Estimating the Preference of Countries and Multinational Corporations Using 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 Political Science
in the Graduate School of Duke University
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Abstract

A foreign direct investment (FDI) project can only materialize with the consent of both the multinational corporation (MNC) and the host country. However, despite this two-sided nature of the FDI market, the literature on FDI has focused only on the preference of MNCs, assuming that all countries are eager to receive FDI. Through various case studies, I show that countries have varied and strategic preference, which plays a substantial role in determining where FDI locates. Failing to recognize this two-sided matching nature of the FDI market, not only do existing models of FDI produce wrong estimates of MNCs' preference, they also prevent us from understanding countries' FDI policies. Therefore, I introduce the two-sided matching model as a more appropriate approach to the FDI market and the Bayesian Markov chain Monte Carlo algorithm to estimate it. Applying the model to study Japanese FDI in Southeast Asia, I show how to estimate the preference of MNCs and countries for one another. With this model, scholars can better understand what drives FDI location, and policy makers can better simulate FDI movement under hypothetical policy changes.

For my wife and my parents.

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List of Abbreviations and Symbols

Abbreviations

AmCham	American Chamber of Commerce
ASEAN	Association of Southeast Asian nations
DGP	Data generating process
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
MOM	Method of moments
MSM	Method of simulated moments
MVN	Multivariate normal
SOE	State-owned enterprise
UNCTAD	United Nations Conference on Trade and Development

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1

Introduction

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).[1] Within the scholarly field of International Political Economy (IPE), much of the literature starts with the view that countries will always seek FDI for its various benefits (Jensen, 2008a). Works in IPE tend to 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).[2]

However, such an assumption is no longer tenable given the mounting evidence

[1] While FDI into developed economies dropped almost 50% during the 2000 recession and the 2008 financial crisis, FDI into developing countries only experienced a plateau or a small reduction. More recently, as global FDI flow slipped in 2016 and 2017, FDI into developing countries still remained stable (UNCTAD, 2018).

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

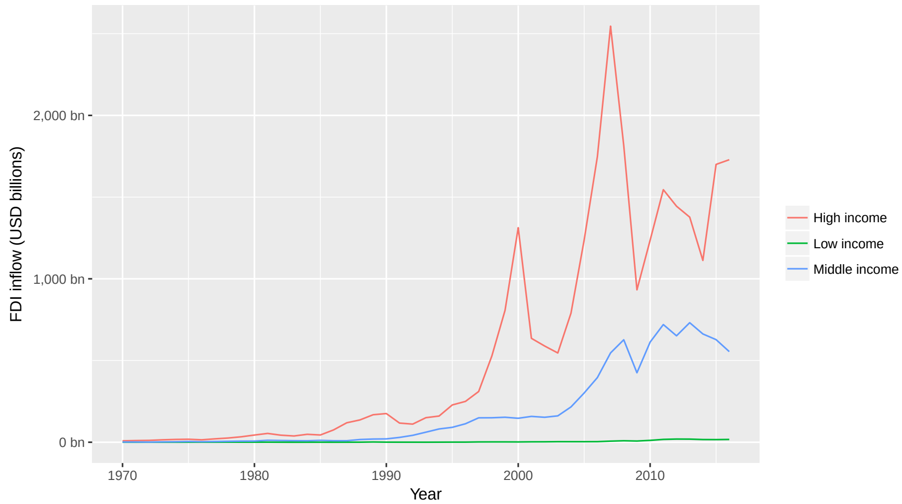

FIGURE 1.1: FDI global inflow, 1970-2006. The last four decades witness the growth of FDI into the most important source of global capital. Source: World Bank's World Development Indicators.

that not all FDI are the same and that its effects are highly conditional. Countries' benefit from FDI, if any, depends on the sophistication of their labor force, the technical capability of their domestic business, and various government policies. Indeed, reviewing the vast yet inclusive literature on the effects of FDI, Lipsey and Sjoholm (2005) suggest "the main lesson might be that the search for universal relationships [between FDI and host country economic performance] may be futile."

If the effects of FDI are so conditional, it is unreasonable 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" (RTB) thesis of globalization. According to the RTB thesis, because footloose global capital can threaten to move if it deems a country's policies unfavorable, countries will converge towards the same business-friendly policies in the hope of retaining capital. However, the RTB thesis has proven to be empirically wrong. Because constituencies across countries hold different preference over economic growth, inequality, social protection, regulation, and many other dimensions, each country will offer a different bundle of these goods, suitably crafted for its own constituency. Indeed, scholars have shown that governments maintain substantial autonomy and variation in the realm of fiscal, social, and environmental policies (Mosley, 2005). There is thus no reason to believe that FDI policies are somehow uniform across the globe.

Arguably, political scientists should be dissatisfied with the current literature on the political determinants of FDI. The status quo often involves adding a political variable to an existing economic model of FDI and checking for its effect. In this approach, states are just billiard balls of different shapes and size for MNCs to pick and choose, and left unpacked is the effect of internal politics on FDI policies. Furthermore, even if we only care about MNCs' preference with regards to countries' characteristics, to get an accurate estimate we must still take into account countries' preference. For example, take the received wisdom that democracies receive more FDI (Jensen, 2008b). Without taking into account countries' preferences, it is difficult to interpret this finding as democracies actively pursuing MNCs or as MNCs finding democracies attractive.

1.1 Plan of the research

My research 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.[3] 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 groundbreaking, 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" vs "pull" factors of FDI flow.[4] Using a two-sided matching model, I will naturally be able to estimate both sides' preference.

Second, I am able to estimate countries' preference for different types of FDI. While the IPE literature has largely focused on the quantity of FDI flow, countries care deeply about its type. They use various incentives and restrictions to target FDI that invests in a remote region, brings new technology, or improves the balance of payment by exporting and bringing back foreign currencies (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). As UNCTAD (2015) proclaims, "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." Two-sided matching model can be used to estimate countries' preference for different types of FDI. Just as it can estimate MNCs' utility function for countries' characteristics (e.g. market size, level of development), two-sided matching model can estimate countries' utility function for MNCs' types (e.g. technological sophistication, export strategy).

Third, while the majority of the literature uses FDI flow data, these data are

[3] Evans et al. (1985)'s book, "Bringing the state back in," argues that states are weighty actors with their own capabilities and initiatives, and are not merely an arena for societal and interest groups to negotiate their share. Here, I argue that states are weighty actors with their own preferences regarding which MNC is allowed inside its border, and are not merely passive receivers of FDI.

[4] "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.

accounting constructs created to keep track of countries' balance of payment. They 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.

In sum, my research 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.

I also develop the methods to estimate the two-sided matching model. If we could observe not only subsidiaries' locations but also their set of options (called their "opportunity set" in the matching literature), estimating this model would be straightforward with existing methods.[5] 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

[5] 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. However, by not taking into account the two-sided nature of the FDI market, these models assume that all countries are available as potential locations for all MNCs. Thus, to use discrete choice models in studying FDI location choice is to ignore the fact that not all MNCs have the same set of location options (Arauzo-Carod et al., 2010).

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."

1.2 Relevance of the research to FDI policy formulation

During my time at the World Bank in 2017, an official opined that many of his country clients needed help with formulating their FDI attraction policies. Regardless of their situations, most country clients want to increase their FDI inflow, ideally in high-tech industries, relying on fiscal incentives such as tax holiday, land concession, or lower utility price. Economists tend to look askance at such heavy-handed industrial policy. Rather than encouraging governments to pick winners, the World Bank gives governments the sanctioned advice of getting the fundamentals right, i.e. liberalizing trade and investment, upholding rule of law, eradicating corruption, and upgrading its labor force. Perhaps not coincidentally, most of the FDI literature has also focused on studying what country characteristics are attractive to MNCs, settling on the same familiar list of desirables.

These two approaches to industrial policy veer towards the extremes, one trusting and the other dismissive. At the same time, they are also similar. Both neglect the fact that a country's FDI inflow depends not only on its policies but also on the competitive landscape in which it is situated. In formulating their FDI strategies, policy makers should neither solipsistically determine what sectors they want, nor abstractly ask what macro conditions are associated with FDI inflow. Rather, they are better off preparing strategically for realistic scenarios. For example, given China's rising wage and tougher environmental regulations, how much and what type of FDI will diversify out of China? What share of that outflow can our country capture at the current condition? How much can we capture if we improve our labor productivity by 5% or 15%? How much can we capture if other countries also increase their GDP per capita by 10% in the mean time? Once I estimate MNCs' and countries' preference, I can simulate their decisions under such scenarios, allowing policy makers to better strategize their FDI attraction. To quote Sun Tzu's "The Art of War" (as the business community is apt to do), "If you know the enemy and yourself, you need not fear the result of a hundred battles."

In other words, my research gives policy makers the tool to formulate better informed FDI policy. The time is right for such an approach. First, the opportunity is there to target the FDI that China no longer attracts. As China becomes more expensive, aims to move into high-tech manufacturing, and reverses their preferential treatment, MNCs are looking towards diversifying into other countries. Despite Chinese president Xi Jinping's globalist tone at the 2017 World Economic Forum in Davos, affirming that "China's door will not close to the world but open wider," MNCs are increasingly skeptical.[6] In 2013, an American lawyer in Phnom Penh said that, "Every couple days, I'm getting calls from manufacturers who want to move their businesses here from China" (Bradsher, 2013). By 2017, in the annual survey by the American Chamber of Commerce (AmCham) in China, a quarter of respondents reported that they had either moved operations out of China or were planning to do so, with nearly half moving to other parts of Asia (AmCham China, 2018). To form an effective response to this capital movement, countries need the tool to simulate what share of this FDI outflow can they capture, especially in consideration of other countries' competitive response.

Second, there has been a resurgent appetite for industrial policy in the development community, including the World Bank, the largest and most influential banker-cum-consultant for the developing world. For a long time, World Bank economists disavow industrial policy so completely that the East Asian miracle,

[6] https://www.nytimes.com/2017/12/06/business/china-global-business-xi-jinping.html

arguably the clearest example of state-led industrialization, was interpreted as the result of "market-conforming" policies (World Bank, 1993, 355).[7] However, since the appointment of Chief Economist Justin Yifu Lin in 2008, the World Bank has supported programs that aim to restructure the economy towards high-value added sectors (Wade, 2012). These programs look like industrial policy, talk like industrial policy, but are called "Competitive Industries" instead.[8] Purists at the World Bank may remain skeptical, but operational economists and specialists are understandably onboard. Their daily job is to provide country clients with money and advice on how to spend it—there is no wonder why they warmly support a development strategy based on targeting specific industries. Effective or not, such a development program happens to provide ample opportunities for lucrative advice-giving. Today, ten years after the first sign of resurgence, the support for industrial policy has become mainstream albeit under other names. Indeed, the director of Trade and Competitiveness, one of the World Bank's 14 global practices, recently exclaimed in an official blog post, "FDI matters, but not all FDI is created equal," and promised to help countries target the "right" kind of FDI (Fruman, 2016).

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[7] See Amsden (1994) and Rodrik (1994) for a forceful rebuttal. Indeed, the East Asian miracle, i.e. the rapid growth with equity of eight high-performing Asian economies (Hong Kong, Korea, Singapore, Taiwan, China, Indonesia, Malaysia, and Thailand), was a Rorschach test for the international development world. Looking at the same set of facts, some saw the state micro-manage the market, while others, like the World Bank, saw the state getting the macro conditions right.

[8] In an advertising brochure, the Competitive Industries practice describes itself as "Going *beyond macroeconomic reform agenda* to identify and address the *real microeconomic barriers* to the growth of *industries with high economic and social benefits*" and "*Intervening aggressively* . . . to enable those industries to seize their 'windows of opportunity' to grow, compete and generate inclusive, productive employment" (emphasis added) (World Bank, 2011). In recent years, the program has expanded into the "Competitive Industries and Innovation Program," a multi-donor partnership with the support of the World Bank, the European Union, and several donor governments. "Industrial policy" may still be a taboo at the World Bank, but "competitiveness" and "innovation" are fully embraced as they hide the state and highlight the private sector.

1.3 Roadmap

The rest of my research project proceeds as follows. In Chapter 2, 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 3, I describe the two-sided matching model, including both its game-theoretic origin and its statistical estimation. Chapter 4 uses simulation and US labor data to demonstrate the correctness of the model and explore its characteristics. 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 explores potential improvements and other applications of the two-sided matching model in different areas of Political Science.

2

Current issues in the FDI literature

At first glance, it makes sense to assume that all countries would be eager to receive FDI. Indeed, FDI can bring capital, creates jobs, contributes tax revenue, and promises technological spillover to the local economy. Consider the impact of an Intel's factory on Vietnam's economy. In 2006, Intel chose Saigon Hi-tech Park in Ho Chi Minh City as the site for its $1 billion chip testing and assembly facility, its largest in the world. In 2016, Intel Products Vietnam (IPV) employed 4000 workers at full capacity, exported $3.45 billion worth of goods (or 18.2% of Vietnam's electronics export), and generated more than $100 million for Vietnam's GDP in tax payment, salary, and profit. In addition, IPV developed an engineering education program in partnership with Arizona State University and local universities, educating thousands of young Vietnamese engineers. As a result, IPV's workers were vastly more productive. While IPV's workforce only constituted 5% of all workers, its export value amounted to 72% of all export at the Saigon Hi-tech Park. Intel's decision to choose Ho Chi Minh City over other candidate sites, including Chennai (India), Bangkok (Thailand), and Dalian (China), was also a significant marketing boost to Vietnam's image as a destination capable of high-tech manufacturing. Following Intel, many other MNCs opened high-tech facilities in Vietnam, including Samsung's three factories (in 2009, 2013, and 2014), Nokia/Microsoft (2012), and LG (2013) (Dinh, 2016; UNCTAD, 2008).

In addition, economists have also developed long-standing theories about the benefits of FDI. According to Findlay (1978), FDI plays a key role in economic growth by upgrading the local economy's technological capability. As well-known from neoclassical growth theory, diminishing returns to capital will at one point stop capital from accumulating further, preventing long-run economic growth from being driven by capital accumulation alone (Solow, 1956). FDI counteracts this dynamic by helping local workers and suppliers upgrade their productivity, either via training or demonstration.

Economic theories and captivating anecdotes notwithstanding, there are reasons to believe that FDI benefits are not a given and that countries' preference for FDI is not homogeneous. Indeed, cross-country studies show little evidence of FDI inflow having a systematic and positive effect on growth (Nair-Reichert and Weinhold, 2001; Carkovic and Levine, 2002) or poverty reduction (Gohou and Soumaré, 2012). Instead, the benefits of FDI is highly conditional on the absorptive capacity of the host economies, i.e. its level of human capital, technological sophistication, or financial market development (Durham, 2004; Nunnenkamp and Spatz, 2004; Fu, 2008; Willem, 2004). Therefore, a country's openness towards FDI may depend on its economic conditions. Furthermore, even if the capital brought and jobs created by FDI may be good for the overall economy, its distributional effects cut across constituencies, creating political cleavage across both sectoral and geographical divides (Chintrakarn et al., 2012; Goldberg and Pavcnik, 2007; Nunnenkamp et al., 2007). There are winners and losers for each FDI project, and their relative political strength may determine the country's attitude towards FDI.

For these reasons, we should reject the standard assumption in the FDI literature that countries universally want to attract FDI. In this chapter, I take apart this assumption, providing qualitative evidence of countries having a restrictive attitude towards FDI (Section 2.1), and a strategic targeting of specific kinds of FDI (Section 2.2). Finally, I discuss the limitation of FDI flow data, the main dependent variable of the FDI literature (Section 2.3). Not only does FDI flow data not map to political science concepts, its aggregated nature also prevents political scientists from studying different types of FDI. The data limitation thus reinforces the conceptual neglect of variation in countries' preference. Fortunately, my two-sided matching model is able to deal with all of these issues at the same time.

2.1 Countries' demand for FDI

2.1.1 The untenable assumption of universal demand for FDI

The IPE literature on the political determinants of FDI has largely focused on what MNCs demand from countries. In this literature, politics matters, but only in terms of what political factors make countries attractive to MNCs. As Jensen (2008a) states in the introduction of "*Nation-states and the Multinational Corporation*":

> Which government policies prove beneficial to multinational corporations? Which political institutions provide multinational corporations with credible commitments to these market-friendly policies? These emerge as the central questions of this book.[1]

In theorizing FDI inflow largely as a function of MNCs' preference, the FDI literature implicitly assumes that countries are eager to receive as much FDI as possible. On the contrary, a historical and comparative examination of FDI policies makes it clear that countries have at best had a mixed attitude towards foreign capital. As an

[1] Other scholars share the same line of inquiry, e.g. Ahlquist (2006); Busse and Hefeker (2007); Büthe and Milner (2008); Li and Resnick (2003).

example, consider the FDI policies of a rapidly industrializing country, who within 30 years of intense globalization had overtook incumbent industrial giants to become the factory of the world and the largest recipient of FDI. I am writing, of course, about the US at the turn of the 20^{th} century. From 1879 to 1909, the US transformed itself from an economy dominated by agriculture (53%) to one dominated by industry (62%). In 1914, it surpassed Britain's industrial output, producing more than one third of the global output. During this period, the US was the most popular destination for global capital and the world's greatest debtor nation (Wilkins, 1989, part II).

Despite its current advocacy for liberal FDI policies, the US had a mixed attitude towards attitude when it was a net FDI recipient. While American businesses were aware of the benefits, e.g. funding for risky ventures in mining and railroad, complaints against FDI were equally common. Some grumbled that the "tribute" paid to foreign financiers were odious. Others in the railroad industry felt that foreign management could not understand American problems and might ruin the industry with demands for restructuring. Yet other protests stemmed from a nationalistic belief that that "our land" should not be controlled by European absentee owners. Such sentiments led to various state legislation that, among other things, forbade non-resident alien ownership of land, or tightened regulations around foreign financial institutions, including banks, insurance companies, and mortgage lenders. Similarly, in 1913 the federal government forbade foreign citizens from serving as directors of US national banks, and only allowed them to buy share of US banks if they were willing to be represented by US citizens on the board (Wilkins, 1989, part II). Many of these entry restrictions are still familiar tools of countries today.

A similarly restrictive attitude towards FDI characterized South Korea's policies during its industrializing period. After almost half a century of oppression under Japanese colonialism, South Korea was deeply averse to a large foreign presence in their economy. This nationalistic impulse translated into a host of restrictions on FDI entry and ownership. Throughout the 1960s and 1970s, instead of keeping a small list of restricted sectors, Korea used a positive list system that forbade FDI in all sectors except those explicitly allowed by the government. Even in sectors that allowed FDI, majority foreign ownership was also forbidden (Thurbon and Weiss, 2006). Even as late as the 1980s, after mounting internal pressure for a more liberal FDI policies, 50% of all industries and 20% of manufacturing industries were still closed to MNCs, and only 5% of MNCs in Korea were wholly owned by the foreign investor (Chang, 2004). On top of these explicit restrictions, a FDI project must also be approved by numerous agencies, including the Ministry of Trade and Industry, the Ministry of Science and Technology, and the Ministry of Finance. The subsequent red tape and delay further deterred MNCs from entering.[2] Instead of attracting FDI, Korea relied much more on foreign debt for its capital need. As a result, from 1962 to 1983, FDI made up only 5.1% of foreign capital in Korea while the rest was debt (author's calculation based on data reported in Amsden (1989, 92, Table 4.5)).

More importantly, countries are not just naively open or restrictive towards FDI, but very strategic in formulating FDI policies that fit their political and economic conditions. Therefore, if we make blanket assumption about countries' demand for FDI instead of studying its variation, we overlook this strategic component entirely. For example, consider the case of China, whose demand for FDI has ebbed and flowed dramatically over time. Before, during, and after its economic reform, China's attitude towards FDI swung from extreme hostility, to red carpet treat-

[2] The arduous approval process for FDI projects was a deliberate policy choice by the Korean government and not the result of lacking state capacity. Indeed, as Evans (1995) describes, Korea had a strong and autonomous state, capable of outlining and executing a developmental strategy for the country. Its FDI policies were an integral part of this strategy, as outlined in the Economic Planning Board (EPB)'s *White Paper on Foreign Investment* (EPB, 1981). Korea's policy of meticulous vetting stands in stark contrast with recent efforts to fast track FDI projects (often called the "one-stop shop") promoted by international organizations, e.g. in Dominican Republic (UNCTAD, 2016), Nigeria (UNCTAD, 2009), and many others.

ment, and finally chilly co-existence. Indeed, prior to 1979, there was virtually no foreign capital in China as Chinese leaders self-congratulated on their nationalistic self-sufficiency. They even turned down foreign aid from the International Red Cross for the 1976 Tangshang earthquake, announcing that such disasters "teach the value of self-reliance and hard struggle" (Butterfield, 1976). However, when the disastrous result of central planning and the Cultural Revolution became apparent, especially in stark contrast with the shining achievements of its neighboring Asian tigers, China committed to Deng Xiaoping's "open door policy" in 1979. With the promulgation of the "Law on Chinese Foreign Equity Joint Ventures," the flood gate opened for foreign capital (Wei, 1996). Throughout the reform period, China's FDI policies continuously grew friendlier. In 1986, after Deng Xiaoping's famous Southern tour to shore up support for reform, China moved from "permitting" to "encouraging" FDI, allowed wholly owned foreign enterprises, and adopted a negative list approach that accepted FDI in all sectors unless specifically banned. Finally, after China joined the WTO in 2001, China abolished various performance requirements (e.g. export ratio, local content, technology transfers, etc.) previously imposed on foreign firms (Long, 2005).

During this reform period, China did not just allowed FDI—it even discriminated against the domestic sector in favor of foreign firms. While Chinese leaders continued to view the domestic sector with suspicion, they had no problem with foreign firms, whose main goal was to make money and not to raise political trouble (Gallagher, 2002). As a result, China created a dualist legal regime that much better protected foreign firms than domestic ones. For example, China created a 1979 law and a 1982 constitutional amendment not to expropriate from foreign enterprises. There was no such guarantee for the domestic sector. Compared to domestic firms, foreign businesses also seemed to enjoy fewer audits, more favorable judgment during labor dispute, and more assistance from the government (Huang, 2003, 2011). During the early years of reform, FDI firms enjoyed such large benefits that even state-owned enterprises (SOEs) were eager to form joint venture with them (Gu, 1997, 59).

However, as China shifted its growth strategy to nurturing its domestic sector into a world class competitor, its attitude towards FDI and domestic firms reversed. In 2010, some European firms started grumbling about unfair treatments, especially in sectors where intellectual property was important, while others remained happy with making good money. As an observer remarked, "China still welcomes FDI, but ... it is becoming more insistent on setting the terms," including favoritism towards domestic firms for government contracts, higher tax rate, or a limit on the number of non-Chinese staff (Grant, 2010). By 2016, the accusations of discrimination against foreign firms had become mainstream. A former deputy trade representative for the US complained that foreign insurers had to apply for one license at a time, taking six to eight months total. In contrast, despite claims of equal treatment from the government, Chinese rivals could submit their whole package and got approved much quicker. In its annual business climate survey, the American Chamber of Commerce in China reported that, between 2015 and 2017, 75% to 81% of businesses felt that they were less welcome than before (AmCham China, 2018, 39).[3] James McGregor, former bureau chief of the Wall Street Journal, chairman of AmCham China, and a business executive who lived in China for more than two decades, observed (Wu, 2016):

> For foreign companies in China, right now is perhaps the most distressing and unhappy time that I have seen. ... They feel that the best days for foreign companies in China are reaching an end.

In sum, the prevailing assumption in the FDI literature that all countries are eager for FDI is untenable. Many countries, including those that eventually become

[3] The business climate survey first asked this question in 2015.

staunch supporters of liberalizing FDI policies, have held restrictive policies on FDI when they were net recipient of FDI. More importantly, countries also show a dynamic demand for FDI, adapting their policies to meet their political and economic goals.

Unfortunately, the two common empirical approaches in the FDI literature strongly rely on this assumption. In the first approach, researchers build a regression model with FDI inflow as the dependent variable and a political factor as the independent variable of interest. In this model, it is impossible to interpret the political factor as an attraction to MNC or as a motivator of countries' demand for FDI. Consider Jensen and McGillivray (2005)'s finding that federalism is positively associated with FDI inflow. The authors interpret this correlation as federalism constraining the whim of the central government, increasing policy stability, and thus making the country attractive to MNCs. However, the alternative explanation is that local governments in a decentralized system compete more intensely for FDI, driving up the FDI inflow. For example, as China decentralized in the late 1980s and early 1990s, local governments gained the authority to approve foreign investment up to a certain size, thus able to court MNCs without asking the central government for permission.[4] In addition, local governments could keep all revenue in excess of a quota pre-negotiated with the central government, further motivating them to bring in MNCs as a lucrative source of tax revenue. Having both the authority and the incentive to attract MNCs, Chinese local governments engaged in an intense competition for MNCs. While there were only 117 development zones in 1991, the number

[4] Similar to China's broader economic reform, decentralization in China's FDI policies happened incrementally. In 1979, China first allowed FDI in four Special Economic Zones, i.e. Shenzhen, Zhuhai, Shantou (near Hong Kong), and Xiamen (near Taiwan). As the economic benefits of FDI became clear, provinces started clamoring for the ability to attract FDI themselves. Therefore, in 1984, China allowed 14 coastal cities to approve FDI projects, and in the early 1990s, allowed inland regions to do the same. Gallagher (2002) and Shirk (1993) discuss how the coalition for decentralization expanded over this period, and Coase and Wang (2012) provides a historical account of China's economic reform more broadly.

exploded to 2700 in 1992, of which only 95 were initiated by central ministries (Montinola et al., 1995). Far from Jensen and McGillivray (2005)'s argument, China's federalism did not increase FDI inflow by producing a static policy environment that MNCs like. On the contrary, federalism incentivized Chinese local governments to demand FDI, fostering local policy experiments that were anything but stable.[5]

In the second approach, researchers estimate MNCs' preference using the discrete choice model. The dependent variable is the MNC's choice of a location over all the other options, and the independent variable of interest is a characteristic of the location (Arauzo-Carod et al., 2010). In the discrete choice model, the assumption is that all locations are available for the MNC to pick and choose, effectively ruling out the possibility that the host country can decline the MNC's investment proposal. Such an assumption is unfounded. For example, in 2007, Da Nang, a central province of Vietnam known for its public governance quality, turned down $2.5 billion dollars from a Taiwanese-Japanese steel factory and a Japanese paper pulp factory for environmental concerns (Dung, 2007). In 2014, even during tough times, when Da Nang's and Vietnam's FDI inflow was merely half of the previous year, its attitude towards FDI remained selective. According to Mr. Lam Quang Minh, Director of Da Nang's investment promotion agency, the province declined a $200-million Hong Kong textile factory and a 30-hectare Korean dyeing facility, even when "these [refusals] have contributed to Da Nang's lackluster FDI attraction recently" (Hai Chau, 2015). While Da Nang is the most well-known, other Vietnamese provinces have also refused large FDI projects that use too much land, exploit natural resources, or cause environmental degradation (Quoc Hung, 2015).

[5] A very similar account of decentralization causing provincial demand and competition for FDI happened in Vietnam as well (Malesky, 2004).

2.1.2 *Current approaches to estimate countries' demand for FDI*

Unlike the FDI literature, the broader field of IPE has recognized that countries' preference remains an important force even in a globalized era. Despite early pessimism about countries engaging in a race to the bottom to attract footloose global capital, scholars have shown substantial variation in countries' trade, welfare, environmental, and fiscal policies (Drezner, 2001). The FDI literature has lagged behind in this aspect.

Recognizing this gap, 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.[6] For this approach to be valid, ev-

[6] 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

ery 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.[7]

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 US Overseas Business 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 Overseas Business Reports 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

second stage is considered the country's "FDI openness" in that year.

[7] 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).

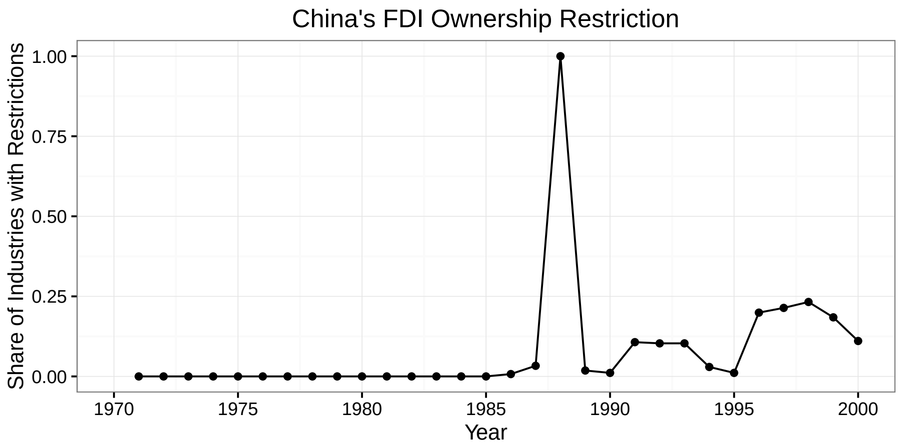

FIGURE 2.1: China's FDI ownership restriction, as coded in Pandya (2010). Prior to 1986, FDI in China was limited to few experimental Special Economic Zones, and thus not mentioned in US Investment Reports. The sharp spike in 1988 also does not seem to correspond to any actual change in policy, and likely another artifact of reporting. (See Zebregs and Tseng (2002) for a historical overview of China's FDI policy.)

closed or very open to FDI. This concern is not hypothetical. Figure 2.1 shows that, following the coding of the US Overseas Business 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.

2.2 Countries' preference for types of FDI

2.2.1 The untenable assumption of countries' homogeneous preference for types of FDI

In the literature of political determinants of FDI, the most common dependent variable is aggregate FDI inflow in a country-year.[8] While relying on this dependent variable, researchers focus almost exclusively on the quantity of FDI, treating all FDI as one homogeneous flow of capital. Such emphasis on aggregate FDI quantity is likely just an artifact of the data limitation. Indeed, country case studies show that countries have a rich tapestry of policies targeting specific types of FDI, tailored to their own political and economic conditions. Below, I discuss such targeting strategy of Korea, Taiwan, and Costa Rica.

Korea. Not only did Korea restrict FDI entry in general, they also aggressively screened FDI proposals for desirable qualities. To ensure that FDI served its developmental strategy, Korea let its developmental pilot bureau, the Economic Planning Board (EPB), take charge of FDI policies. The EPB displayed a sophisticated understanding of the costs and benefits of FDI. Its 1981 *White Paper on Foreign Investment* recognized that FDI could benefit Korea by bringing capital, job creation, potential technological upgrading, and hard currency. At the same time, it cautioned that MNCs might engage in transfer pricing, demand distortionary import-export protection, crowd out domestic investors, delay domestic technological capability, and even exert political influence on the government (EPB, 1981, 50-64, quoted in Chang (2004)).[9] Therefore, in pursuit of Korea's "national ownership" growth strategy, the EPB heavily restricted MNCs that sought access to the domestic market, especially in labor-intensive sectors where the government believed there were domestic alterna-

[8] Only the OECD has a dataset of FDI broken down by sectors, limited to 34 OECD member countries. Source: OECD International direct investment database.

[9] It is remarkable that the White Paper touched on all arguments in academic circles, showing that the Korean government paid close attention to the effects of FDI.

tives. On the other hand, the EPB prioritized FDI projects that were export oriented or more technologically advanced than Korean firms. The EPB especially coveted MNCs that would improve the capabilities of Korean producers, e.g. by procuring from local suppliers, transferring technologies to local partners, providing access to foreign markets, even divesting the foreign-held equities to the Korean counterpart after a specified period. Of $1.3 billion in FDI that flowed into Korea between 1962 and 1983, Korean partners repurchased $263.5 million (20%) by 1983, after they had gained the production knowledge (Mardon, 1990, 135). Korea accomplished this feat partly by providing subsidized loans to the domestic partners, but more importantly by being willing to turn down MNCs that did not agree to the stringent terms. According to Mardon (1990)'s survey of 45 foreign investors, such requirements were the norm to enter the Korean economy. In 1986, 38% of foreign firms committed to exporting a fixed amount, 80% to transferring technology, 36% to supplying raw materials not available domestically, and 28% to helping Korean producers access untapped export markets.

Taiwan. In the 1960s, capital-strapped Taiwan was permissive in admitting FDI, not screening for high-quality projects. However, in the 1970s, Taiwan became increasingly selective, evaluating investment proposals based on "how much they open new markets, build new exports, transfer technology, intensify input-output links, make Taiwan more valuable to multinationals as a foreign investment site and as a source for important components, and enhance Taiwan's international political support" (Wade, 1990, 151). Taiwan was so firm on their targeting strategy that, in 1963, they overrode local firms' objection and allowed Singer Sewing Machine Company, arguing that this FDI foreign project could provide much needed currency and improve the quality of local parts. Indeed, after one year, Singer did so much in terms of transferring technology and boosting exports that local producers changed their mind (Ranis and Schive, 1985). Another example of Taiwan's commitment to their FDI targeting strategy was how they selected the MNC to build a polyethylene plant for the domestic market. Taiwan insisted that the MNC exported any surplus over domestic needs, refrained from building any other facilities in the downstream sector (lest they compete with Taiwanese firms), and agreed to sell half of their equities to Taiwanese partners after five years.[10] These demands were not cheap talk. During the negotiation process, Taiwan rejected a Japanese investor who refused to comply to these terms, and pick National Distiller, an US firm that fit Taiwan's target (Wade, 1990, 151).

Interestingly, with China's shadow constantly loomed large, Taiwan's FDI strategy depended not only on its economic strategy but at times also on its security need. In the late 1970s, when the relationship between the US and mainland China thawed, jeopardizing Taiwan's survival, the government made a big effort to attract famous US MNCs. In contrast to the ruthless terms of other FDI deals, Taiwan's invitation to GM to invest was extremely generous, providing import protections and allowing GM to pull out at any time if it deemed that the government failed to adequately protect its market power. However, by 1982, when the US derecognition of Taiwan turned out not to be apocalyptic, GM's affiliation with the US was no longer such a desirable. Taiwan thus withdrew its concessions, prompting GM to leave (Noble, 1987).

Costa Rica. With the spread of WTO membership, free trade agreements, and investment treaties, the aggressive FDI policies adopted by the Korean and Taiwanese governments may no longer be available to countries today.[11] However, while

[10] The deal was not all sticks and no carrots. In exchange for the stringent terms, Taiwan offered a five-year tax holiday, restrictions on import of competing products, guaranteed supply of an important chemical input, and unlimited repatriation of profits.

[11] The WTO's Agreement on Trade-Related Investment Measures (TRIMS) forbids the practice of local content requirement, which forces MNCs to purchase local products, impeding free trade. Several Bilateral Investment Treaties (BITs) and Free Trade Agreements (FTAs) further ban other performance requirements, such as technology transfer. In addition, most investment agreements include obligations on "national treatment," ensuring that countries cannot treat foreign firms worse

the discriminatory tactics are gone, countries' desire to target types of FDI remains, manifesting less often as requirements and more as encouragement. Costa Rica's success in targeting high-tech FDI was a prime example. In mid-1990s, as other Central American competitors entered the apparel export industry after a bout of civil wars, Costa Rica was determined to diversify away from the textile industry, breaking away from the cycle of competing on wage and offering unsustainable fiscal incentives. Setting its sight on technologically advanced industries, Costa Rica actively courted MNCs in these sectors. Leading the effort was Costa Rica Investment Promotion Agency (CINDE), a private organization whose lobbying efforts were initially financed by USAID and politically supported by an alliance of bankers, exporters, and economists (Clark, 1995). CINDE had typical investment promotion functions, including image building, investment facilitation and aftercare, investment targeting, and policy advocacy for a better business environment. However, CINDE provided these services only to targeted industries, i.e. advanced manufacturing, life science, and services. For MNCs in these sectors, CINDE systematically addressed investors' concern, assisted with the establishment process, held regular check-in sessions, and advocated for their interests pro-actively. In contrast, when a non-targeted firm raised a complaint with CINDE, it simply relayed the message to the relevant government agencies (OECD, 2013).

Costa Rica's extraordinary effort to target desirable FDI was evident during the negotiation to attract Intel's $300 million assembly facility. At the time, Intel's shortlist of candidate sites include Brazil, Chile, Indonesia, Thailand, Mexico, and Costa Rica. The two finalists, Costa Rica and Mexico, reflecting Intel's goal to diversify its geographical risk by expanding into Latin America. Seizing this opportunity, CINDE coordinated Ministry of Energy and Environment, Transportation, Finance,

than domestic firms. Under the current policy regime, many of Korea's and Taiwan's FDI policies are no longer legal and have become less frequently used, albeit not completely abandoned, by other countries (Cosbey, 2015).

Science, and Technology to promptly address Intel's concern, setting up electricity substations, a dedicated call center, more frequent flights, consulates in the Philippines and Malaysia, and many more. Even President Figueres also took a personal interest in the project, traveling to Intel headquarters in Arizona to demonstrate Costa Rica's commitment. The endeavor proved Costa Rica's strong preference for high-tech FDI like Intel. In the end, Intel's decision to open the facility in Costa Rica was a "stamp of approval" for Costa Rica's targeting strategy (Mortimore and Vergara, 2004, 511).[12]

2.2.2 Current approaches to estimate countries' preference for types of FDI

Despite qualitative evidence of countries targeting specific types of FDI, two data limitations prevent researchers from studying this variation in countries' preference. First, FDI flow data typically does not disaggregate into types of FDI. Studying FDI flow to the OECD, Alfaro and Charlton (2007) attempt to get around this problem by using Germany's sectoral skill intensity as the proxy for the FDI quality in a certain sector. However, 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 websites of investment promotion agencies (IPA) 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 2.2 shows that there is little varia-

[12] See Spar (1998) for a detailed account of how Costa Rica beat out much more advantaged competitors like Mexico and Brazil, convincing Intel to invest despite initial reservations about Costa Rica's size and level of development.

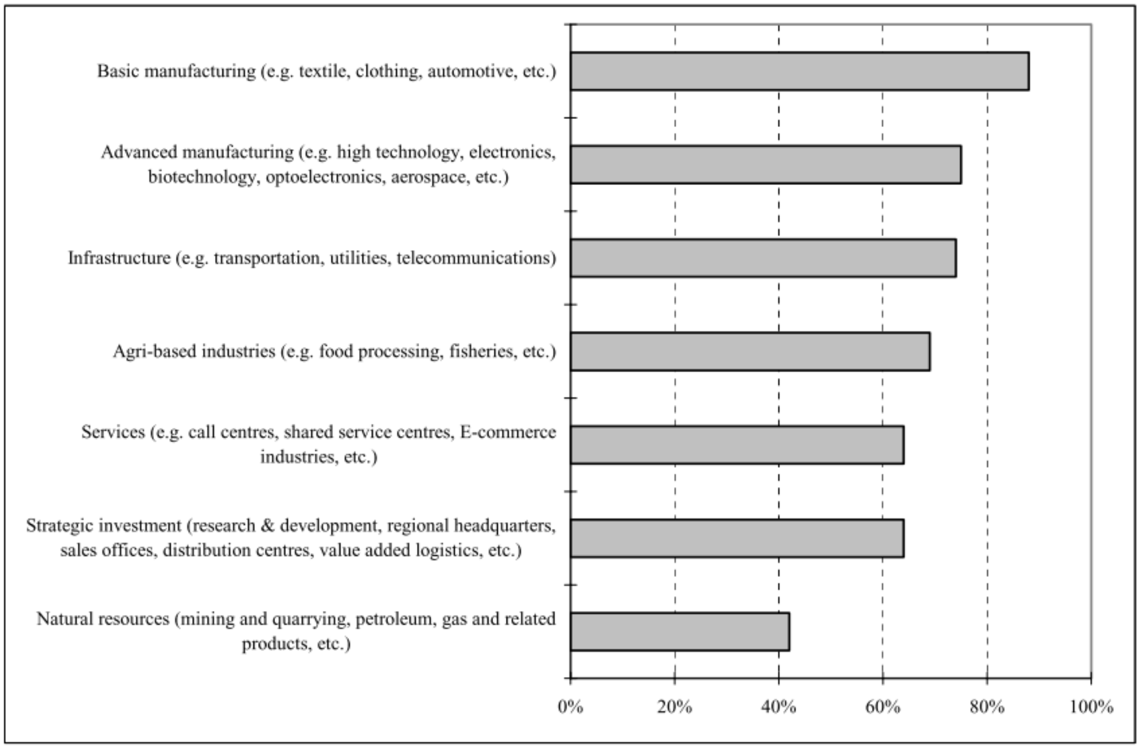

FIGURE 2.2: Target industries by IPAs around the world. Because of the image building aspect of investment promotion, almost all IPAs say that they want to attract "manufacturing," "advanced manufacturing," and "infrastructure." Therefore, using what is listed as investment priorities may not be a reliable way to measure countries' preference for FDI. Source: UNCTAD (2001).

tion 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 must also take into account the fact that countries which 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.

To address these challenges, we can use FDI firm-level data, which provides 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. Then, using firms' characteristics as covariates in the two-sided matching model, I will be able to estimate countries' preferences for these traits.

2.3 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 irrelevant components that only matter 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) theorize 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 of profit repatriation or intra-company loans.[13] 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. 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

[13] 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.

flow statistics.

Third, scholars argue that MNCs 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 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 much more important to labor quality than the amount of capital.[14]

This mismatch between theory and empirics may also be a reason behind the 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 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).[15] 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?[16] The vast majority of these studies

[14] 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).

[15] This practice is 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

[16] Arguably, political scientists are not interested in the flow of capital in and of itself. Instead,

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, the mobile MNC can threaten to invest elsewhere and thus has the stronger bargaining power. However, after the MNC has committed fixed capital on the ground, the host government gets the upper hand. 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 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 (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 is illiquid, 24% is "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 physical capital, i.e. Plant, Property, and Equipment (PPE),

the flow of global capital matters 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.

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.[17] 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 other 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 quan-

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

tities 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.[18]

2.4 Implications for the broader IPE literature

In the sections above, I have discussed how the FDI literature can improve its empirical research by taking into account countries' preference for FDI. But coming up with better estimates is not the only reason for studying countries' preference. More importantly, in thinking about the variation in countries' FDI policies, FDI researchers can engage with the IPE literature about the role of governments in the era of footloose global capital. As the international financial market develops and MNCs become more common, private firms can easily "adopt strategies of exit and evasion," to such an extent that capital control seems futile (Goodman and Pauly, 1993). In this environment, do countries capitulate to MNCs' threat of relocation and acquiesce to their policy demand, or do countries retain substantial policy autonomy? These questions are not just a matter of theoretical interest for political scientists. They also have real world implications for millions of citizens who are wondering if their social contract with the state may erode, crumbling under the pressure of global capital in particular and of globalization in general.

[18] 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).

The FDI literature can help answering the question of state autonomy in two ways. First, it can study how much domestic politics influence FDI policies. While MNCs may threaten to leave or not to invest in the first place, other domestic constituencies can also exert political pressure on the government. For example, Korea's focus on "national ownership" and reluctance to allow MNCs can be interpreted as the result of the symbiotic relationship between domestic business and the state. The state nurtured domestic business by shielding the domestic market from international competition and by forcing MNCs to transfer technology to local partners. In turn, domestic business provided the government with the fund for political campaign and repression, sustaining its rule (Kang, 2002, ch 4). To study the effect of domestic politics on FDI policies, FDI researchers must take the first step of recognizing and estimating the variation in countries' FDI policies.

Second, countries may be free to set policies along certain dimensions if they are highly desirable to MNCs in other dimensions. For example, even though China has become more expensive and less welcoming towards FDI, its market size is alluring enough that many MNCs are staying put. In 2017, China was considered the 2$^{\text{nd}}$ favorite FDI destination in the world, barely behind the US, with the former being considered a top prospective host economy by 36% of executive and the later by 40% (UNCTAD, 2017, Fig I.8). US tech companies are so determined to get a share of the Chinese market that some are willing to risk upgrading local partners into competitors, leaking technologies to China's military, and giving up data to government censors (Dou and Clark, 2015; Rauhala and Dwoskin, 2016). Therefore, to understand countries' room to set FDI policies, we need to estimate MNCs' relative preference for different characteristics of a country. While the FDI literature has already examined MNCs' preference, the current results are not accurate without taking into account countries' preference as pointed out in Section 2.1.

Compared to the FDI literature, the broader IPE field has made more headway in studying the relationship between globalization and state autonomy. This is unlikely because FDI researchers are uninterested in the issue. Rather, they have been hitherto constrained by data limitation. While IPE scholars can study countries' preference via their tax policies, public sector size, inflation target, environmental regulations, or labor standards, FDI researchers have mainly relied on FDI inflow data. Because the amount of FDI inflow is caused by both MNCs' and countries' preference, it is impossible to tease out countries' preference using just FDI inflow data. As suggested in Section 2.3, firm-level FDI data provides a new opportunity to go beyond FDI inflow.

2.5 Next steps

In sum, the current FDI literature would benefit from studying countries' demand 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.[19]

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 an MNC chooses to open a subsidiary in a country, that subsidiary is by definition not located in another. Therefore, the values of firm-country dyads de-

[19] 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.

terministically constrain one another and cannot be modeled as independent draws from a common distribution.[20]

The two-sided matching model can 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 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.

[20] 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 prevents us from understanding the preference of actors, how these preference are correlated with other characteristics, and how they may evolve over time.

3

Two-sided matching model

As discussed in Chapter 2, developing the two-sided matching model for the FDI market can address long-standing issues in the FDI literature. To do so, I draw insights from studies of matching markets in other domains. Marriage is a prominent example of a matching market. Others include the matching between firms and workers, federal judges and law clerks, or the *formateur* of a coalition government and other minority parties. 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 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 Markov chain Monte Carlo (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).

3.1 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 a preference over the women, which can be represented as an ordered list, ranking each woman based on how much he likes her. Vice versa, each woman also has a preference over the men.

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 such a stable matching.[2] This result provides some justifications for the

[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

assumption 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 substitutes, not complements (Roth and Sotomayor, 1992). In other words, firms never

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.

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.

3.2 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 take the observed matching as given and attempt to estimate agents' preference.

Unfortunately, most extant empirical models in political science 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 my research.

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. My research aims to make use of such matching data to estimate agents' *revealed* preference.

Since the dynamics of two-sided matching is prevalent in the labor market, labor economists have been at the forefront of developing empirical models for matching markets. For example, Boyd et al. (2013) study the public school teacher labor market, with teachers on one side and public schools on the other. In this market, wage is sticky due to collective bargaining and public decision making, causing the market not to equilibrate, leaving some jobs plainly better than others. Teachers will sort into these "good" jobs conditional on how highly schools rank them as candidates. This sorting phenomenon distinguishes the public school teacher market from conventional labor market, suggesting that a matching model would be more appropriate.

Therefore, Boyd et al. (2013) apply the insights from the game theoretical two-sided matching literature to build a structural model for the teacher labor market. In this model, teachers and schools have utility functions that take into account the characteristics of the other side. For example, a teacher may rank a school based on its location, students, and budget. Following the game theory literature, the authors then assume that the decentralized job matching mechanism leads to a stable matching of teachers to schools, implying that there is no school and teacher that would prefer each other than their current match. This assumption imposes a structure on the model, relating actors' preferences and characteristics with the observed match.

However, it is difficult to estimate this model because its likelihood is not analytically available. To write down the likelihood of any matching, we need to enumerate all possible rankings of schools and teachers that will lead to that particular matching. While it is straightforward to derive a stable matching outcome from given values of characteristics and preference (e.g. following the deferred acceptance algorithm), the inverse problem does not have a known solution.

This difficulty motivates Boyd et al. (2013) to estimate the model using method of simulated moments (MSM), an extension of the method of moments (MOM) estimation strategy. As in the typical MOM approach, the authors match population moments with their sample analogs. For example, a moment used by the authors is the expected difference between the attributes of the school where an individual work and the expected mean attributes given their qualifications. However, unlike the typical MOM approach, the moment in this case is not analytically available. Indeed, the mean attributes of an individual's jobs given their qualifications is a complicated term integrating over other candidates and schools in the markets. Because this term does not have a closed form, the authors simulate it by running the matching process multiple times, writing down the attributes of the individual' jobs, and averaging them across simulations. This approach is thus called method of *simulated* moments.

Following Boyd et al. (2013), Agarwal (2015) also uses MSM to analyze the matching market of medical residency in the US. Agarwal (2015) notices that the variation of resident observable characteristics within a program provides additional information about the program's preference. Indeed, in a stable match, residents within the same program must be of the same caliber. Otherwise, the program could replace lower quality residents with better ones, or higher quality residents could leave for a better program. Therefore, if we see that residents in a program are highly correlated on some characteristics, then those characteristics must be an important part of the program's utility function. This insight allows Agarwal (2015) to identify more moments to be used in estimation, namely the within-program variance of resident observables.[5]

In addition to academic research, companies have also developed a commercial interest in studying 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

[5] While the MSM approach is the most developed, there are other attempts to empirically model matching markets. See Fox (2009) for a review.

matches.[6] 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, ultimately they need to estimate the preference 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.[7] 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 contrast, social scientists likely want to estimate the preference of pre-defined types such as genders, age ranges, or occupation groups. Therefore, while the LDA model is suitable for exploratory and predictive purposes, it does not have the interpretability that social scientists desire.

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[6] 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.

[7] 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.

3.3 Two-sided logit model

In this section, I present the two-sided logit model, a statistical model especially designed to study many-to-one matching market, 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 3.1, 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.

3.3.1 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:

$$U_j(i) = \boldsymbol{\beta}'_j X_i + \epsilon_{1ij} \tag{3.1}$$

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:

$$U_j(\neg i) = b_j + \epsilon_{0ij} \tag{3.2}$$

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.[8] 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 interchangeable pieces 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 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

[8] 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 3.1, this assumption is necessary to prove the existence of stable matching in the case of many-to-one matching.

of workers being considered.[9]

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.[10] 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:

$$\begin{aligned} Pr(o_{ij} = 1) &= Pr(U_j(i) > U_j(\neg i)) && (3.3) \\ &= Pr(\epsilon_{0ij} - \epsilon_{1ij} < \boldsymbol{\beta}_j' X_i - b_j) && (3.4) \\ &= \frac{\exp(\boldsymbol{\beta}_j' X_i)}{1 + \exp(\boldsymbol{\beta}_j' X_i)} && (3.5) \end{aligned}$$

$$Pr(o_{ij} = 0) = 1 - Pr(o_{ij} = 1) = \frac{1}{1 + \exp(\boldsymbol{\beta}_j' X_i)} \tag{3.6}$$

In Equation (3.5), 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, denoted O_i. Since unemployment is always an available option, every opportunity set includes unemployment as an "offer."

[9] 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.

[10] 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).

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

$$p(O_i|\boldsymbol{\beta}) = \prod_{j\in O_i} p(o_{ij} = 1|\boldsymbol{\beta}) \prod_{j\notin O_i} p(o_{ij} = 0|\boldsymbol{\beta}) \tag{3.7}$$

$$= \prod_{j\in O_i} \frac{\exp(\boldsymbol{\beta_j'} X_i)}{1+\exp(\boldsymbol{\beta_j'} X_i)} \prod_{j\notin O_i} \frac{1}{1+\exp(\boldsymbol{\beta_j'} X_i)} \tag{3.8}$$

3.3.2 Modeling workers' decision making

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

$$V_i(j) = \alpha' W_j + v_{ij} \tag{3.9}$$

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.[11] 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. To minimize this problem, we need to model 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.[12]

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):

$$p(A_i = a_i | O_i, \alpha_i) = \frac{\exp(\alpha' W_{a_i})}{\sum\limits_{j:j \in O_i} \exp(\alpha' W_j)} \tag{3.10}$$

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

3.3.3 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

[11] 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."

[12] 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). My innovation is to estimate the model using a Bayesian MCMC approach, which offers several advantages. First, my MCMC approach produces the full posterior distribution, making inference and prediction easy. In contrast, EM only produces point estimates out of the box.[13] Second, my MCMC approach can be faster than EM when the latent variable, i.e. the opportunity set, is high dimensional (Rydén, 2008).[14] Third, within the Bayesian framework, I can naturally put a hierarchical structure on firms' preference. This allows me to borrow information across firms, producing more precise estimates even

[13] 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.

[14] Indeed, the 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.

when there is not a lot of data for a specific firm.[15]

3.3.4 Model estimation using Bayesian 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.[16] Specifically,

$$p(\alpha, \beta, O|A) = \frac{p(A|\alpha, \beta, O)p(\alpha, \beta, O)}{p(A)} \tag{3.11}$$

$$\propto p(A|O, \alpha)p(O|\beta)p(\alpha)p(\beta) \tag{3.12}$$

where $p(A|O, \alpha)$ is derived in (3.10), $p(O|\beta)$ is derived in (3.8), $p(\alpha)$ 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 (3.12), 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 $MH_\theta = \frac{p(\theta^*)q(\theta|\theta*)}{p(\theta)q(\theta^*|\theta)}$

---

[15] While it is possible to build frequentist hierarchical model, inference is less straightforward. See a discussion at Hornik (2017).

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

4. Accept the proposed value θ^* with probability $\max(1, MH_\theta)$

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

$$MH_O = \frac{p(O_i^*|A_i, \alpha, \boldsymbol{\beta})}{p(O_i|A_i, \alpha, \boldsymbol{\beta})} \tag{3.13}$$

$$= \frac{\sum\limits_{j:j \in O_i} \exp(\alpha' W_j)}{\sum\limits_{j:j \in O_i} \exp(\alpha' W_j) \pm \exp(\alpha' W_{j*})} \times \exp(\pm \boldsymbol{\beta}'_{j*} X_i) \tag{3.14}$$

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:[17]

$$MH_\alpha = \frac{\alpha^*|A, O, \beta)}{p(\alpha|A, O, \beta)} \tag{3.15}$$

$$\begin{aligned}\log MH_\alpha = \sum_i \Big[&(\alpha^* - \alpha)' W_{a_i} + \\ &\log\left(\sum_{j:j \in O_i} \exp(\alpha' W_j)\right) - \log\left(\sum_{j:j \in O_i} \exp(\alpha^{*\prime} W_j)\right)\Big] + \\ &\log p(\alpha^*) - \log p(\alpha)\end{aligned} \tag{3.16}$$

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:

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

$$MH_\beta = \frac{p(\beta * |A, O, \alpha)}{p(\beta|A, O, \alpha)} \tag{3.17}$$

$$\log MH_\beta = \sum_i \left[\sum_{j \in O_i} \left(\beta_j^{*\prime} X_i - \beta_j^\prime X_i \right) + \sum_j \left(\log(1 + \exp(\beta_j^\prime X_i)) - \log(1 + \exp(\beta_j^{*\prime} X_i)) \right) \right]$$
$$+ \log p(\boldsymbol{\beta}^*) - \log p(\boldsymbol{\beta}) \tag{3.18}$$

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:

$$p(\mu_\beta) \sim MVN(\mu_0, \Sigma_0) \tag{3.19}$$
$$p(\mu_\beta|\beta, \tau_\beta) \sim MVN(m, V) \text{ where} \tag{3.20}$$
$$V = (\Sigma_0^{-1} + n\tau_\beta)^{-1} \tag{3.21}$$
$$m = (\Sigma_0^{-1} + n\tau_\beta)^{-1}(\Sigma_0^{-1}\mu_0 + n\tau_\beta\bar{\beta}) \tag{3.22}$$

The full conditional distribution of τ_β is:

$$p(\tau_\beta) \sim \text{Wishart}(\nu_0, S_0^{-1}) \tag{3.23}$$

$$p(\tau_\beta|\beta, \mu_\beta) \sim \text{Wishart}(\nu, S^{-1}) \text{ where} \tag{3.24}$$

$$\nu = \nu_0 + n \tag{3.25}$$

$$S^{-1} = \left(S_0 + \sum(\beta - \mu_\beta)(\beta - \mu_\beta)'\right)^{-1} \tag{3.26}$$

3.4 Conclusion

This chapter reviews the game theoretic two-sided matching models, identifying key assumptions and properties that empirical models 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 and an analysis of US labor data, demonstrating the correctness of my estimation procedure and exploring other properties of the model.

4

Properties of the two-sided logit model

In this chapter I use simulation to examine the properties of the two-sided logit model. In a basic simulation study, the analyst assigns values to the parameters underlying the data generating process (DGP), generates a simulated dataset, applies the proposed statistical model, and studies the resulting estimate in relation to the known parameter values. In doing so, the analyst can empirically compare different models. For example, in this chapter, I compare the one-sided and the two-sided models, showing that the one-sided model produces biased estimates of MNCs' preference while the two-sided model does not. It would have been impossible to make this comparison via an analysis of real FDI data because MNCs' preference is not known in the real world. This finding corroborates my argument in Chapter 2 that the one-sided approach currently used by the FDI literature is inappropriate.

In addition, as a agent-based model, my simulation of the matching market can flexibly incorporate modification in actors' characteristics, preference, information, behavioral rule, and many other aspects.[1] The simulated DGPs can achieve consid-

[1] See de Marchi and Page (2014) for a review of agent-based model in Political Science and how flexible it can be.

erable degree of realism with these modifications. For example, in Chapter 3, the agents in the labor matching market are firms and workers who form matches based on one another's characteristics to maximize their utilities. In this model, there are heterogeneous firm types, each having a different utility function with its own weights for workers' characteristics. I can extend the model by adding heterogeneous worker types. More ambitiously, I can modify the model so that agents do not have global information, making matching decision based on the locally observable options. Or I can assign each agent a location from which they cannot move too far, thus limiting them to locally available options. I can also model agents as having finite computational power, unable to make utility-maximizing choice, and consequently relying on heuristic rules such as choosing a firm based on their similarity with the people working there. After making these modifications, I can check if our statistical model still perform reasonably well even though the modified DGPs deviate from its assumption. While these modifications are not implemented in this chapter, it is important to note that the simulation approach allows substantial flexibility in this regards.

Finally, and very practically, a simulation study helps me ascertain that the software implementation of the Bayesian MCMC is correct. In theory, once I have described the sampling procedure as in Chapter 3, implementing the model is the simple matter of translating the algorithm into code. In practice, doing so is not trivial. Detecting software bugs from MCMC result is hard because a poor result can come from many different problems, including prior values that are inappropriate, posterior distributions that are difficult to sample from, or modeling assumptions that simply do not fit the data. By contrast, because I control the DGP in a simulation, I can eliminate these alternative causes of poor results and thus better identify implementation bugs.

This chapter proceeds as follows. First, 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.

Finally, I apply the two-sided matching model to real US labor data of male workers, 1982-1990, estimating both workers' and firms' preference for each other. The estimates are substantively plausible, thus increasing the confidence in my estimation procedure.

4.1 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.[2] On one side of the matching market is 2149 workers, a representative sample of US male workers between 25 and 44 years old. Table 4.1 shows the summary statistics for these workers. On average, a worker is 33 ($\pm$ 5.7) years old and has 13

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

years ($\pm$ 3.1) of education. 11% of workers in our sample are non-white.

Table 4.1: 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 4.2 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.[3] 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 the average autonomy scores of all workers.

4.2 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 4.3 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

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

Table 4.2: 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

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.[4] 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 3.3.1.

[4] 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

Table 4.3: 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 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.

scaling and normalization in discrete choice models.

4.3 Simulation results

I estimate the two-sided logit model using the MCMC approach described in Chapter 3. 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 4.1 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 4.1: 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 $\times 5$ thinning interval).

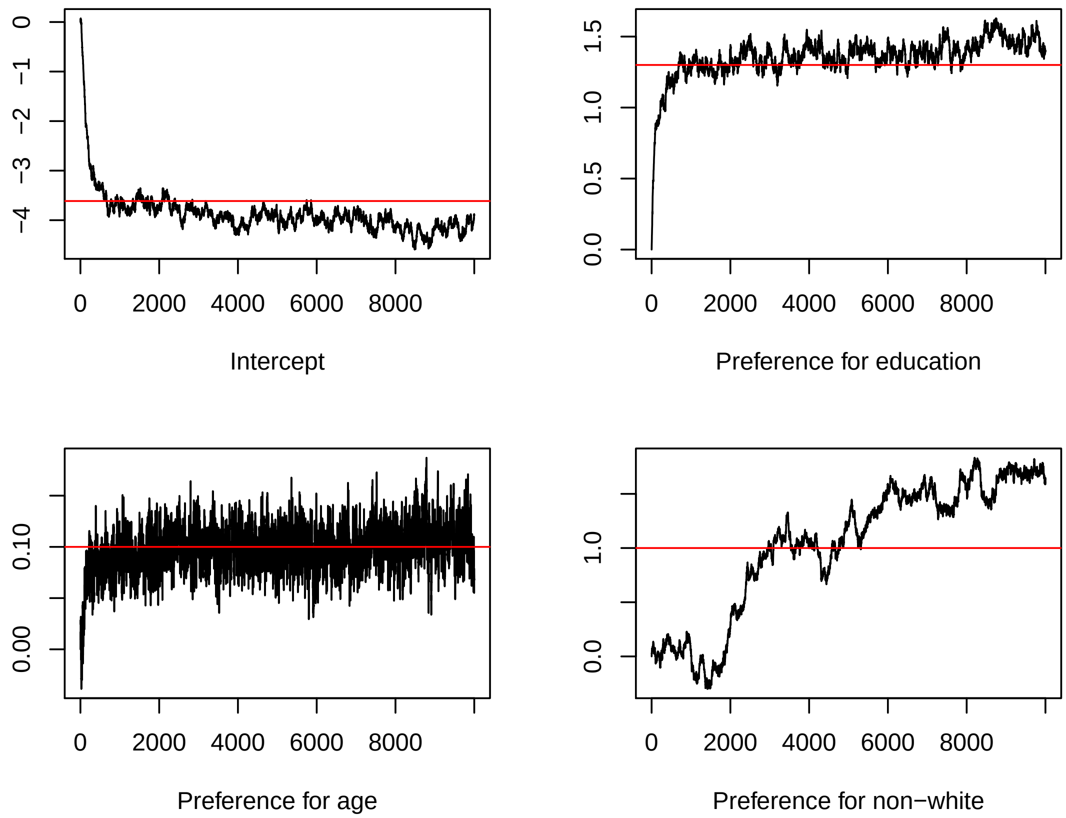

FIGURE 4.2: Two-sided logit estimates for professional firm's preference. The MCMC chain is able to converge to the true parameter value, indicated by the red line, albeit with more autocorrelation than the MCMC chain for worker's preference in Figure 4.1.

Figure 4.2 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.[5] 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

[5] 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 4.3.

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 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 our sample has very few *non-white* workers 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 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 4.5 will discuss this issue and potential remedies in more details.

4.4 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 dis-

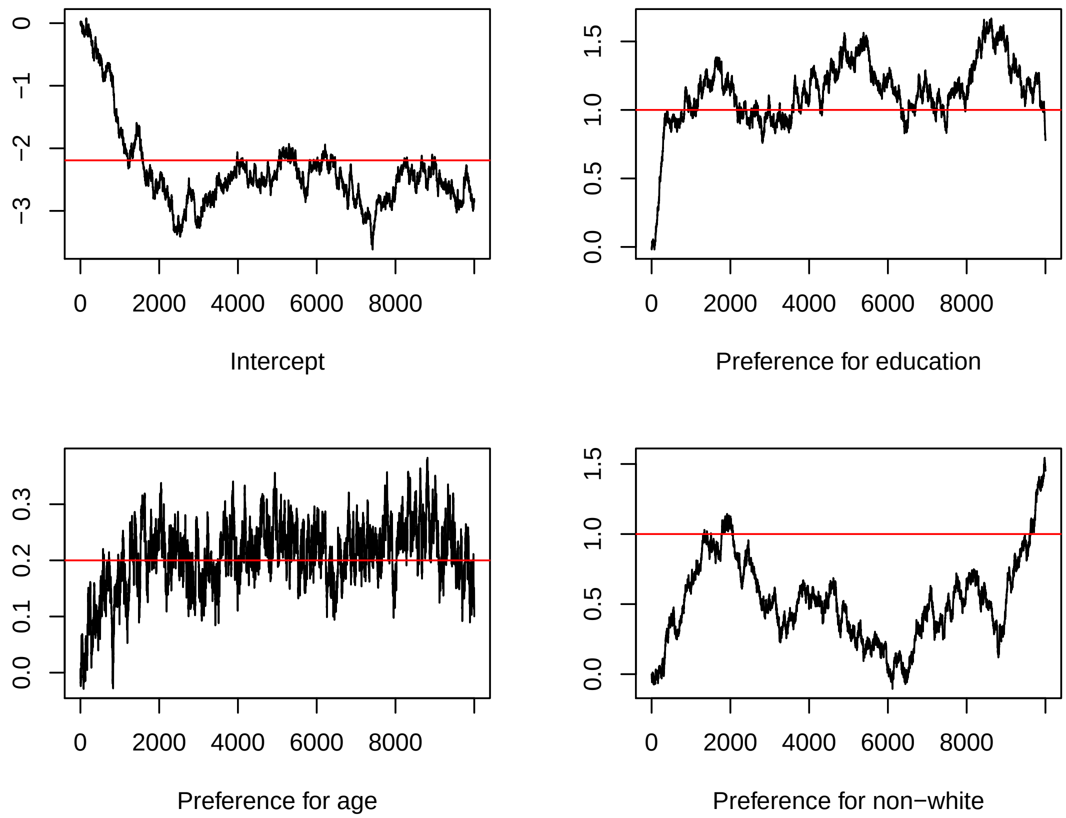

FIGURE 4.3: Two-sided logit estimates for managerial firm's preference. Because the managerial firm only has a small sample size of 40 workers, or 1.9% of the total sample, its preference is estimated more poorly than other's.

crete 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 US.[6] 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

[6] 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.

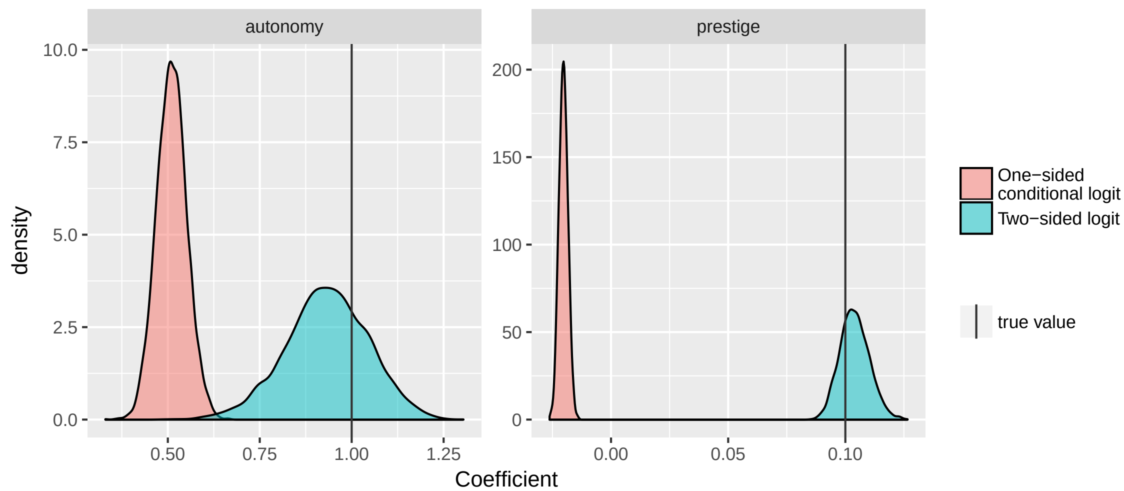

FIGURE 4.4: Estimates of workers' preference, produced by two-sided logit and conditional logit. The density plots show that the two-sided logit's 95% credible interval includes the true value, indicated by the black line, while the conditional logit's 95% confidence interval is far from it.

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 4.4 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.[7]

It is informative to examine the big difference between the two-sided and one-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 4.5 (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

[7] 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.

the fact that they have similar utility functions and make offers to the same kind of workers. In contrast, in the observed choice (Figure 4.5, 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.

4.5 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 4.6). 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.

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

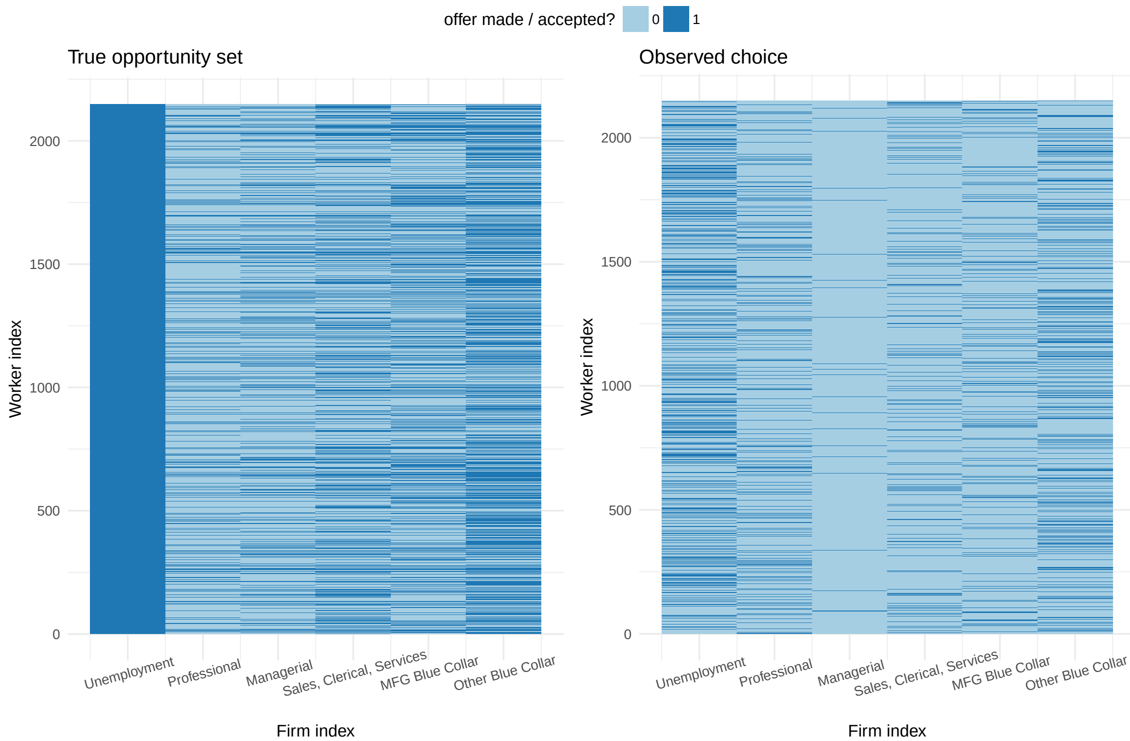

FIGURE 4.5: Binary heat map for the true opportunity set (left) and observed choice (right). A dark blue cell indicates that an offer was made (or accepted) between the firm in the corresponding column and the worker in the corresponding row.

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 worker. While the concept is simple, this approach is not straightforward to engineer, and is left for future research.[8]

[8] 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.

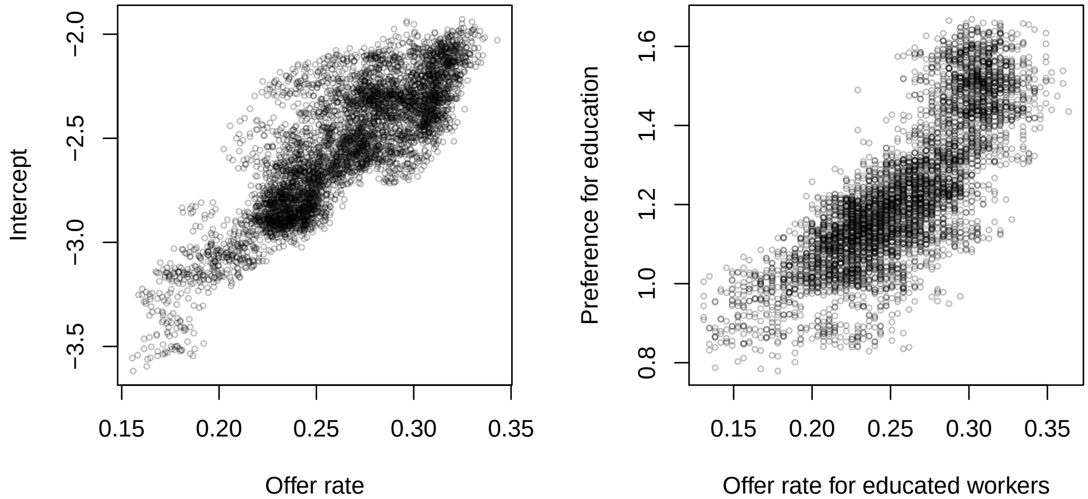

FIGURE 4.6: Correlation between the opportunity set and β. The left panel shows the correlation between the β intercept and the offer rate of a firm. When the intercept is high, the firm is also much more likely to extend an offer. The right panel shows the correlation between the β for education and 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.

4.6 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 the other side offers.[9] 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

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

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 4.7 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.[10] 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 4.8 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 panel.[11]

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.

[10] 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.

[11] 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.

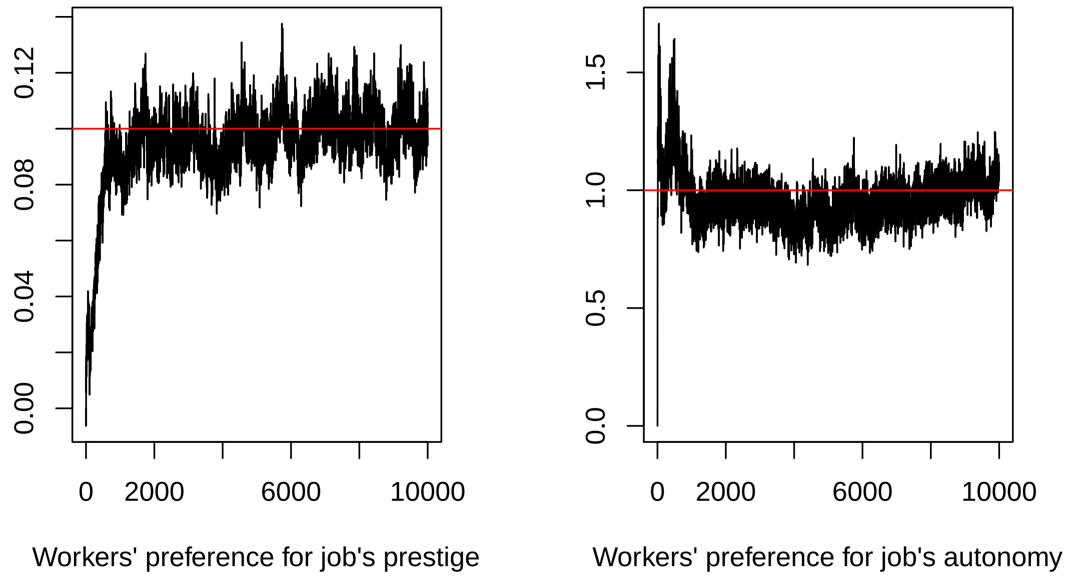

FIGURE 4.7: Estimates of workers' preference are unchanged even when we do not observe workers that choose unemployment (i.e., the reservation choice).

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 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

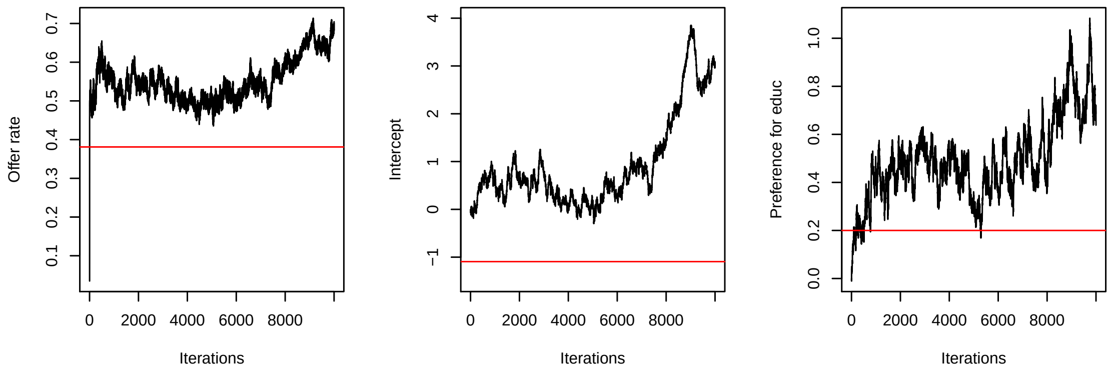

FIGURE 4.8: Estimates of firms' preference are biased when we do not observe workers that choose unemployment (i.e. the reservation choice).

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 4.9 shows the our estimates for its parameters are still correct, unlike the estimate for 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.

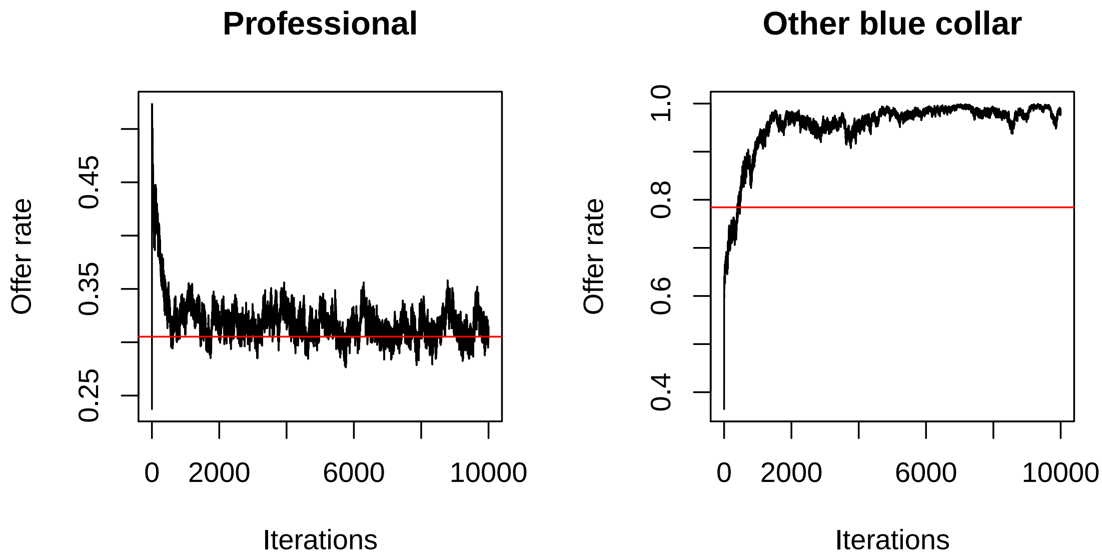

FIGURE 4.9: The estimates

4.7 Analysis of US labor market data

In this section I apply the two-sided logit model on the US labor data of males workers, 1982-1990, and compare my result with Logan (1996)'s findings.

Figure 4.10 shows workers' preference for two job characteristics, prestige and autonomy. While worker's preference for prestige is positive and statistically significant, the attitude towards autonomy seems more mixed. The posterior means for the coefficients of prestige and autonomy are 0.08 (± 0.007) and -0.02 (± 0.12), which are largely in line with Logan (1996)'s estimates.

Figure 4.11 shows firms' preference for workers' education and age. The result is substantively plausible. The coefficient for education is positive and statistically significant for services, professional, and managerial firms, indicating that they want highly educated workers. On the other hand, other blue collar and manufacturing blue collar firms have a negative preference for educated workers, perhaps because they consider these workers a poor fit that leaves when a new opportunity arises.

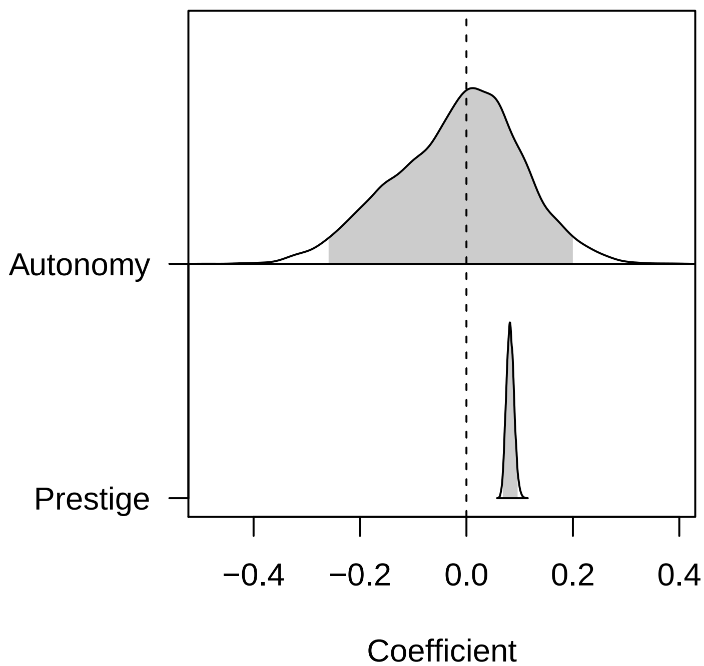

FIGURE 4.10: Workers' preference for firms' characteristics. The density plot and the shaded region show the posterior distribution and the 95% credible interval after burn-in. While prestige is highly valued by workers, autonomy seems to be less importance.

The relative weight of education and age in firms' utility functions is also revealing. While both managerial and professional firms care about education, managerial firms seem to care relatively more about a worker's age, likely as a proxy for his experience. Indeed, managerial firm's coefficients for education and age are 0.36 and 0.1, meaning that managerial firm values one year of education as much as 3.6 years of age. In contrast, professional firm values one year of education as much as 26.5 years of age.

In addition to interpreting the effect of workers' characteristics on firms' utility, we can also calculate their substantive effect in terms of the probability of getting

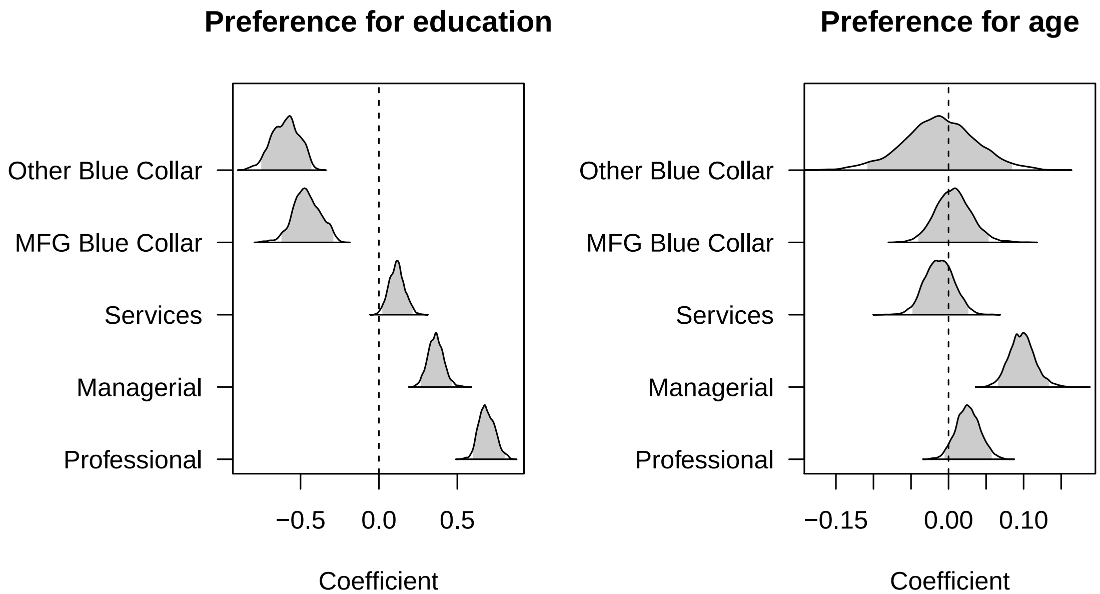

FIGURE 4.11: Firms' preference for workers' education and age. Professional and managerial firms have a strong and positive preference for highly educated workers. While most firms do not highly value older workers, managerial firm stands out in their preference for age (likely as a proxy for experience).

hired. Such interpretation would be more relevant to a worker deciding whether to get more education or not. Figure 4.12 shows the probability of being hired for a typical worker (i.e. one whose age is set at the median and race is set at the mode). For a worker seeking a service job, an extra year of education seems to have a positive and relatively linear effect on the probability of getting hired. In contrast, to get hired by a professional firm, an extra year does not have much of an effect until a worker crosses the tipping point of having 12 years of education. This result suggests that professional firm values college education much more than high-school education.[12]

[12] The diagnostics plots, included in Appendix C, also show quick convergence for the MCMC of this analysis.

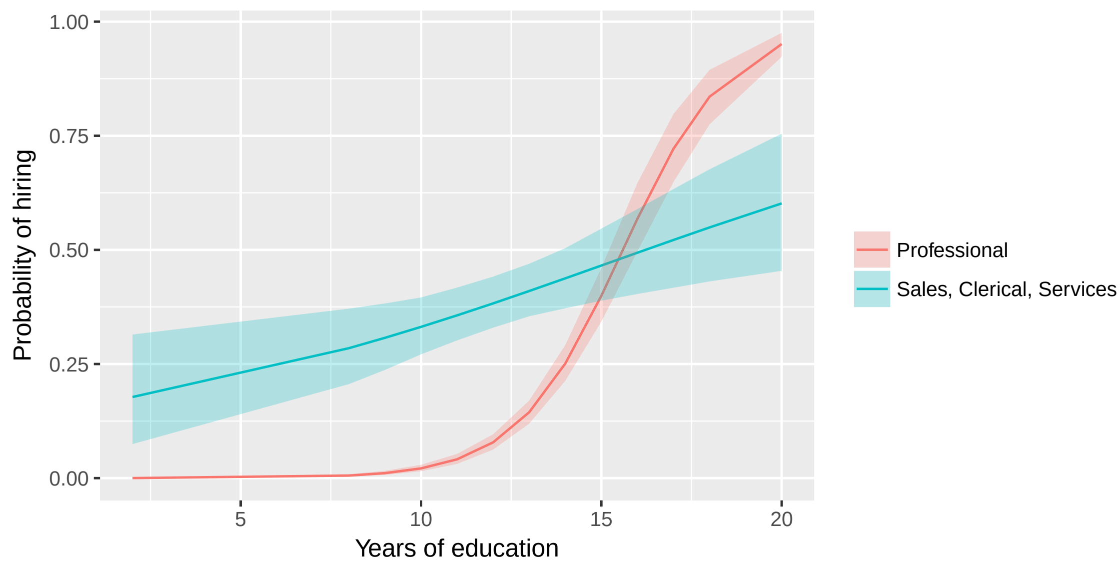

FIGURE 4.12: The effect of education on the probability of a worker being hired into a professional and a services job.

4.8 Conclusion

In this chapter, I explore the properties of the two-sided matching model via simulation and an analysis of US labor data. The key finding is that the two-sided logit model is superior to the one-sided approach in studying matching market. Despite its wide use, the one-sided approach produces misleading result that confounds the preference of one side with the other's. For example, I simulate a scenario in which professional and managerial firms, both highly desirable, compete for the same small pool of skilled workers. Because professional firm is slightly more prestigious, the majority of this worker pool flocks to the professional firm over the managerial firm. In this example, the fact that the managerial firm is able to attract only a few workers is caused by both managerial firm's selectiveness and its slight inferiority in comparison with professional firm. However, the one-sided approach is unable to make this distinction and mistakenly considers the managerial firm to be highly undesirable by workers. This finding confirms my argument in Chapter 2. Because the FDI literature has not taken into account countries' preference in a two-sided approach, its estimate of MNCs' preference is suspect.

In addition, I examine how the two-sided logit model performs when the "reservation choice" is not observed. This issue is important to the study of FDI matching market because we typically do not observe those MNCs that make the "reservation choice," i.e. to stay at home instead of investing overseas. I find that this data limitation does not affect the estimate of MNCs' preference. However, it does bias the estimate of countries' preference. Intuitively, without observing firms that are unable to invest overseas, our sample only includes highly desirable MNCs that are invited by at least one country. Therefore, it appears as if countries hardly reject any MNC, causing countries' demand for FDI to be estimated as more permissive than it really is. There are two potential remedies to this problem. First, we can focus on the estimate for the most desirable countries, which is least affected by this problem. Second, I can use an informative prior that constrains the demand intercept in countries' utility functions to a small value, counteracting the effect of the unobserved reservation choice.

In the next chapter, I take into account these considerations in applying the two-sided logit model to the Japanese FDI data.

5

Two-sided matching model on Japanese FDI

In this chapter, I apply the two-sided matching model to analyze Japanese FDI (JFDI) 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 demand for FDI. Second, I show how countries value different characteristics in a subsidiary. Third, I use firm-level operational data that maps closer to our theoretical concept of FDI than FDI flow statistics.

This chapter proceeds as follows. Section 5.1 motivates the study of JFDI in Asia. Section 5.2 qualitatively describes the FDI preference of three Southeast Asian high growth economies, namely Malaysia, Thailand, and Indonesia. Section 5.3 describes the dataset. Section 5.4 justifies the variables used in the model. Finally, Section 5.5 discusses the result.

5.1 The role of JFDI in Asia

In the 1980s and 1990s, JFDI 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, JFD also shifted its focus away from North America and Europe, making Asia its top destination. This new wave of JFDI also had a different goal. While Japanese MNCs in North America and Europe was motivated by market expansion or trade barriers avoidance, JFDI in Asia mainly aimed to take advantage of low labor cost, countering Japan's own rising cost of production (Jomo et al., 1997, 44).

Scholars have argued that this wave of JFDI 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 Southeast Asian countries' preference for FDI

In Chapter 2, I discussed the FDI openness and targeting strategies of Korea and Taiwan, showing their selectiveness towards FDI entry. Pursuing a development strategy based on national ownership, especially after their initial years of economic hardship, Korea and Taiwan only allowed FDI projects that either 1) contributed to the balance of payments via export or 2) were willing to transfer advanced technologies to domestic partners. In this section, I describe the FDI openness and targeting strategies of the three Southeast Asian newly industrializing economies (NIEs), including Malaysia, Thailand, and Indonesia, focusing on their preference for export-oriented and high-tech FDI. Compared to Korea and Taiwan, the Southeast Asian NIEs did not aggressively pursue a national ownership development strategy. Therefore, their industrial policy with regards to FDI aimed not to build up their domestic infant industries but to integrate fully into the MNCs global production value chain. In general, this strategy meant attracting export-oriented FDI that performed low-cost assembly then re-exported the product. In the 1990s, facing rising labor costs and stagnating productivity from the FDI sector, some countries, especially Malaysia and Thailand, attempted to move up the global value chain by attracting higher value added FDI, albeit with varying degrees of success.[1]

Malaysia. Initially, FDI flowed into Malaysia largely because of its import substitution incentives program, launched in 1958. However, as the domestic market reached its consumption capacity in the late 1960s, Malaysia pivoted its incentive program to promote export-oriented manufacturing. Malaysia set up ten Free Trade Zones (FTZs) that were well suited for companies participating in the global value chains, providing services such as expedited customs processing and reduced import and export taxes. The Promotion of Investments Act in 1986 generalized the benefits enjoyed by exporters in the FTZs to the entire economies, thus fully committed Malaysia to an export-led growth strategy (Jomo, 2003, 96-100).

In the 1960s and 1970s, Malaysia focused on job creation and did not screen FDI for their technological content. However, in the 1980s and especially the 1990s, Malaysia became more pro-active in targeting high-tech FDI. Starting with the 1986 Promotion of Investments Act, the government attempted to offered tax incentives for firms' R&D activities, albeit with little effect since MNCs already enjoyed broad and generous exemptions. In 1991, Malaysia phased out full tax exemption that was available to almost all exporting firms, now exempting only 60% instead of 100% of corporate profits. By doing so, the government could use full exemption to attract more technologically advanced FDI. In 1995, the government fully reformed their

[1] This section relies on a series of books edited by Jomo K. S. on Southeast Asia's industrial policy, including Jomo et al. (1997); Jomo (2001, 2003).

investment promotion and included a special incentive program for "high-technology" and "strategic" FDI projects, namely those that had at least \$21,500 of capital per employee, 30% value added, 15% of employees in managerial or technical positions, or were located in outlying states (Felker, 2001).

Thailand. Like Malaysia, Thailand pursued an import substitution program that ran out of steam in the 1980s, prompting the government to reform the economy towards export-led growth. However, unlike Malaysia, Thailand had developed a larger class of domestic business over two decades of import substitutions, who now resisted the government's attempt to remove protectionist measures. Unable to garner inter-ministerial support for domestic reform, Prime Minister Prem, who had full control of investment promotion via the Board of Investment (BOI), used incentives to attract export-oriented FDI instead. In the early the 1990s, the Anand administration (1991-92), which rose to power through a military coup and was thus relatively insulated from the pressure of domestic business groups, further removed protectionist policies and pushed for export-oriented FDI (Felker, 2001).

On the other hand, Thailand was less targeted with attracting high-tech FDI. Indeed, as a BOI Secretary-General complained in 1999, the political influence of domestic business caused the incentive programs to be used indiscriminately, even in sectors that suffered from over-capacity (Felker and Jomo, 2003, 90).

Indonesia Compared to Malaysia and Thailand, Indonesia attitude towards FDI was less consistent, swinging between indifference and welcome depending on the temporary need of the state. After Suharto's rose to power in 1967, his Western-trained technocrats put together a liberal macroeconomic programs, including property rights guarantee and a range of incentives for FDI. However, during the oil booms of 1970s, the cash-flush government created SOEs in more sectors while closing them off to FDI. When the oil price crashed in the 1980s, Indonesia once again invited FDI to diversify its export portfolio away from oil. Finally, a major reform in June

1994 fully committed Indonesia to FDI liberalization, removing sectoral barriers and allowing wholly owned subsidiaries.

While Indonesia eventually opened up, it was both slower and less aggressive than Malaysia and Thailand in pursuing export-led, high-tech FDI. When the government designate a sector as "strategic," it was meant to be controlled by SOEs and not to be targeted for FDI attraction. Even during periods of reform, Indonesian technocrats shunned using incentives to attract specific types of FDI and simply removed restrictions from the onerous negative list (Felker and Jomo, 2003, 118-124).

5.3 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.[2] 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.[3]

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

[3] 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 JFDI 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.[4]

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

[4] 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).

5.4 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 JFDI 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).[5]

- 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

[5] 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.

5.5 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 4.6, 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.[6]

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 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.

Surprisingly, 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. Contrary to our expectation of JFDI as efficiency-

[6] 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. Therefore, I allow substantial variation across countries, while keeping the average demand intercept slightly negative at -1. Because MNCs' characteristics are centered, the negative demand intercept reflects my assumption that the average country does not extend an offer to the average MNC, taking into account Asian countries' increasing selectiveness towards FDI in the 1990s. In choosing these priors, I try to find one that is informative enough to keep the demand intercept from blowing up, yet not so strong that it overwhelms the data.

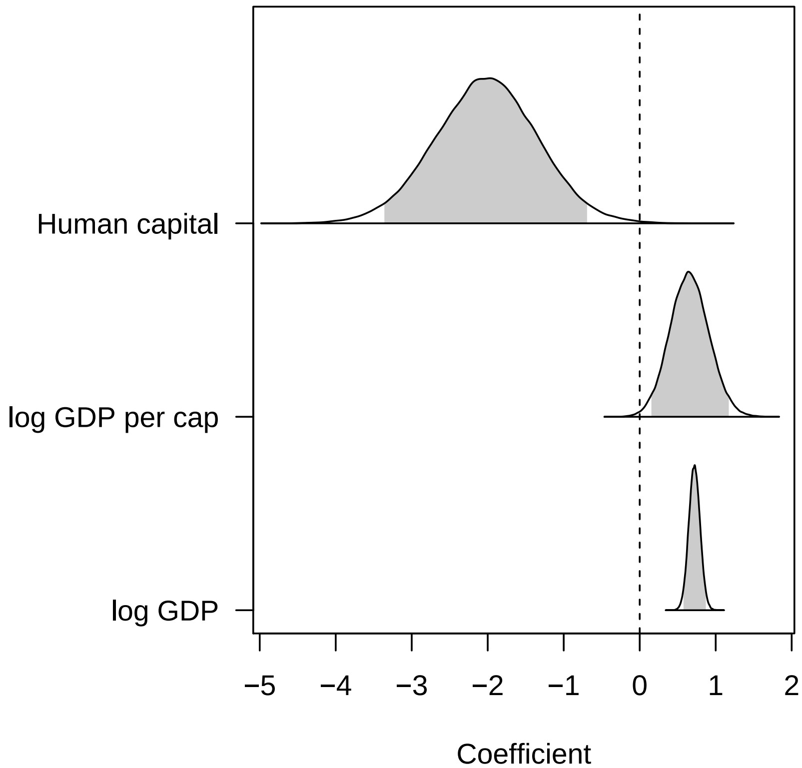

FIGURE 5.1: MNCs' preference for countries' characteristics. The density plot and the shaded region show the posterior distribution and the 95% credible interval.

seeking, this finding suggests that JFDI in 1996 was looking to enter Asia's domestic markets. One potential explanation is that, as Southeast Asia quickly raised its labor cost and expanded its market size, the nature of JFDI may be changing as well (Jomo, 2003, 44).

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 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[7]

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

[7] Essentially we are constructing the posterior predictive distribution for the share of MNCs in Thailand, integrating out the preference parameters via simulation.

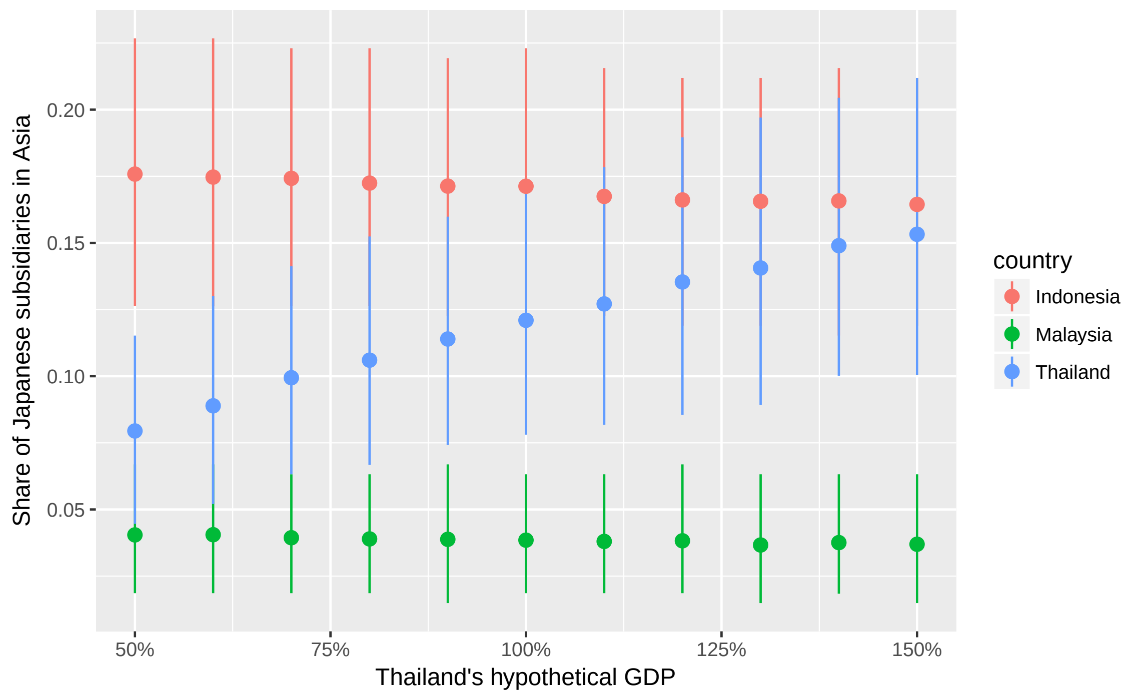

FIGURE 5.2: Effect on Thailand's GDP on its share of MNCs. The point and line range show the mean and the 95% credible interval.

and Malaysia, two competitors of Thailand in ASEAN, declines slightly as Thailand becomes more attractive. The result suggests that these three countries tend to attract MNCs from a common pool, and Thailand's gain will be the others' loss.

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.[8]

While the relative size of preference parameters within a country is meaningful, we cannot readily compare preference parameters across countries. This is because

[8] I present the results for Taiwan and Indonesia here because they are two countries highly desired by MNCs. As discussed in Section 4.6, the estimate for highly desirable countries are more accurate.

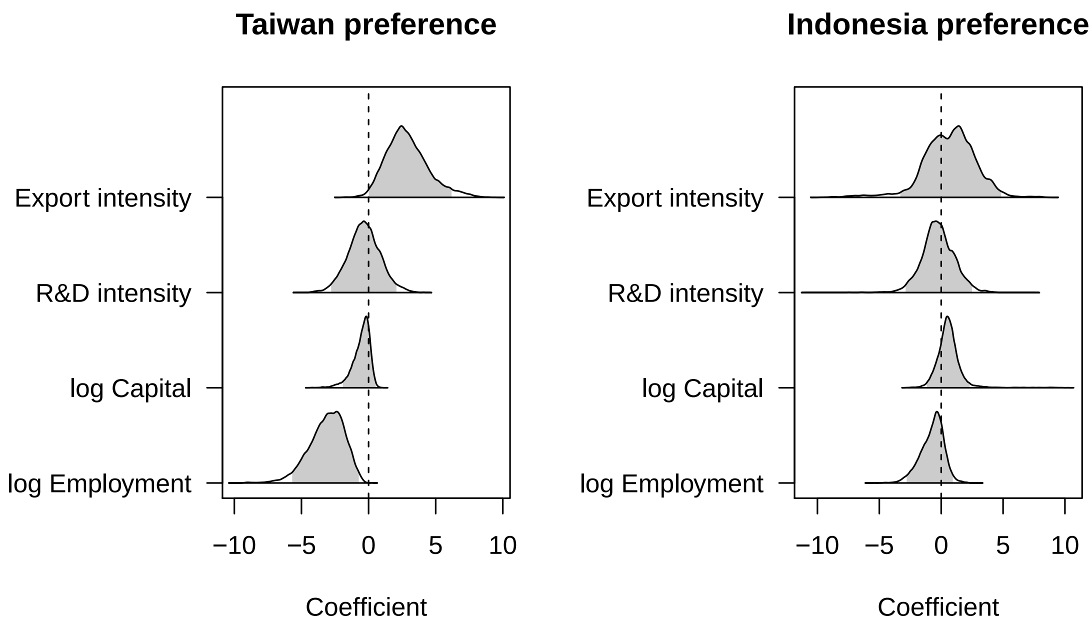

FIGURE 5.3: Preference of Taiwan and Indonesia for MNCs' characteristics.

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 finding meets our expectation that high-growth East Asian (Korea, Taiwan) and Southeast Asian (Malaysia, Thailand) were steering away from labor-intensive manufacturing in the 1990s. In addition, several countries including Taiwan, Malaysia, and Thailand, seem

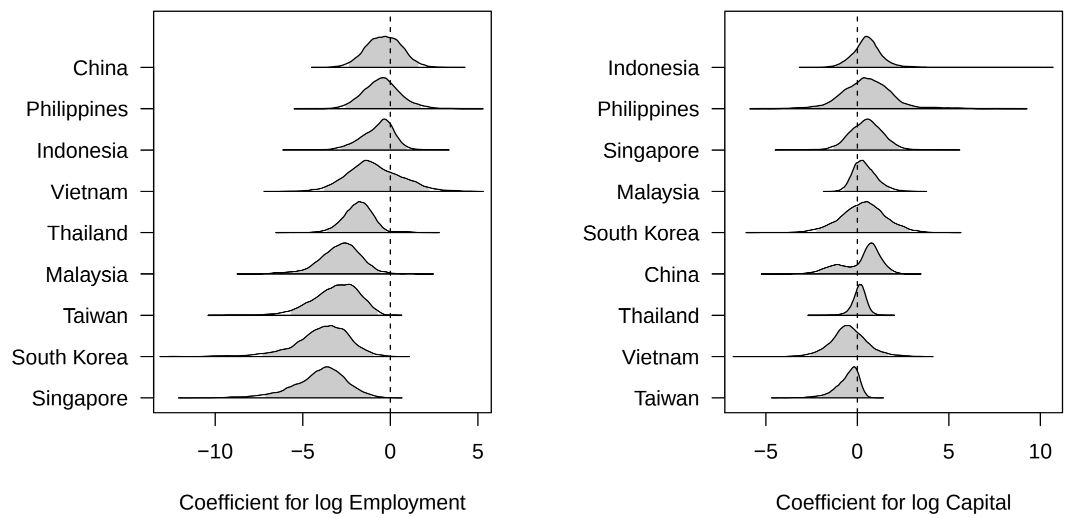

FIGURE 5.4: Countries' preference for subsidiaries' size, measured by their labor force (left) and capital (right). The density plot and the shaded region show the posterior distribution and the 95% credible interval.

to prefer subsidiaries that focus on export. This finding affirms our understanding of these economies as being export-driven. On the other hand, no countries have a positive preference for MNCs' R&D intensity despite qualitative evidence of countries' effort in upgrading their FDI quality. One interpretation is that our variable of *parent firm's* R&D intensity is a poor proxy for the technological sophistication of the subsidiary. Indeed, since Japanese MNCs in Asia mainly used local labor to fulfill low value-added steps in its value chain, the parent firm's high R&D intensity does not necessarily imply that the subsidiary is high-tech.

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

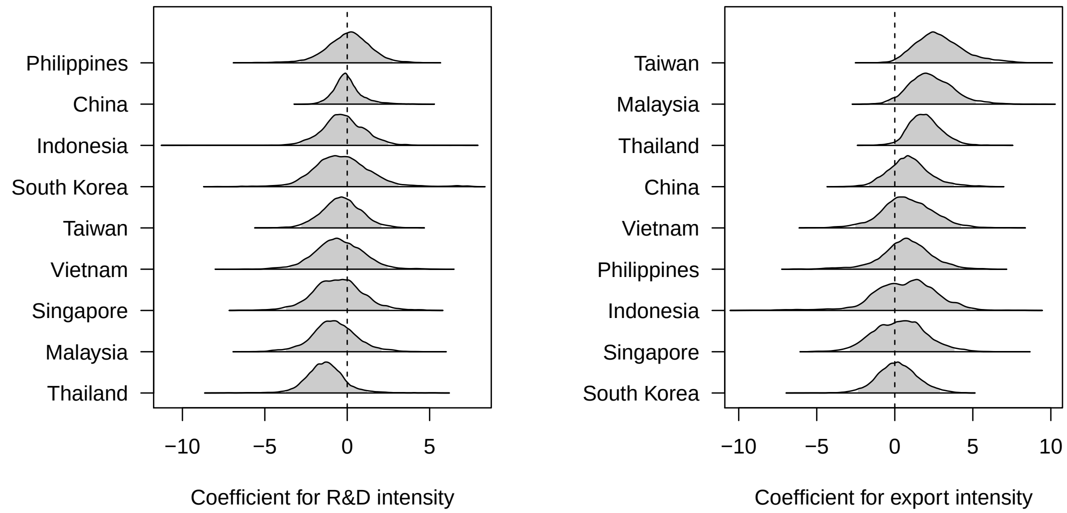

FIGURE 5.5: Countries' preference for firms' intangible assets, i.e R&D intensity (left) and export intensity (right). The density plot and the shaded region show the posterior distribution and the 95% credible interval.

decreased to match South Korea's on average), the share of MNCs located in China 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.

5.6 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

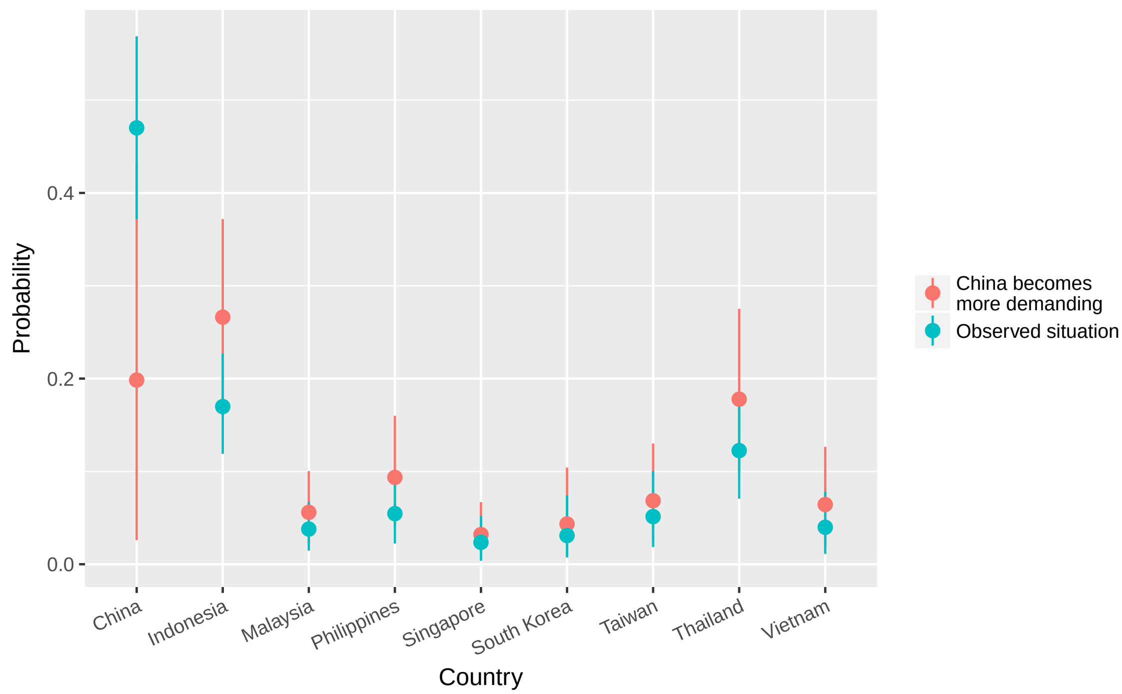

FIGURE 5.6: Effect of China's demand for MNCs on MNCs' location across Asia. If China becomes as picky as South Korea, its share of MNCs will decrease from 47% to 20%. The majority of these MNCs will relocate to Indonesia and Thailand.

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.[9] In comparison, one-sided logit models predict less well. Figure 5.8 shows the results of one-sided logit models predicting whether a firm is located in China or not (left) and in Indonesia or not (right).[10] The AUC for these models is around 0.6, a decent albeit not remarkable performance.

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

[9] On the other hand, the model performs less well in predicting the location of any particular firm. Averaging across firms, my model correctly predicts a firm's location only 30.4% of the times. This result is expected given the difficulty of granular prediction at firm level.

[10] I choose China and Indonesia because these are two countries with the most data points. This way, I'm giving one-sided models the best chance to predict well.

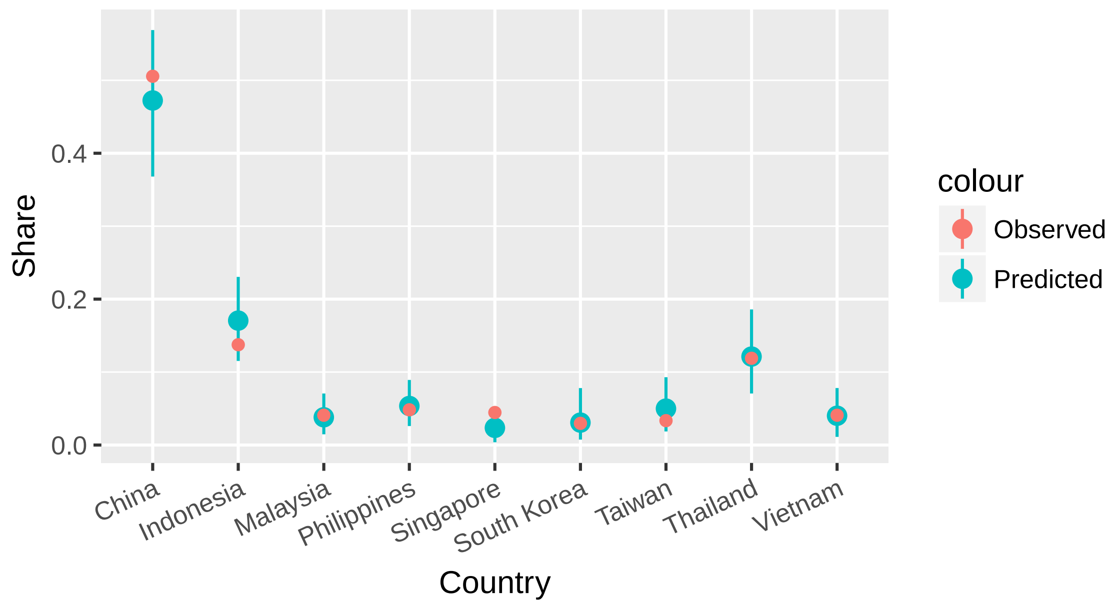

FIGURE 5.7: Predicted and observed share of MNCs across countries. The point and the error bar show the posterior mean and the 95% credible interval.

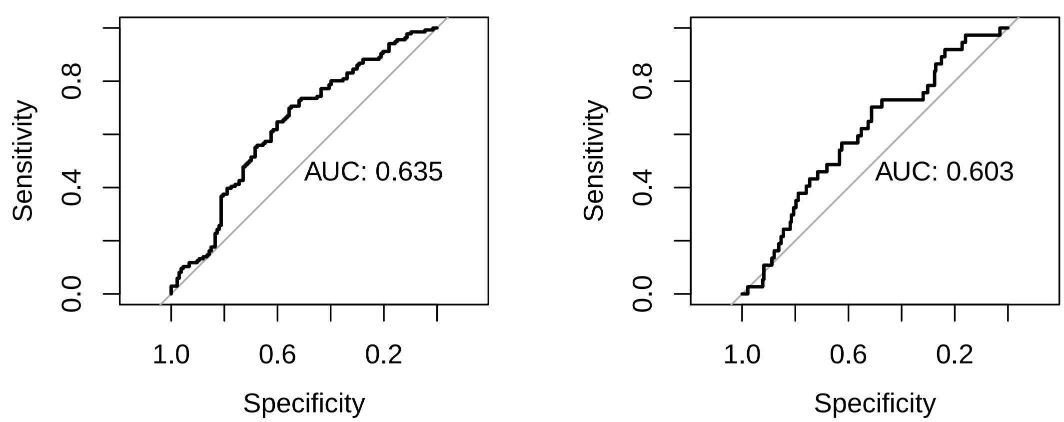

FIGURE 5.8: ROC curve of one-sided logit models, predicting whether a firm is located in China or not (left) and Indonesia or not (right).

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 5.9 and Figure 5.10 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.

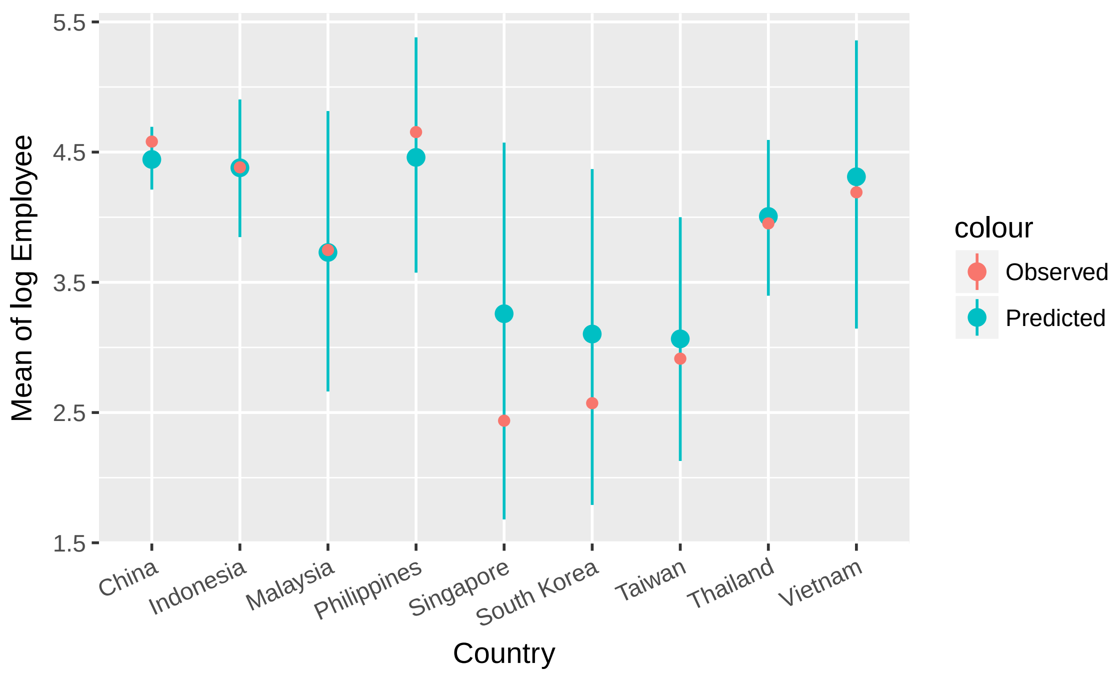

FIGURE 5.9: Average of MNCs' labor size across countries.

5.7 Conclusion

In this chapter, I apply the two-sided logit model on a dataset of JFDI in Asia in 1996, estimating the preference of Asian countries and Japanese MNCs for one another. I find that Japanese MNCs negatively valued a country's human capital index. The result confirms the qualitative evidence that JFDI was efficiency-seeking, mainly in search of low-skilled, low-cost labor. On the other hand, my model shows that Japanese MNCs positively valued a country's market size and level of development. While JFDI has been described as export-oriented instead of market-seeking, this finding suggests that Japanese MNCs might have their sight on the expanding domestic markets of Asian countries by 1996.

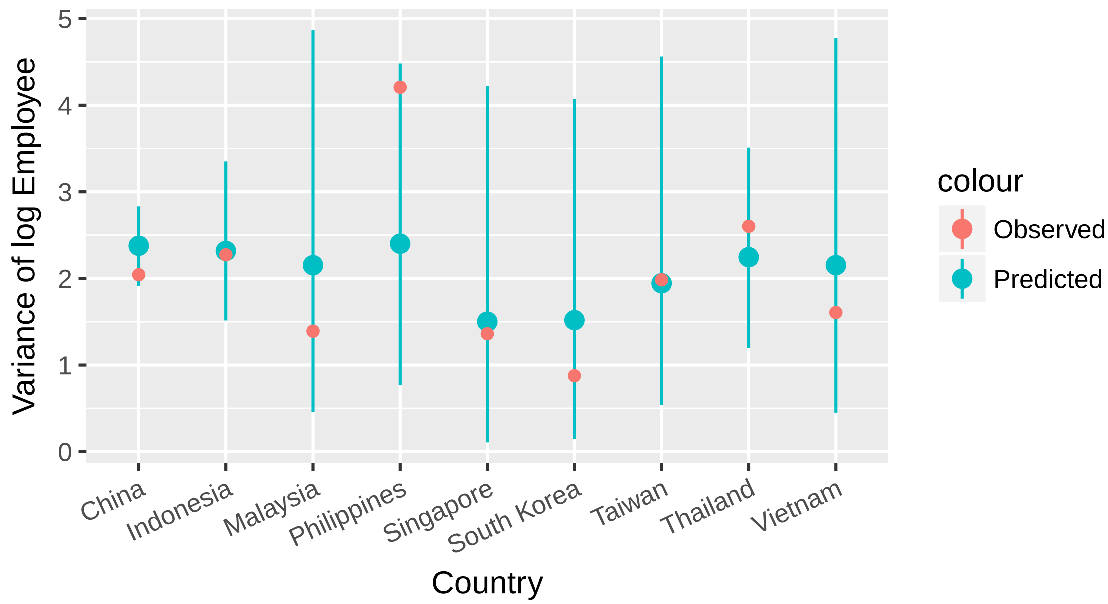

FIGURE 5.10: Variance of MNCs' labor size across countries.

The estimate for countries' preference has more limitations. As discussed in Chapter 4, because our sample includes only MNCs that are desirable enough to be invited by at least one country, the model produces estimate that make countries seem more permissive towards FDI than they really are. To mitigate this issue, I put an informative prior on the demand intercept of countries' preference. The procedure for choosing this prior admittedly needs improvement. Currently, I allow substantial variation across countries' demand intercept while setting the mean of the demand intercept to be slightly negative. This prior reflects my assumption that the average country does not extend an offer to the average MNC, taking into account the increasing effort by Asian countries to upgrade the quality of their FDI inflow in the 1990s.

Keeping in mind these caveats, I find promising results in the model. For example, Taiwan, Malaysia, and Thailand positively valued export-oriented MNCs, supporting our qualitative understanding of their FDI policies. Most importantly, the model has a good fit for the pattern of MNCs across countries. This result suggests that the two-sided logit model can be an important tool for policy makers. Using the model, policy makers can simulate how their inflow of MNCs changes under hypothetical scenarios, such as China reducing their FDI demand, or a neighboring competitor becoming more attractive to MNCs. With these predictions, policy makers can then formulate an informed competitive response.

6

Conclusion

In this chapter, I discuss potential improvements to the two-sided matching model of FDI. In addition, I explore other areas of Political Science that the two-sided matching model may be applicable. Finally, I conclude with final thoughts about how the FDI literature can better contribute to the pressing issue of globalization.

6.1 Potential improvements

In Chapter 5, the analysis uses FDI location data from only one year. Instead, we can use the entire panel of data to estimate countries' preference. To do so, we add one more level to our hierarchical model. In this new setup, the lowest level is a country-year, whose preference parameters are drawn from a normal distribution centered on the preference matters of the corresponding country. With this model, we can study how countries' preference evolve over time, a phenomenon that qualitative case studies in Chapter 2 and Chapter 5 have demonstrated.

In addition, we can "explain" countries' preference by building a regression model after we have estimated their preference. In this model, the dependent variable is the estimate for countries' preference and the independent variables are factors such as regime type or the government's time horizon. For example, we may hypothesize that governments with a longer time horizon attract more R&D heavy FDI because they are likely to be in power long enough to reap the rewards of R&D. Currently, such a regression model does not have much power due to the small sample size of countries. If we could expand the model to analyze panel data, in which each country-year is one observation, we would have more statistical power to study what factors shape countries' preference for FDI.

If we had data on the specific offers that MNCs receive from countries, we can also produce more precise estimate of MNCs' preference. As the case studies of Korea and Taiwan in Chapter 2 demonstrate, countries and MNCs engaged in intense negotiation, making tailored offers and specific requirements. While it is unlikely to systematically collect such a detailed dataset of individual deals, data on fiscal incentives, especially tax holiday, are sometimes available in business surveys.[1]

6.2 Other applications for two-sided matching model

6.2.1 US federal clerkship market

In the US, graduates at top law schools vie for the best federal clerkship every year. These temporary, one-to-two-year positions are the launching pad for Supreme Court clerkship, 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, ranging 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

[1] For example, Vietnam's Provincial Competitiveness Index (PCI) routinely asks foreign firms about the incentives they receive from Vietnam's provincial governments.

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 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, 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, e.g. 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 need to consider what clerks think about the offer because they focus on Supreme Court clerkship, 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.

6.2.2 The market for forming a coalition government

Besides election, government formation is the most consequential political process in determining which government citizens are subject to. Most extant studies of government formation are either game theoretic models or thick, "inside-the-Beltway" narratives. We can potentially advance the literature by considering government formation as a many-to-one matching market, with the *formateur* party on one side and other minority parties on the other.[2]

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.[3] 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.

[2] 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.

[3] 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 turn a coalition into a winning one by using its controlled seats. The two-sided matching model is not suitable for this case because parties are not looking for their policy match.

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.

6.2.3 Final thoughts

Once a match is formed in a two-sided matching market, the two involved parties are committed and no longer available to others on the market. Therefore, matching markets tend to involve weighty decisions: marriage, job, organ donation, or government formation. To study matching markets is to examine some of the most consequential social processes.

With FDI inflow making up 9.4% of the global fixed capital formation in 2016, the FDI market is one such consequential process (UNCTAD, 2017). The importance of FDI attracts substantial attention from IPE scholars, yet none has paid attention to its two-sided nature and to the preference of countries in this market. Such neglect is surprising given that political scientists are first and foremost interested in politics. The formation of countries' preference is inherently political, and should be of interest to our field. Perhaps the inattention to the preference of countries in the FDI market stems mainly from the methodological challenge of analyzing a two-sided market. In this case, I hope that my research has made it less of a barrier.

If future FDI research pays more attention to countries' preference, the benefit extends beyond just the ability to come up with better estimates. More importantly, the FDI literature will be able to speak to the broad and important issue of government policies in the era of globalization. What policies will countries adopt in reaction to global capital? And which domestic constituencies will shape their policies?

These questions are not new. The 1999 Seattle Protests surrounding the WTO

Ministerial Conference were a physical and violent embodiment of these concerns. Labor unions protested the outsourcing of jobs, environmentalists fought MNCs' pollution, labor rights activists confronted working conditions in third world factories—different groups had different enemies, but everyone was connected in the collective cause of shielding local politics from global interest and protecting people from corporations.

These questions are not passé either. In 2007, political scientist Kenneth Scheve and economist Matthew Slaughter warned that less-skilled US workers were increasingly anxious about being the losers of globalization, causing protectionism to be on the rise. In response, they called for "A New Deal for globalization," which would rebuild the support for globalization by compensating those hurt in the process (Scheve and Slaughter, 2007). Their call went unheeded, and their warning came true. The US 2016 election was in large part a referendum on globalization, and large swaths of American voters said, "Not for me."

In a role reversal, it is developing countries that are now enthusiastic believers, providing "the strongest support across the board for foreign investment, trade and the benefits to be derived from globalization."[4] As beneficiaries, developing countries will likely maintain their strong support for FDI in particular and globalization in general. At the same time, their challenge is to upgrade the quality of their FDI and build up their domestic business, allowing them to participate in a higher value added step in the global value chain. Without a market and cash reserve the size of China's, it is unclear whether developing countries can adopt the policies to do so.

In conclusion, I hope that my two-sided approach to the FDI market has not only sparked scholars' interest in countries' FDI policy but also provided the tool to study it. I have taken the first step in this research agenda by estimating countries' preference—the next challenge is to study their trends and examine their determi-

[4] http://www.pewglobal.org/2014/09/16/faith-and-skepticism-about-trade-foreign-investment/

nants. I am excited to see future developments in this field.

Appendix A

Derivation of the Metropolis-Hastings Acceptance Ratio

A.0.1 Opportunity sets O

Target distribution for a firm i

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

$$MH_O = \frac{p(O_i^*|A_i, \alpha, \boldsymbol{\beta})}{p(O_i|A_i, \alpha, \boldsymbol{\beta})} = \frac{p(O_i^*, A_i, \alpha, \boldsymbol{\beta})}{p(A_i, \alpha, \boldsymbol{\beta})} \times \frac{p(A_i, \alpha, \boldsymbol{\beta})}{p(O_i, A_i, \alpha, \boldsymbol{\beta})} \tag{A.2}$$

$$= \frac{p(O_i^*, A_i, \alpha, \boldsymbol{\beta})}{p(O_i, A_i, \alpha, \boldsymbol{\beta})} \tag{A.3}$$

$$= \frac{p(A_i|O_i^*, \alpha)p(O_i^*|\boldsymbol{\beta})}{p(A_i|O_i, \alpha)p(O_i|\boldsymbol{\beta})} \tag{A.4}$$

$$\tag{A.5}$$

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 (3.10) and (3.8)

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

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 (3.10),

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

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

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

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

$$+ \log p(\alpha^*) - \log p(\alpha) \tag{A.14}$$

A.0.3 Firms' parameters, β

Target distribution:

$$p(\boldsymbol{\beta}|A, O, \alpha) = \frac{p(O, A, \alpha, \boldsymbol{\beta})}{p(A, O, \alpha)} \tag{A.15}$$

Metropolis-Hasting acceptance ratio:

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

$$= \frac{p(O_i|\boldsymbol{\beta}^*) p(\boldsymbol{\beta}^*|\mu_\beta, \tau_\beta)}{p(O_i|\boldsymbol{\beta}) p(\boldsymbol{\beta}|\mu_\beta, \tau_\beta)} \tag{A.17}$$

where (A.16) is due to the symmetric proposal distribution.

We plug in (3.8),

$$MH_\beta = \prod_i \left[\prod_{j \in O_i} \frac{\exp(\beta_j^{*\prime} X_i)}{\exp(\beta_j' X_i)} \times \prod_j \frac{1 + \exp(\beta_j^{*\prime} X_i)}{1 + \exp(\beta_j' X_i)} \right] \times \frac{MVN(\boldsymbol{\beta}^* | \mu_\beta, \tau_\beta)}{MVN(\boldsymbol{\beta} | \mu_\beta, \tau_\beta)} \quad \text{(A.18)}$$

$$\log MH_\beta = \sum_i \left[\sum_{j \in O_i} \beta_j^{*\prime} X_i - \beta_j' X_i + \sum_j \log(1 + \exp(\beta_j^{*\prime} X_i)) - \log(1 + \exp(\beta_j' X_i)) \right] \quad \text{(A.19)}$$

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

Appendix B

FDI terminology

Samsung, headquartered in South Korea, opened a factory in Vietnam called Samsung Electronics Vietnam in 2009.

In this scenario, Samsung Korea is the *parent company*. Samsung Electronics Vietnam is the *(foreign) subsidiary*, also the *(foreign) affiliate*. Empirically, the parent company and the subsidiary are two distinct entities, 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, market, and firms as the local economy, local market, and local firms.

Appendix C

Diagnostics plots

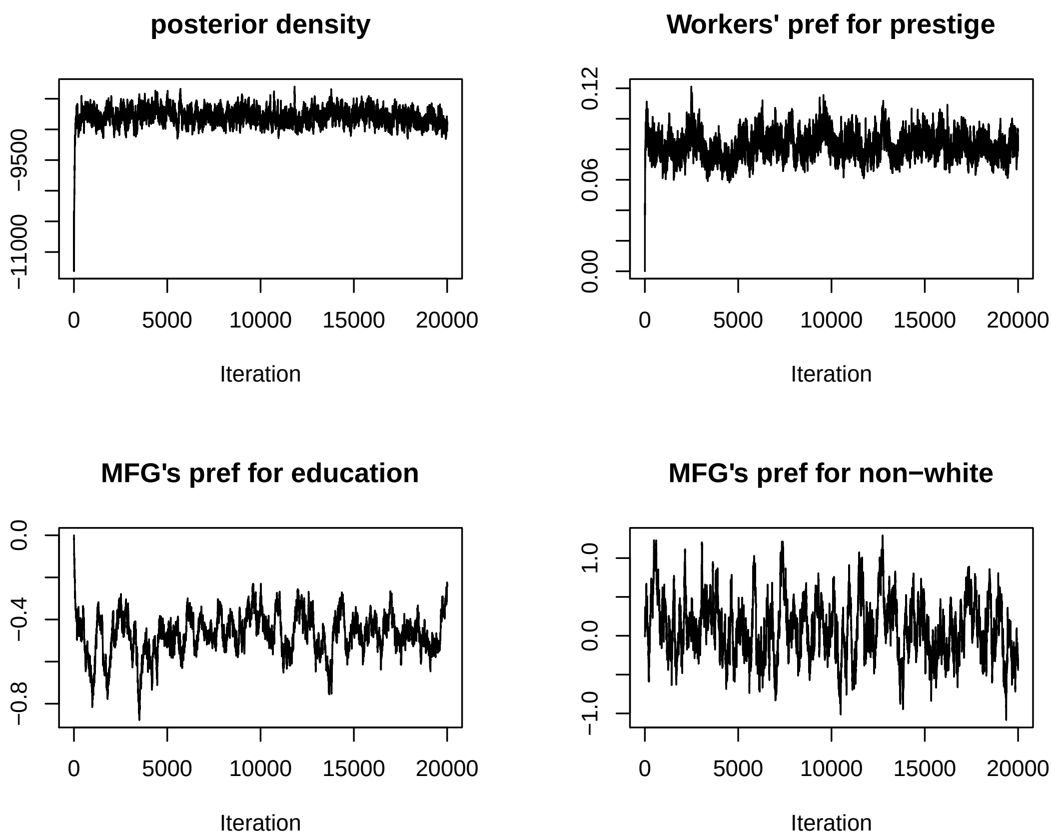

FIGURE C.1: Trace plots for model of the US labor market, showing quick convergence.

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Biography

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