservation choice" is unemployment. In the FDI market, it is staying in the home country and not opening up a subsidiary abroad. Since most firm-level FDI data is collected by surveying firms that have made an investment abroad, we are not observing the firms who consider investing abroad but decide to stay put. Intuitively, we have a sample selection problem where we only observe firms who have made it abroad. This problem has different consequences depending on whether we are estimating firms' preference or countries' preference. This section investigates how missing this information affects the estimates of our model.

To imitate the FDI market data, at the end of the labor matching process I remove all the unemployed workers, resulting in a sample of 1530 workers across 5 firms.

Figure 3.7 shows that our estimates of workers' preference are unaffected. This result makes sense—since we are still observing 1530 workers choosing one firm over others, we still get a lot of information about their preference. Not observing the workers who decide to stay unemployed reduces our sample size, but otherwise does not pose any problem.[9] Therefore, when applying the two-sided logit model to the FDI market, the estimates for MNCs' preference will still be reliable.

On the other hand, our estimates for firms' preference can have serious bias. Figure 3.8 shows the trace plots of the preference of the managerial firm, which no longer overlaps with the true values, indicated by the red line. The estimate of the rate at which the managerial firm makes an offer is too high, as demonstrated both by the high offer rate in the first panel and the high intercept term in the second

[8] I call unemployment the "reservation choice" in reference to the "reservation wage" in game theory and economic models.

[9] In a sense, we avoid this problem by assuming that all workers have the same preference. Thus, even though we do not observe workers that are unemployed, there is still only one set of preference parameters and for all workers, which can be estimated from the workers that we do observe.

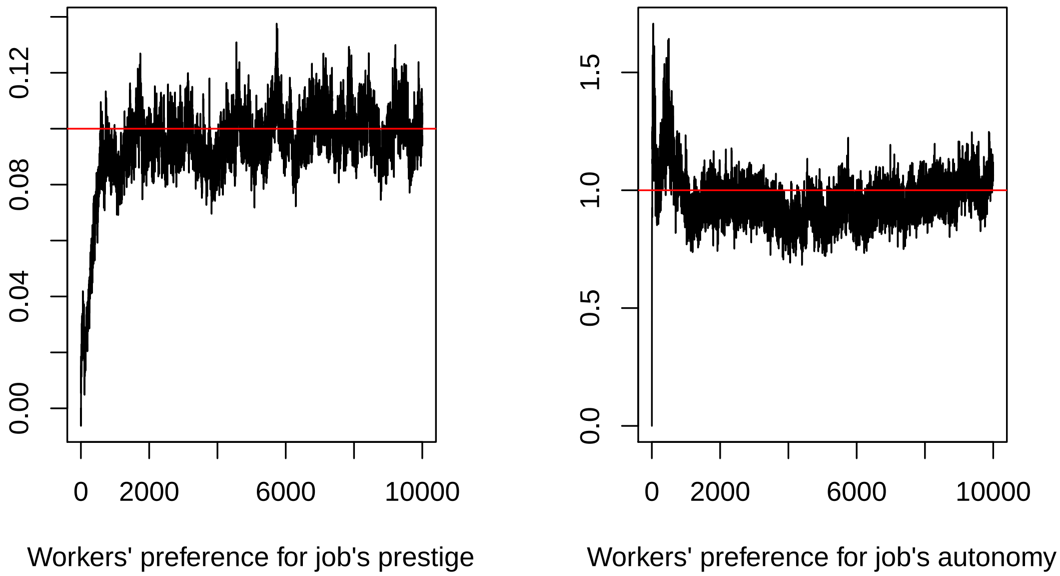

FIGURE 3.7: Estimates of workers' preference are unchanged even when we do not observe workers that choose unemployment (i.e., the reservation choice).

panel.[10]

This bias happens because we are only observing high quality workers, who receive good enough offers that they decide to accept them instead of remaining unemployed. Since our sample only include only these high quality workers, it looks as if firms extend an offer to everyone, causing our model to think that firms are more generous than they are. Therefore, the sampled intercept term will be too high and the sampled opportunity set will have more offers than the true opportunity set.

Another way to get the intuition around this problem is to consider how the opportunity set is sampled. Whenever a good offer is proposed to be added in the opportunity set, if we observe that the worker works work at a bad job, then it is unlikely that the good offer was really made. Otherwise, the worker would have

[10] The firm makes an offer if the utility function is positive. Hence, if the intercept term is too high, the probability of this firm making an offer is also too high.

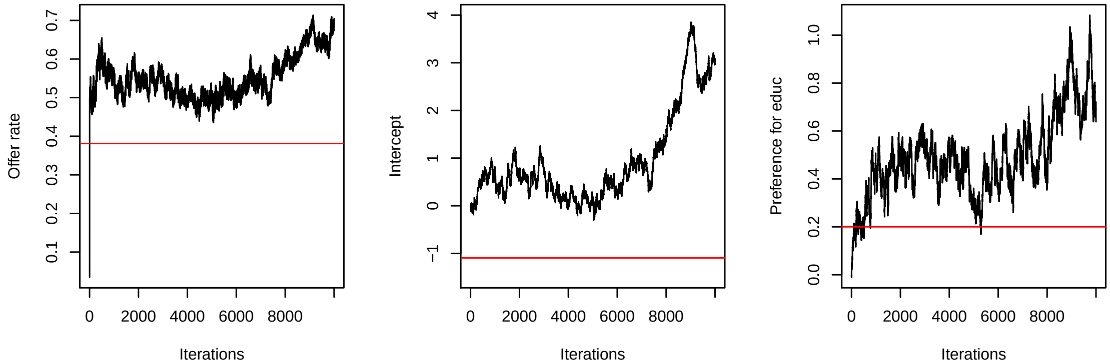

FIGURE 3.8: Estimates of firms' preference are biased when we do not observe workers that choose unemployment (i.e. the reservation choice).

taken it! This is how the sampling of the opportunity set avoids adding spurious offers.

For this process to work well, unemployment needs to be an option so that we can anchor other jobs against this bad option. Essentially, by observing a lot of people who are unemployed, we know that other firms have not extended an offer to these people, and thus allowing us to better estimate their preference. When we do not observe the unemployed workers, we no longer have this information. Therefore, our estimate are no longer accurate.

In sum, these findings have several implications. First, the estimate of the workers' preference is unaffected. For the FDI market, this means that we can still rely on the estimates of MNCs' preference without any change. Second, given that we need a "bad" choice to anchor the estimate of firms' preference, we can still rely on the estimates for the highly desirable firms. For these firms, even without unemployment, there are still other worse firms to compare to. Therefore, the estimates of their preference will still be accurate. For example, conditional the estimated workers' preference, professional firm is the most highly coveted job. Indeed Figure 3.9 shows the our estimates for its parameters are still correct, unlike the estimate for

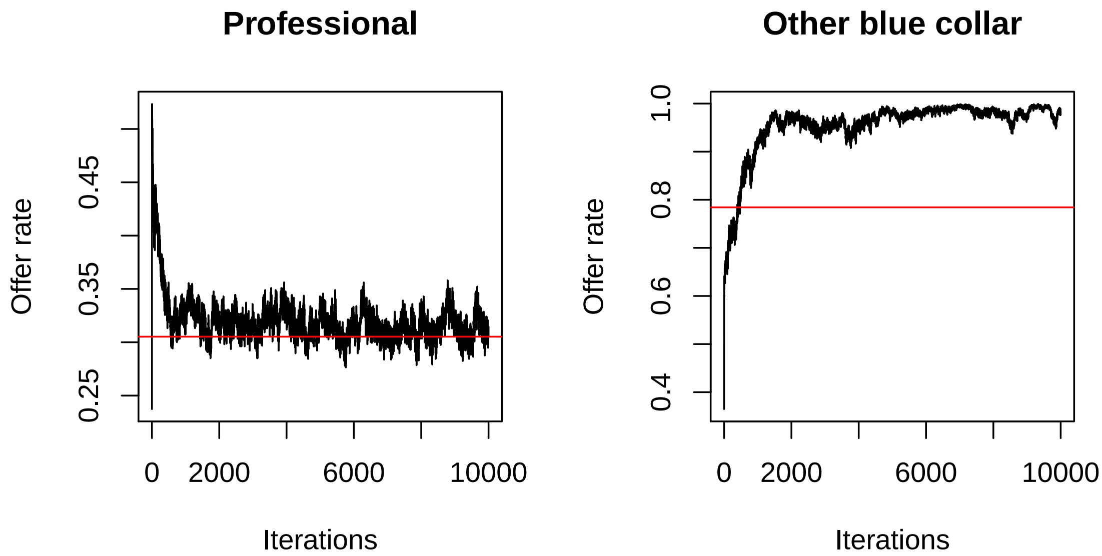

FIGURE 3.9: The estimate for the best firm is still accurate

other blue collar, a much less desirable job. For the FDI market, this means that preference of highly desirable countries are the most reliable, and others' less so.

4

US labor market

In this chapter I apply the two-sided logit model on the US labor market data, where the two sided logit model is originally developed for.

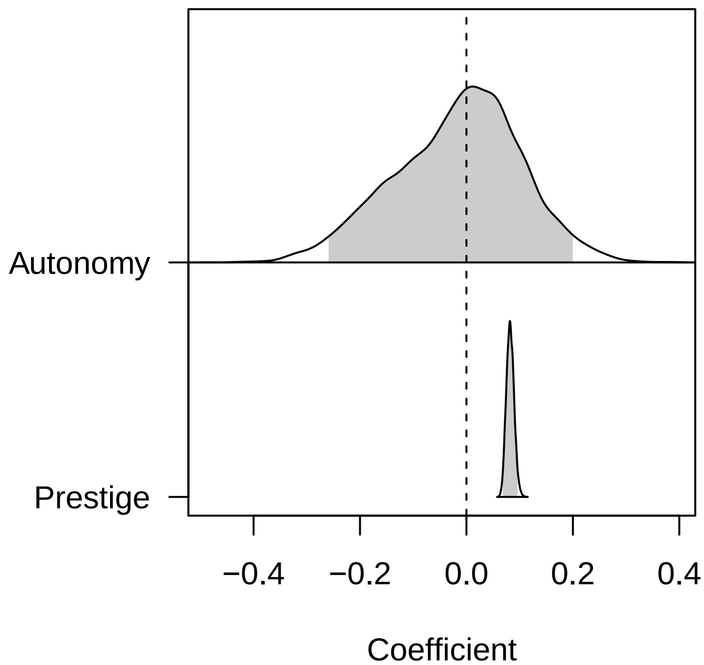

Figure 4.1: Preference of workers for firms' characteristics. The density plot and the shaded region show the posterior distribution and the 95% credible interval after burn-in. While prestige is highly valued by workers, autonomy seems to be less importance.

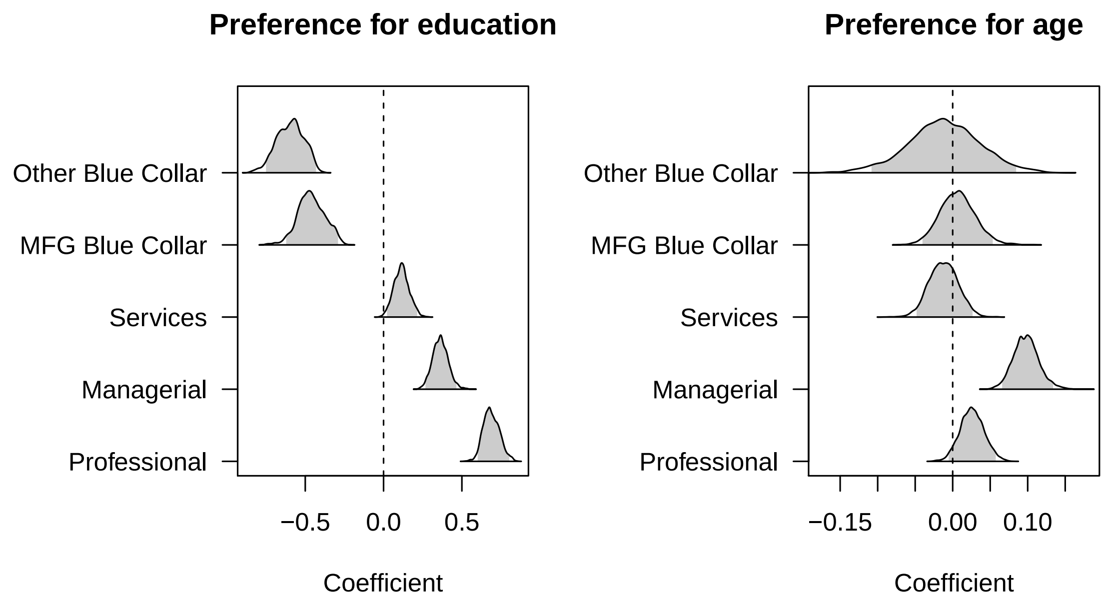

FIGURE 4.2: Preference of firms for workers' education and age. Professional and managerial firms have a strong and positive preference for highly educated workers. While most firms do not highly value older workers, managerial firm stands out in their preference for age (likely as a proxy for experience).

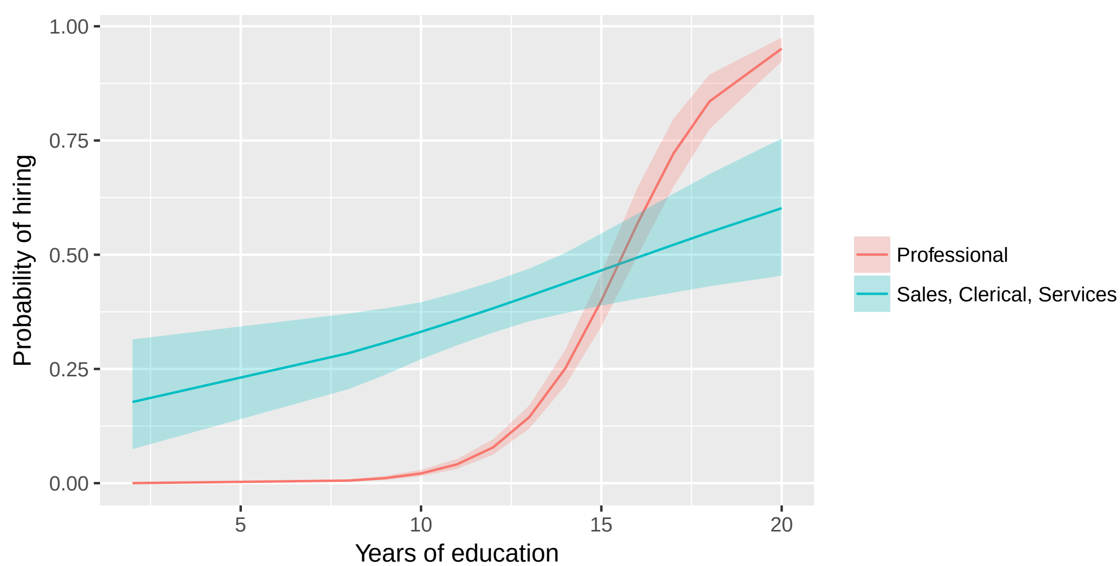

FIGURE 4.3: The effect of education on the probability of a worker being hired into a professional and a services job.

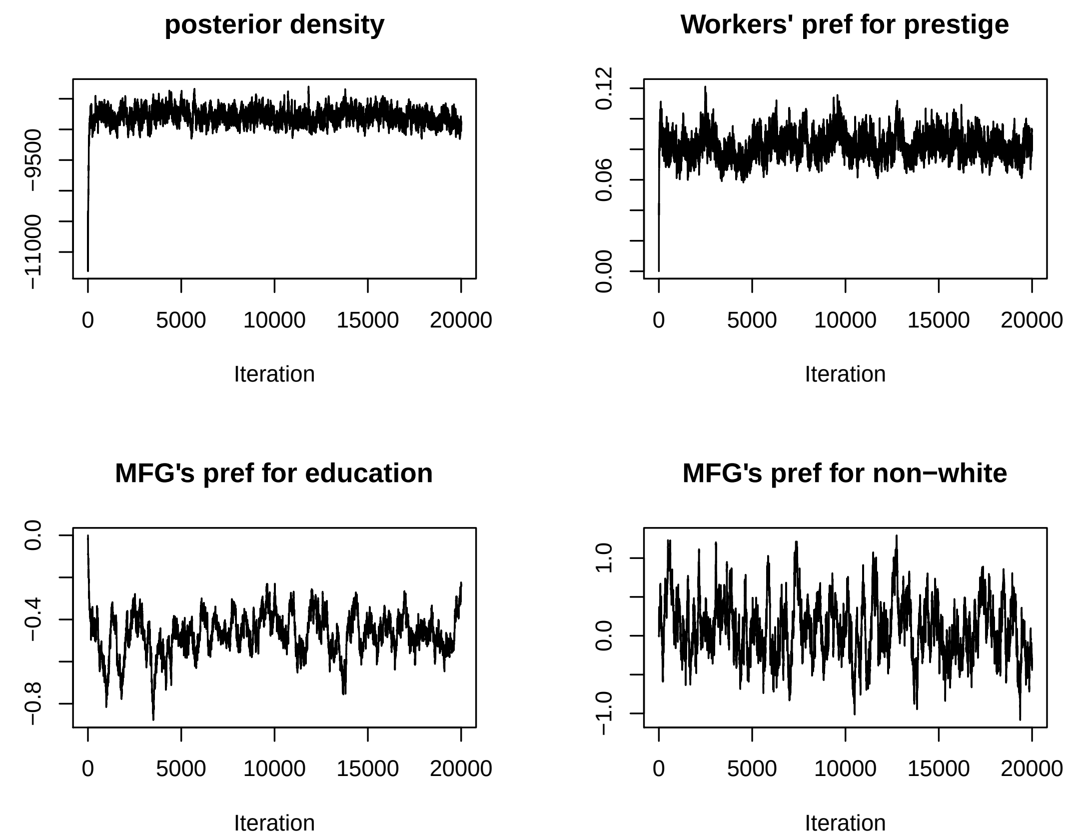

FIGURE 4.4: Trace plots of the posterior density and parameter samples, showing quick convergence.

5

Two-sided matching model on Japanese FDI

In this chapter, I apply the two-sided matching model to analyze Japanese FDI in Asia. In doing so, I demonstrate how the two-sided matching model can address the three issues in the current FDI literature. First, I estimate countries' varying preference for FDI. Second, I show how countries value different things in a subsidiary. Third, I use firm-level operational data that maps closer to our theoretical concept of FDI than FDI flow statistics.

Section 5.1 motivates the study of Japanese FDI in Asia. Section 5.2 describes the dataset. Section 5.3 discusses the variables used in the model. Section 5.4 shows the result.

5.1 The role of Japanese FDI in Asia

In the 1980s and 1990s, Japan FDI began to surge, becoming the second largest source of FDI, trailing only the US. An important factor behind this development is the decision to float the hitherto undervalued yen. As the yen began to rise in the 1980s and peak in 1995 against the dollar, Japanese companies invested heavily abroad since they now could buy foreign assets for cheap (Delios and Keeley, 2001).

During this period, Japanese FDI also shifted its focus away from the US and Europe, making Asia its top destination. Scholars have argued that this wave of Japanese FDI was instrumental to Asia's economic growth by bringing not just capital but also technological know-how and the opportunity to become integrated in the global production network. In this so-called "flying geese" model of economic development, industrial development spread from Japan, the leading goose, to the rest of Asia, e.g. the Four Asian Tigers (Hong Kong, Singapore, South Korea, Taiwan), ASEAN, and China, etc. (Bernard and Ravenhill, 1995; Kojima, 2000).

5.2 Data and sample choice

The dataset was compiled by Andrew Delios from the *Kaigai Shinshutsu Kigyou Souran* (Japanese Overseas Investments—by Country), 1986-1999 editions.[1] Japanese Overseas Investments is a biennial publication that contains operational data on all foreign affiliates of Japanese firms, collected by Tokyo Keizai, Inc. via a survey of these affiliates. The dataset is reputed to include all Japanese firms overseas (Yamawaki, 1991). Comparing the Japanese Overseas Investments data with other data sources on publicly listed firms, Delios and Keeley (2001) find that the dataset covers 98.5% of public firms, which in turn control 99.5% of the foreign subsidiaries. This high level of coverage ensures that our data captures the entire set of options available to countries and firms, obviating any worry about whether the choice set in the data represents the choice set in reality.[2]

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

[2] The mismatch between the choice set in the sample and in the population is an unexplored theoretical aspect of two-sided matching models. Consider an example where we analyze a sample of 1000 men and women in the US to estimate their mate preferences. How are our estimates affected by the assumption that each man's potential choice set includes all the women (and vice versa)? Not only does an individual not have that many acquaintances, his social circle is also not a representative sample of the entire dataset (Logan et al., 2008, 568). Fortunately, this is not a problem for our application. Given that there are only 9 Asian investment locations and approximately 200 Japanese subsidiaries being built each year, we can reasonably assume that they are all available to one another as potential options.

From this dataset, I make several choices restricting the sample to better fit with the assumption of the two-sided matching model.

First, I limit the sample to manufacturing subsidiaries in Asia. This way, it is more reasonable for our model to assume that all subsidiaries have the same set of preference parameters. Indeed, Pak and Park (2005) find that Japanese FDI in the West and in the East are fundamentally different—while subsidiaries in the West seek to augment their asset via R&D and marketing, subsidiaries in the East seek to exploit their asset by setting up local production with Japanese superior management. In addition, manufacturing FDI mainly consists of physical capital in the forms of property, plant, and equipment. Therefore, our data on the size of subsidiaries' capital maps more precisely to the concept of illiquid capital subjecting to the "obsolescing bargain" in Political Science theories.

Second, I limit the sample to subsidiaries that are founded in the year 1996. Because the MNCs' utility function in our model does not capture the fixed cost of relocating, it would be incorrect to include both subsidiaries that have already invested and those that are considering, then assume that they have the same set of preference. Indeed, as a linear combination of only country covariates, the utility function does not take into account the fact that, if the moving cost is too high, a subsidiary may not relocate to a new country even if the new country is available and is a better option.[3]

While the decision to limit the sample to subsidiaries founded in a particular year is theoretically motivated, the decision to choose the particular year of 1996 is simply to get the largest sample size. There may be concerns about 1996 being unique as the peak of an economic bubble, leading up to the 1997 Asian Financial

[3] Past applications of the two-sided matching model ignore this point and do not limit their sample to only agents that participate in the matching market around the same time (Logan, 1996; Logan et al., 2008). However, given that a defining characteristic of FDI is its relative immobility compared to other form of global capital, if we do not limit our sample, the model's assumption of zero switching cost would be too unreasonable.

Table 5.1: Number of Japanese manufacturing subsidiaries founded in 1996, by countries.

nation	n	percent
China	136	50.56
Indonesia	37	13.75
Malaysia	11	4.09
Philippines	13	4.83
Singapore	12	4.46
South Korea	8	2.97
Taiwan	9	3.35
Thailand	32	11.90
Vietnam	11	4.09

Crisis. However, our sample only includes manufacturing FDI, which, unlike equity investors and land developers, were largely unaffected by the financial crisis. In addition, FDI trend remained stable before and after the crisis in terms of inflow, exit rate, and profitability (Delios and Keeley, 2001; UNCTAD, 1998). In hindsight, this is not surprising as FDI firms tend to focus on countries' fundamentals and are thus unaffected by the fluctuations in the financial markets (Ahlquist, 2006).

In sum, the final sample includes 269 Japanese manufacturing subsidiaries in 1996, spreading across 9 Asian economies. China is the top destination, attracting 136 or 51% of Japanese subsidiaries (Table 5.1).

5.3 Variables

For subsidiaries' characteristics that countries consider, I include:

- Capital size (in real 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 often cannot muster much domestic capital from their poor population and underdeveloped financial market. Therefore, we may expect countries to prefer MNCs with a lot of capital.

- Labor size (number of employees): 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. Therefore, we may expect countries to prefer MNCs with a large labor demand.

- R&D intensity (amount spent in R&D as a percentage of revenue): The potential for technological spillover between MNCs' subsidiaries and local firms has been touted as a key to upgrading the host economy's productivity. To measure a subsidiary's technological capability, I use the R&D intensity of the parent firm, calculated as the amount spent on R&D as a percentage of revenue. Using the parent firm's R&D intensity is a reasonable proxy because Japanese FDI in Asia is mainly asset exploitation, i.e. implementing the know-how developed at the parent firm to the production at the subsidiary (Pak and Park, 2005).[4]

- Export intensity (amount earned via export as a percentage of revenue): Scholars have argued that economic growth in Asia is fueled by export and FDI as two mutually reinforcing forces (Liu et al., 2002). The subsidiary of an export-focused parent firm may help local suppliers become integrated into the global production network, improving the quality of their goods to match global standards and eventually being able to export themselves. Therefore, we may expect countries to actively look for investment from Japanese firms with an export focus.

For countries' characteristics that MNCs consider, I include the following variables from the Penn World Table:

- Market size (log GDP, constant 2005 USD): MNCs are expected to prefer

[4] Another measurement of a firm's intangible asset frequently used in the FDI literature is marketing intensity (Girma, 2005). Here I focus on R&D intensity because it is the more important factor for manufacturing firms.

countries with a large market size, which present MNCs with many potential customers and suppliers. In addition, market size is a key variable in the gravity model, a standard model for analyzing FDI (Bergstrand and Egger, 2007).

- Level of development (log GDP per capita, constant 2005 USD): As a measure of country income, development should attract more MNCs as MNCs prefer countries with more disposable income to consume. On the other hand, as a measure of countries' capital abundance, development should reduce FDI inflow as MNCs' capital is no longer a big advantage.

- Human capital (Penn World Table index): As one primary factor of production, labor matters greatly to firms' productivity and profit. To measure labor quality, I use the human capital index developed for the Penn World Table, which incorporates not just years of education but also the productivity level of labor (Feenstra et al., 2015). Because the human capital index does not have a substantively interpretable unit, I standardize the variable so that it has a standard deviation of 1.

In sum, the model for the utility functions are:

- MNC i's utility for country j: $U_i(j) = \boldsymbol{\alpha}' W_j$, where W_j includes log GDP, log GDP per capita, and human capital index.

- Country j's utility for MNC i: $V_j(i) = \beta_{0j} + \boldsymbol{\beta_j'} X_i$, where X_i includes log number of employees, log capital size, R&D intensity, and export intensity.

5.4 Result

The results below are produced by an MCMC chain with 4×10^6 iterations and a thinning interval of 10, resulting in 4×10^5 saved iterations. The starting values for all preference parameters are set at 0. I put a diffuse prior on α, specifically a Normal distribution with mean 0 and variance 100.

As discussed in Section 3.6, since our sample does not include MNCs that choose the reservation choice, i.e. staying home instead of investing abroad, the estimate for the β intercept will be too high. To combat this problem, I use an informative prior so that β_{0j} approximately follows a Normal distribution with mean -1 and variance 10.[5]

Figure 5.1 shows the posterior distribution and the 95% credible interval for MNCs' preference parameters. We can interpret the parameters as the relative weight MNCs attach to countries' characteristics when they decide where to invest. For example, the posterior mean for log GDP and for log GDP per capita is 0.72 and 0.66—this means that to MNCs, a 1% increase in GDP is equivalent to 0.72 / 0.66 = 1.09% increase in GDP per capita.

The coefficients for log GDP and log GDP per capita are both positive and significant, suggesting that Japanese MNCs are looking for large markets with a lot of disposable income. On the other hand, the coefficient for human capital is negative, corroborating earlier findings in the literature that Japanese MNCs in Asia do not aim to be innovative and thus have no need for strong human capital. On the contrary, since the human capital index includes not only years of education but also labor productivity, a high human capital index may signify high labor cost, explaining why Japanese manufacturing MNEs weigh it negatively.

In addition to interpreting the coefficients as weights in the MNCs' utility function, we can also simulate and visualize their impact on MNCs' location choice. For example, we may ask if country A's GDP increases by 20%, what will be the new share of MNCs that invest in country A? Like in the one-sided conditional logit

[5] Specifically, the prior for β_{0j}'s mean is Normal with mean -1 and variance 1. The prior for β_{0j}'s variance is Inverse-Wishart with $\nu = 7$ and $S^{-1} = 10$ so that the variance is loosely centered around 10.

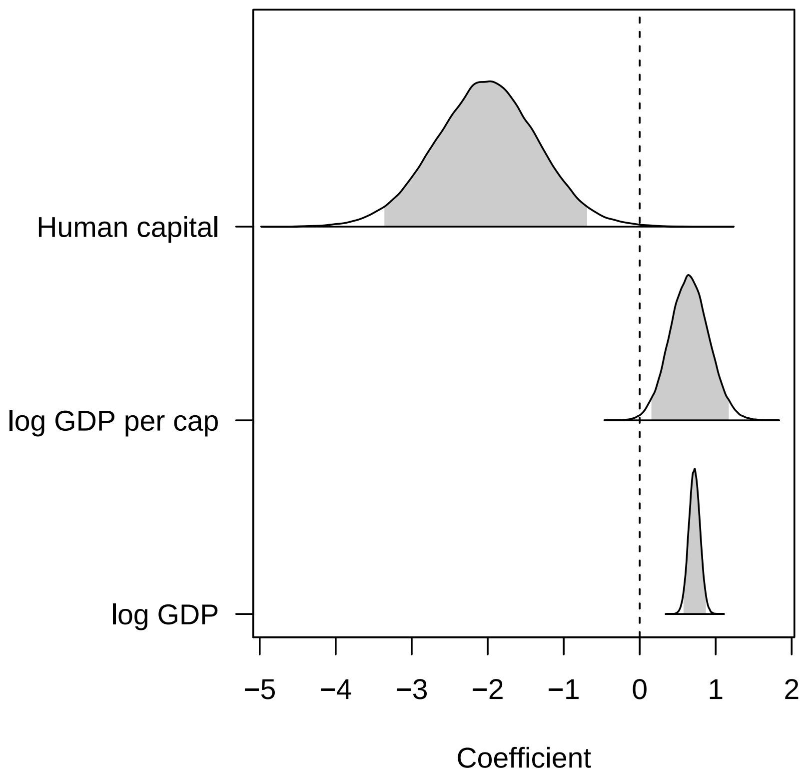

Figure 5.1: MNCs' preference for countries' characteristics. The density plot and the shaded region show the posterior distribution and the 95% credible interval.

model, the share of MNCs investing in country A depends not only on country A's characteristics but also on others'. In addition, in this two-sided model, the share of MNCs investing in a country also depends on the preference of countries. For example, even if country A becomes highly desirable, we may not see much change in the share of MNCs located there if country A's preference is also highly demanding. The interaction between share of MNCs and countries' preferences can be much more complicated. Consider a scenario in which country A and country B have similar preferences and compete for the same set of MNCs. Even if country A becomes more desirable than the rest of the countries, as long as country A is less attractive than country B, the share of MNCs investing in country A will still remain unchanged.

Fortunately, we can easily simulate these effects in the Bayesian framework. For example, to see how the share of MNCs investing in Thailand changes along with hypothetical values of Thailand's GDP, we take the following steps:

1. Construct a scenario in which Thailand has a new GDP, while all other characteristics remain for Thailand and other countries
2. Make one draw for each parameter in the model from its posterior distribution
3. Simulate the matching process in which countries first make offers to MNCs, and MNCs then choose the best option
4. Record the share of MNCs investing in Thailand after the matching process
5. Repeat step (2)-(4) to get a distribution for the share of MNCs in Thailand[6]

Following this process, I calculate the share of Japanese MNCs in Thailand at different hypothetical values of Thailand's GDP. Figure 5.2 shows that as Thailand's GDP increases from 50% to 150% of its true value, the share of MNCs in Thailand increases from 8% to 15%. In addition, the share of MNCs investing in Indonesia and Malaysia, two competitors of Thailand in ASEAN, declines slightly as Thailand becomes more attractive.

Similar to the interpretation of MNCs' preference parameters, we can also interpret countries' preference parameters as the relative weight that countries attach to MNCs' characteristics. Figure 5.3 shows that Taiwan wants to attract MNCs that are export-focused and discourage MNCs that employ a lot of employees. On the other hand, the estimates for Indonesia's preference parameters are not statistically significant, perhaps due to our small sample size.[7]

[6] Essentially we are constructing the posterior predictive distribution for the share of MNCs in

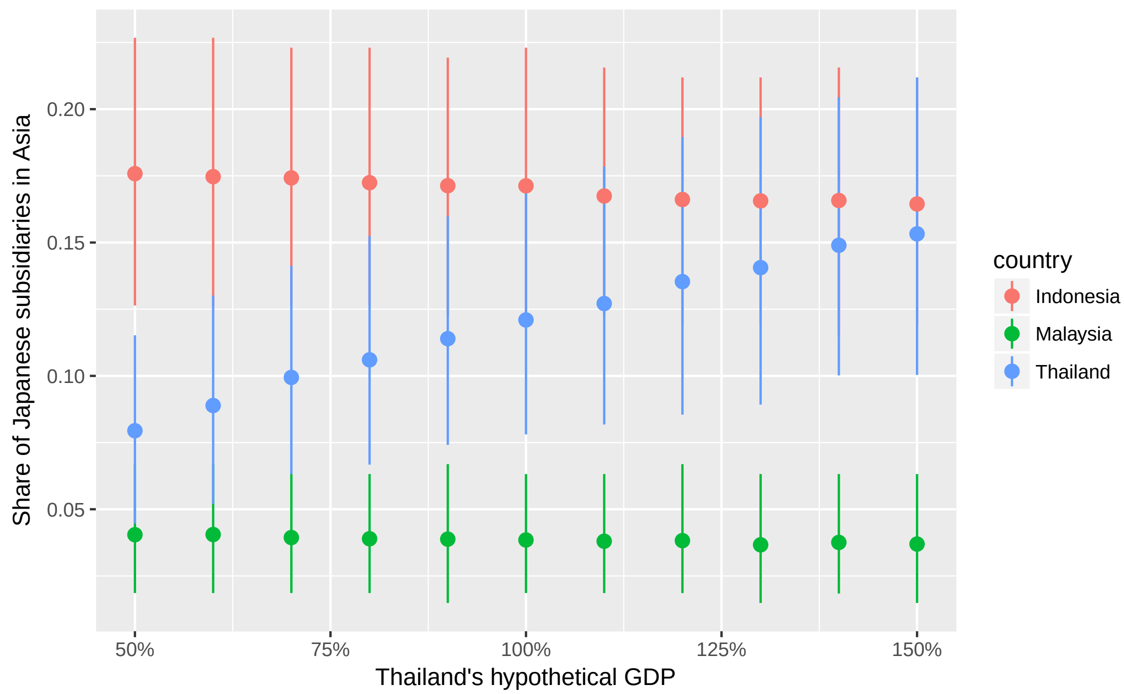

FIGURE 5.2: Effect on Thailand's GDP on its share of MNCs. The point and line range show the mean and the 95% credible interval.

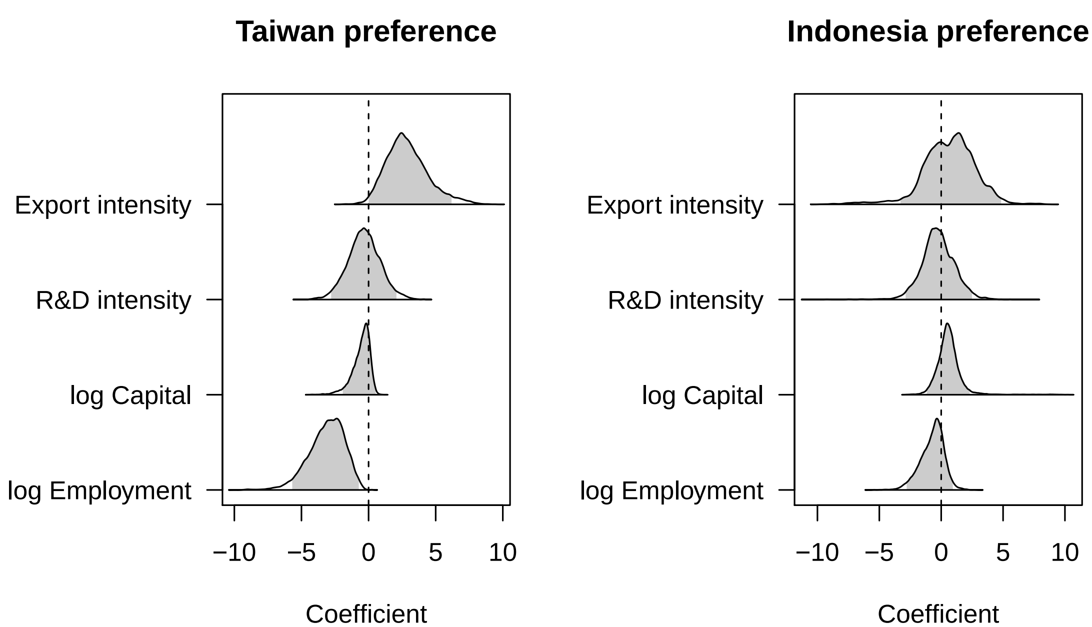

FIGURE 5.3: Preference of Taiwan and Indonesia for MNCs' characteristics.

While the relative size of preference parameters within a country is meaningful, we cannot readily compare preference parameters across countries. This is because coefficients in the logit model is normalized so that the variance of the unobserved factors in the utility function becomes 1. Therefore, the relative size of coefficients across two countries may be affected by the relative variance of the unobserved factors in the utility functions of those two countries (Train, 2009, chap. 2). Since there is no guarantee that the unobserved factors will be the same or have the same variance across countries, we cannot say that, for example, Taiwan values export intensity more than Vietnam because Taiwan's coefficient for export intensity is larger.

We can, however, look at the sign of the estimates to see whether countries evaluate an MNC's trait positively or negatively. Figure 5.4 and Figure 5.5 show countries' preference for labor size, capital size, R&D intensity, and export intensity. Most countries seem to dislike subsidiaries with a large labor force—this is likely because labor size is correlated with other factors that we are not capturing in our model, e.g. certain sectors in manufacturing or the level of productivity. On the other hand, several countries including Taiwan, Malaysia, and Thailand, seem to prefer subsidiaries that focus on export. This finding affirms our understanding of these economies as being export-driven.

In addition, we can simulate and visualize the impact of countries' preference on MNCs' location choice. Using the steps described above to simulate the posterior predictive distribution, Figure 5.6 shows how the distribution of Japanese MNCs across Asian countries will change if China becomes more stringent in its evaluation of MNCs. As China becomes as picky as South Korea (i.e. China's intercept is decreased to match South Korea's on average), the share of MNCs located in China

Thailand, integrating out the preference parameters via simulation.

[7] I present the results for Taiwan and Indonesia here because they are two countries highly desired by MNCs. As discussed in Section 3.6, the estimate for highly desirable countries are more accurate.

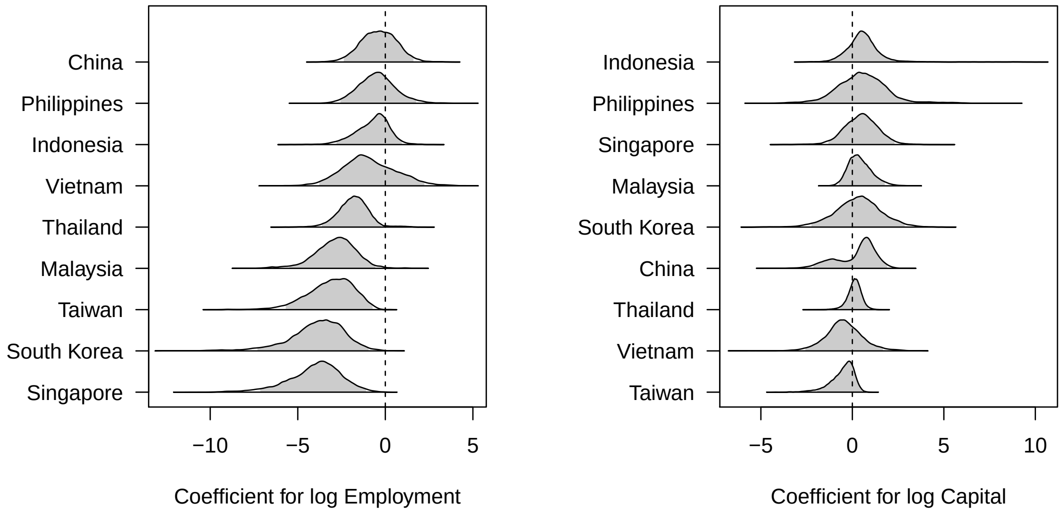

FIGURE 5.4: Countries' preference for subsidiaries' size, measured by their labor force (left) and capital (right). The density plot and the shaded region show the posterior distribution and the 95% credible interval.

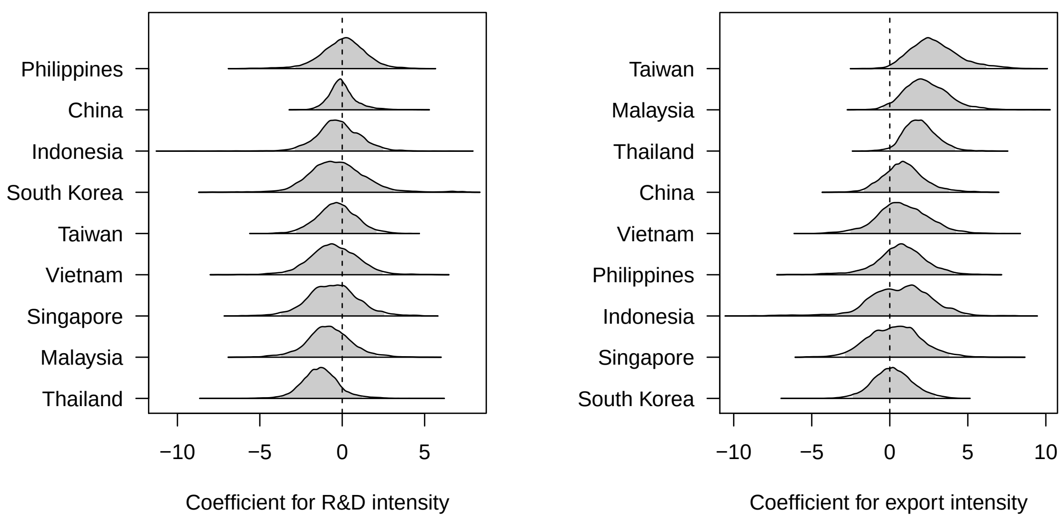

FIGURE 5.5: Countries' preference for firms' intangible assets, i.e R&D intensity (left) and export intensity (right). The density plot and the shaded region show the posterior distribution and the 95% credible interval.

decreases from 47% to 20%, a change of 27 percentage points. Of these 27 percentage points, 20 go to Indonesia and Thailand, the two biggest beneficiaries of China's reduced appetite for FDI. On the other hand, the share of MNCs in Singapore, South Korea, and Taiwan remains virtually unchanged, suggesting that China is not competing for the same MNCs as these countries.

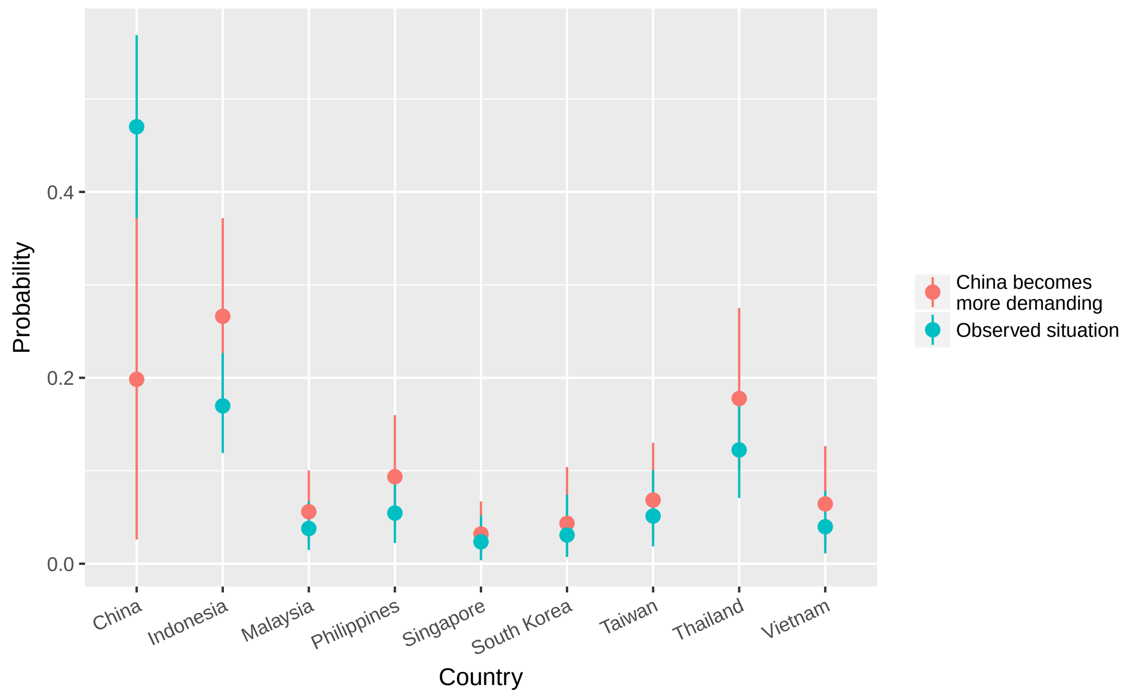

FIGURE 5.6: Effect of China's demand for MNCs on MNCs' location across Asia. If China becomes as picky as South Korea, its share of MNCs will decrease from 47% to 20%. The majority of these MNCs will relocate to Indonesia and Thailand.

5.5 Model fit

To check that our model fits well to the data, we can conduct posterior predictive checks, generating simulated matchings and comparing them with observed matching.

Since the location of MNCs is something we model directly, we at least expect our model to have a good fit with the observed location. Figure 5.7 shows that our model performs well in this regard—the predicted share of MNCs across countries match the observed share exactly in most cases and well within the 95% credible interval for all cases.

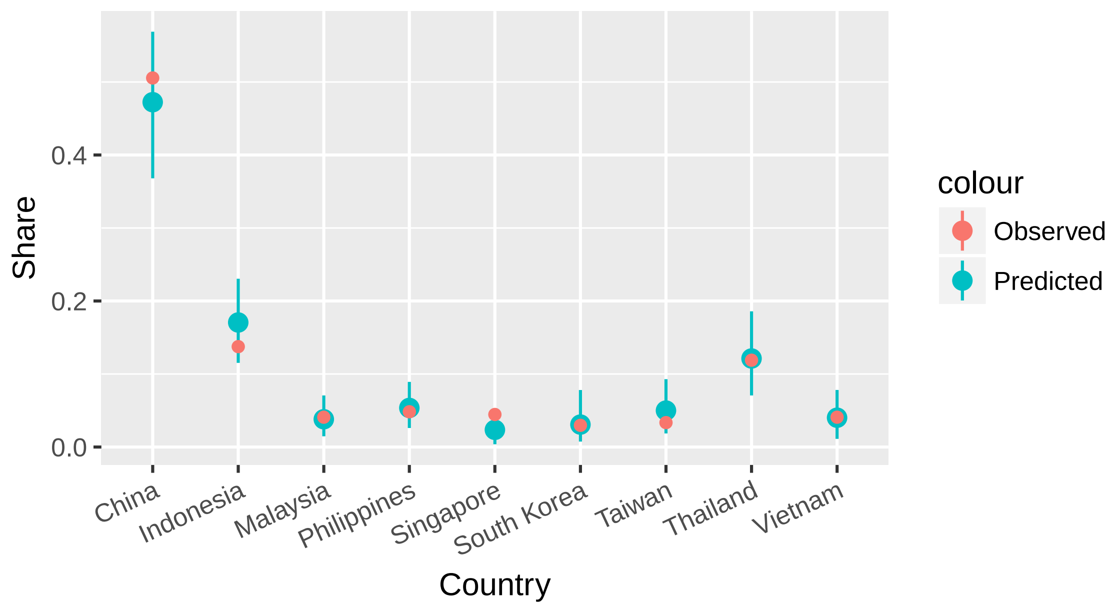

FIGURE 5.7: Predicted and observed share of MNCs across countries. The point and the error bar show the posterior mean and the 95% credible interval.

In addition, by conducting the posterior predictive checks for aspects of the data that we do not model directly, we gain a deeper understanding into what part of reality our model does not capture. Since we may be interested in not only the share of MNCs across countries, but also which types of firms are located in which countries, I conduct the posterior predictive checks for MNCs' characteristics across countries. Figure 5.8 and Figure 5.9 show that our model captures the mean and the variance of of MNCs' size across countries relatively well, with the observed mean and variance of log Employee lying within the 95% interval for all cases. Admittedly the 95% interval is really wide for many countries, reflecting the lack of precision in the estimates for countries' preference, likely due to the small sample size.

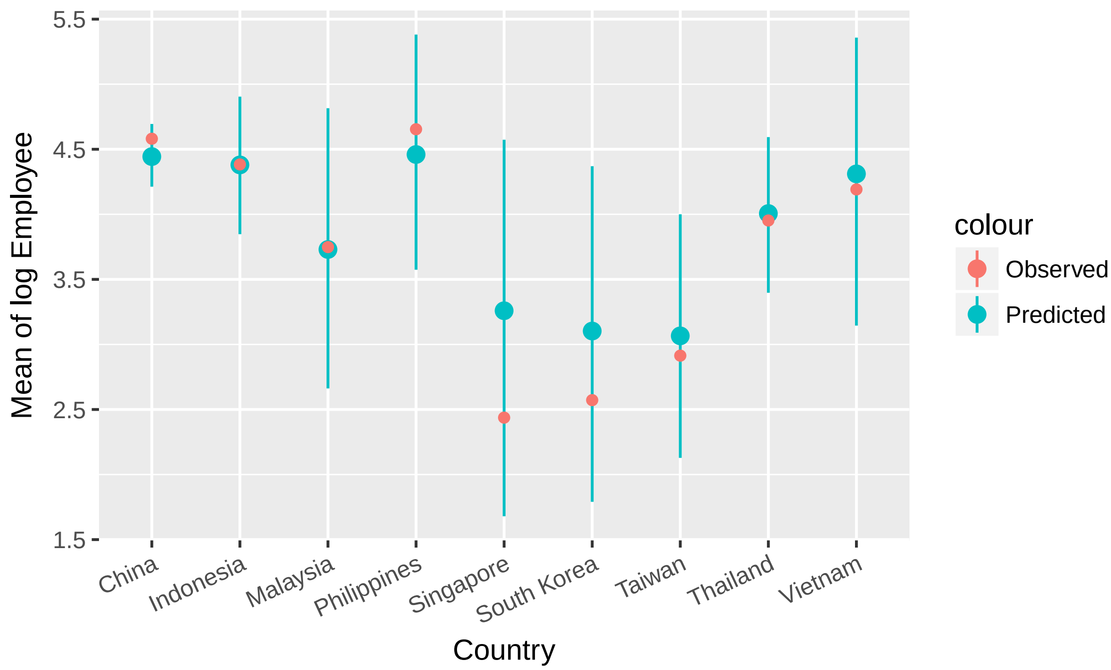

FIGURE 5.8: Average of MNCs' labor size across countries.

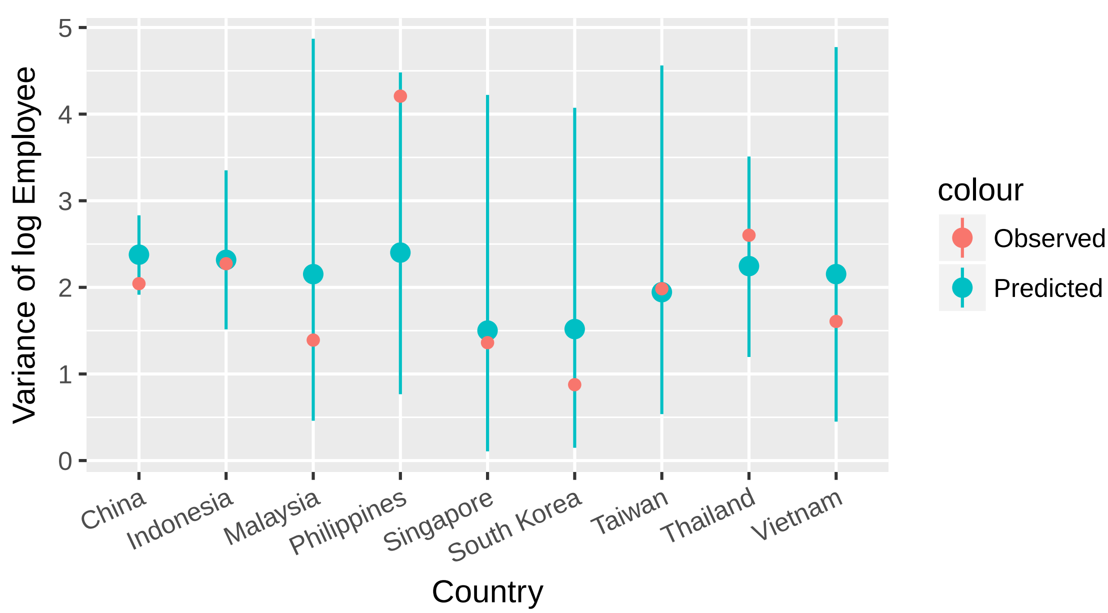

FIGURE 5.9: Variance of MNCs' labor size across countries.

6

Conclusion

6.1 Other applications for two-sided matching model

6.1.1 US federal clerkship market

In the US, graduates at top law schools vie for the best federal clerkships every year. These temporary, one-to-two-year positions are the launching pad for Supreme Court clerkships, prestigious teaching jobs, or employment at top law firms. On the other side, federal judges also compete for the best law graduates, who help reduce the judges' workload from copy-editing to drafting opinions (Gulati and Posner, 2016; Posner, 2001). Because the first clerkship tends to have an outsized ideological influence on law graduates, this matching market has important implications for the polarization of the judicial branch (Ditslear and Baum, 2001; Liptak, 2007).

The market for US federal clerkship has been noted as a classic case of a two-sided market. Clerks look for positions that provide not only prestige and connection but also comfortable quality of life (Posner, 2001). Judges select law graduates based on not only academic credentials but also, some argue, ideology, gender, and race (Slotnick, 1984). This market also suffers from strategic behavior emblematic of a matching market, such as offers being made aggressively early and with a short time to accept (Posner, 2001; Posner et al., 2007).

One approach to estimating the preference of agents in this market is to survey clerks and judges directly (Peppers et al., 2008). However, as discussed, this approach only measures stated preference, which is likely to suffer from social desirability bias when it comes to dimensions that we care about most such as matching based on ideology, gender, or race.

Other approaches estimate revealed preference by using observed hiring outcome. However, no existing study has properly taken into account the two-sided nature of the market, thus confusing the effects of preference and opportunity. For example, Bonica et al. (2017) use political contribution data (DIME dataset) to measure political ideology, then correlate the ideology of the hiring judge and the ideology of his clerks. This approach does not take into account the pool of applicants, leading to conclusions such as conservative judges hire more liberal clerks than conservative clerks (Bonica et al., 2017, 31). This curious finding has a potentially simple explanation: the pool of top law graduates tend to be overwhelmingly liberal, leaving conservative judges with no choice. Despite this issue, the authors proceed to measure judges' ideology by taking the average of their clerks' ideology. Without taking the pool of applicants into account, they may wrongly conclude that conservative judges are more liberal than they actually are.

In another approach, Rozema and Peng (2016) model the process as a discrete choice problem, in which clerks are differentiated products that Supreme Court justices select to maximize their utilities. Their model does not consider what clerks think about the offer because of their focus on Supreme Court clerkships, whose unparalleled prestige ensures that any offer made will be accepted. However, if we want to extend the model to the broader market of federal clerkship, such assumption is untenable.

6.1.2 The market for forming a coalition government

Besides election, government formation is the most consequential political process in determining which government people are subject to. Most extant studies of government formation are either game theoretic models or thick, "inside-the-Beltway" narratives. Potential advances can be made if we consider government formation as a many-to-one matching market, with the *formateur* party on one side and other minority parties on the other.[1]

A two-sided matching model of government formation would complement the game theory literature that models politicians as policy-seeking (as opposed to office-seeking) (Laver, 1998). When politicians are policy-seeking, parties have policy positions that can be modeled as their characteristics. Then, parties choose one another to form a coalition based on their policy positions, akin to men and women choosing one another to form a marriage based on their height or income.[2] As the game theory literature suggests, ideologically compact coalitions are more valuable because they entail a smaller cost in terms of policy compromises (De Swaan, 1973). With the empirical matching model, we can test if parties do indeed prefer others that are ideologically close to themselves.

In addition, an advantage of the two-sided matching approach is its ability to consider multidimensional policy spaces. By considering a party's positions on various policies as their covariates, we would be able to estimate parties' relative preference for ideological proximity across policy dimensions.

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[1] The *formateur* party could be the one with the procedural power to set up the coalition, e.g. the incumbent party, or the largest party in established coalitions.

[2] In contrast, when politicians are office-seeking, the only coin of the realm is the number of legislative seats that a party controls. It determines both the inclusion of the party in the government and its portfolio allocation. In this framework, concepts like power indices and dominant parties are all about how parties can bring its controlled seats to a coalition to turn it into a winning coalition.

Appendix A

Derivation of the Metropolis-Hastings Acceptance Ratio

A.0.1 Opportunity sets O

Target distribution for a firm i

$$p(O_i|A_i, \alpha, \boldsymbol{\beta}) = \frac{p(O_i, A_i, \alpha, \boldsymbol{\beta})}{p(A_i, \alpha, \boldsymbol{\beta})} \tag{A.1}$$

$$\begin{aligned} MH_O = \frac{p(O_i^*|A_i, \alpha, \boldsymbol{\beta})}{p(O_i|A_i, \alpha, \boldsymbol{\beta})} &= \frac{p(O_i^*, A_i, \alpha, \boldsymbol{\beta})}{p(A_i, \alpha, \boldsymbol{\beta})} \times \frac{p(A_i, \alpha, \boldsymbol{\beta})}{p(O_i, A_i, \alpha, \boldsymbol{\beta})} && \text{(A.2)} \\ &= \frac{p(O_i^*, A_i, \alpha, \boldsymbol{\beta})}{p(O_i, A_i, \alpha, \boldsymbol{\beta})} && \text{(A.3)} \\ &= \frac{p(A_i|O_i^*, \alpha)p(O_i^*|\boldsymbol{\beta})}{p(A_i|O_i, \alpha)p(O_i|\boldsymbol{\beta})} && \text{(A.4)} \\ & && \text{(A.5)} \end{aligned}$$

where the factorization of the likelihood in (A.4) 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 (2.10) and (2.8)

$$\frac{p(O_i^*|A_i,\alpha,\boldsymbol{\beta})}{p(O_i|A_i,\alpha,\boldsymbol{\beta})} = \frac{\sum\limits_{j:j\in O_i}\exp(\alpha' W_j)}{\sum\limits_{j:j\in O_i}\exp(\alpha' W_j)+\exp(\alpha' W_{j^*})} \times \exp(\boldsymbol{\beta}'_{j^*}X_i) \tag{A.6}$$

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

$$\frac{p(O_i^*|A_i,\alpha,\boldsymbol{\beta})}{p(O_i|A_i,\alpha,\boldsymbol{\beta})} = \frac{\sum\limits_{j:j\in O_i}\exp(\alpha' W_j)}{\sum\limits_{j:j\in O_i}\exp(\alpha' W_j)-\exp(\alpha' W_{j^*})} \times \exp(-\boldsymbol{\beta}'_{j^*}X_i) \tag{A.7}$$

A.0.2 Workers' parameters, α

Target distribution:

$$p(\alpha|A,O,\boldsymbol{\beta}) = \frac{p(O,A,\alpha,\boldsymbol{\beta})}{p(A,O,\boldsymbol{\beta})} \tag{A.8}$$

Metropolis-Hasting acceptance ratio:

$$MH_\alpha = \frac{p(\alpha^*|A,O,\boldsymbol{\beta})}{p(\alpha|A,O,\boldsymbol{\beta})} = \frac{p(A_i|O_i,\alpha^*)p(O_i|\boldsymbol{\beta})p(\alpha^*)}{p(A_i|O_i,\alpha)p(O_i|\boldsymbol{\beta})p(\alpha)} \tag{A.9}$$

$$= \frac{p(A_i|O_i,\alpha^*)p(\alpha^*)}{p(A_i|O_i,\alpha)p(\alpha)} \tag{A.10}$$

where (A.10) is due to the symmetric proposal distribution (so $\frac{p(\alpha^*|\alpha)}{p(\alpha|\alpha^*)}=1$)

If we plug in (2.10),

$$MH_\alpha = \prod_i \left[\frac{\exp(\alpha^{*\prime} W_{a_i})}{\exp(\alpha' W_{a_i})} \times \frac{\sum\limits_{j:j\in O_i} \exp(\alpha' W_j)}{\sum\limits_{j:j\in O_i} \exp(\alpha^{*\prime} W_j)} \right] \times \frac{p(\alpha^*)}{p(\alpha)} \tag{A.11}$$

$$= \prod_i \left[\exp(\epsilon_\alpha' W_{a_i}) \times \frac{\sum\limits_{j:j\in O_i} \exp(\alpha' W_j)}{\sum\limits_{j:j\in O_i} \exp(\alpha^{*\prime} W_j)} \right] \times \frac{p(\alpha^*)}{p(\alpha)} \tag{A.12}$$

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

$$\log MH_\alpha = \sum_i \left[\epsilon_\alpha' W_{a_i} + \log \left(\sum_{j:j\in O_i} \exp(\alpha' W_j) \right) - \log \left(\sum_{j:j\in O_i} \exp(\alpha^{*\prime} W_j) \right) \right] + \log p(\alpha^*) - \log p(\alpha) \tag{A.13}$$

A.0.3 Firms' parameters, β

Target distribution:

$$p(\boldsymbol{\beta}|A, O, \alpha) = \frac{p(O, A, \alpha, \boldsymbol{\beta})}{p(A, O, \alpha)} \tag{A.14}$$

Metropolis-Hasting acceptance ratio:

$$MH_\beta = \frac{p(\beta^*|A, O, \alpha)}{p(\beta|A, O, \alpha)} = \frac{p(A_i|O_i, \alpha) p(O_i|\boldsymbol{\beta}^*) p(\boldsymbol{\beta}^*|\mu_\beta, \tau_\beta)}{p(A_i|O_i, \alpha) p(O_i|\boldsymbol{\beta}) p(\boldsymbol{\beta}|\mu_\beta, \tau_\beta)} \tag{A.15}$$

$$= \frac{p(O_i|\boldsymbol{\beta}^*) p(\boldsymbol{\beta}^*|\mu_\beta, \tau_\beta)}{p(O_i|\boldsymbol{\beta}) p(\boldsymbol{\beta}|\mu_\beta, \tau_\beta)} \tag{A.16}$$

where (A.15) is due to the symmetric proposal distribution.

We plug in (2.8),

$$MH_\beta = \prod_i \left[\prod_{j \in O_i} \frac{\exp(\beta_j^{*\prime} X_i)}{\exp(\beta_j^{\prime} X_i)} \times \prod_j \frac{1 + \exp(\beta_j^{*\prime} X_i)}{1 + \exp(\beta_j^{\prime} X_i)} \right] \times \frac{MVN(\boldsymbol{\beta}^* | \mu_\beta, \tau_\beta)}{MVN(\boldsymbol{\beta} | \mu_\beta, \tau_\beta)} \tag{A.17}$$

$$\log MH_\beta = \sum_i \left[\sum_{j \in O_i} \beta_j^{*\prime} X_i - \beta_j^{\prime} X_i + \sum_j \log(1 + \exp(\beta_j^{*\prime} X_i)) - \log(1 + \exp(\beta_j^{\prime} X_i)) \right] \tag{A.18}$$

$$+ \log MVN(\boldsymbol{\beta}^* | \mu_\beta, \tau_\beta) - \log MVN(\boldsymbol{\beta} | \mu_\beta, \tau_\beta)$$

Appendix B

FDI terminology

Samsung, headquartered in South Korea, opened a factory in Vietnam called Samsung Electronics Vietnam.

In this scenario, Samsung Korea is the *parent company*, and Samsung Electronics Vietnam is the *subsidiary*, also the *(foreign) affiliate*. Empirically, the parent company and the subsidiary are two distinct entities (i.e. having a different number of employees, revenue size, profitability, etc.) Theoretically, they negotiate with and are evaluated by Vietnam as one entity. Therefore, in theoretical discussion, I refer to Samsung Korea and Samsung Electronics Vietnam jointly as the *MNC*.

South Korea is the *home country*, and Vietnam is the *host country* or the *local country*. I thus refer to Vietnam's economy and firms as the local economy and local firms.

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