Essays on Firms' Foreign Direct Investment Decisions

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A Dissertation presented to the Graduate Faculty of the University of Virginia

in Candidacy for the Degree of Doctor of Philosophy

University of Virginia

November, 2021

Abstract

Multinationals are a key part of the global economy, and many governments have made tremendous efforts to attract FDI. When a firm invests overseas, it faces two choices—a firm can either establish a new facility in its host country or purchase a local firm. These two types of foreign direct investment (FDI) are greenfield investment and cross-border mergers and acquisitions (M&A). The first chapter investigates the question: how do firms choose between the two FDI entry modes? Using a novel US firm-level dataset, I provide the first evidence that multinationals with higher levels of intangible capital systematically invest through GF rather than through M&A.

In the second chapter, I study how the firm's choice of FDI mode affects the economy in the host country. Motivated by the result in the first chapter, I develop and quantify a general equilibrium search model of a multinational firm's choice between M&A and GF. The model implies that equilibrium FDI patterns can be suboptimal from the host country's perspective. In particular, since the gap between the productivities of multinationals and local firms is larger in less developed countries, policymakers there can increase welfare by incentivizing FDI through M&A. By allowing highly productive multinationals to use local intangible capital, this policy increases aggregate productivity more than the laissez-faire outcome.

In the third chapter, I examine the effect of FDI on the local labor market and focus on Japanese automotive firms in the US in the 1980s. Using US census data, I investigate how much Japanese automobile firms' investments contributed to local wage increases over the 1980s. My difference-in-differences estimation shows that the effect is not significant with a whole sample, but different by race. In particular, Black workers experienced a 9.3 percent wage decrease in areas where a Japanese assembly plant opened, and I consistently observed the negative effects in regressions with other specifications. My analysis also suggests a regional difference in the wage increase, and auto workers in the West experienced a larger wage increase than workers in the other regions.

Acknowledgment

I have always been curious about how the economies of different countries are connected since the time I was a child. One of the largest Nissan car plants in the world was in my hometown, and I used to see a lot of cars being shipped to the US. At Deloitte Consulting, I worked on a project for the governments in East Asia. My clients wanted to attract more foreign direct investment (FDI) to their economies, and they strongly believed that having more greenfield investment would increase their countries' welfare. These experiences motivated me to study the difference between greenfield and brownfield FDI in my dissertation and pursue my career as an economist.

I could not have achieved my career goal without support from the people I have interacted with. First, I am very grateful to my advisors: Kerem Coşar, James Harrigan, and John McLaren. Every time I talked to them, I was inspired by their new insights. I struggled a lot when I started research in my third year. Kerem always supported me, helped me make progress in my dissertation proposal, and guided me throughout the research process. Every time I faced a difficulty, I talked to James. I sometimes went into a panic mode because of my self-doubt or just being overwhelmed with work. I am sure I would have dropped out of the PhD program without the moral support from James. John has been an inspiration for me both inside and outside the classroom. When I was first admitted to UVa, he called me personally to convince me to come and work with him. He made me feel so welcome here—I know I made the right choice. I thank you all so much.

I thank many professors and economists who gave me their advice and support during the PhD program. I cannot list all names here, but I especially thank Peter Debaere, Toshihiko Mukoyama, Yoichi Sugita, Yukiko Saito, Zachary Bethune, John Pepper, Karim Chalak, Simon Anderson, Gaurab Aryal, Federico Ciliberto, Hiroaki Kaido, Jordi Jaumandreu, Björn Persson, Chee Sung Lee, Sonal Pandya, Eiichi Tomiura, Kensuke Teshima, Taiji Furusawa, Jota Ishikawa, Tatsufumi Yamagata, Kan Sato, and Hiromasa Kubo.

I am also grateful for the friendships I had during my time in Charlottesville. I thank especially Brett Fischer, Melissa Spencer, Yan Chen, Yooseon Hwang, Travis Elliott, Lindsay

Stuart Hill, Pingyu He, Tomomi Sato, Siqi Yang, Ping Yi, and Kyeongtak Do. Brett, Melissa, and I were officemates. I am grateful that we had supported each other throughout our PhD program, from the core exams to the job market. I learned a lot about American culture from them and received the support I needed to navigate life in grad school and a new country. I cannot thank them enough. I look forward to their friendship for years to come.

Finally, I would like to express my appreciation to my family. I know they've always wanted the best for me, and I am grateful now that I have finished my PhD with the help of everyone mentioned here and have a chance to start my career as an assistant professor in the US. I'm happy about the path that I have chosen, and that my parents no longer need to worry about me.

Haruka Takayama
October 31, 2021
Albany, New York

Contents

Chapter 1

Greenfield or Brownfield? FDI Entry Mode and Intangible Capital

1.1 Introduction

In 2016, multinationals and their foreign affiliates generated one-third of global GDP and accounted for two-thirds of international trade.[1] In light of their economic importance, many governments have offered subsidies and tax incentives to attract multinationals' foreign direct investment (FDI). Host countries can receive two types of FDI—one is *greenfield investment* (the development of new facilities by foreign multinationals), and the other is *brownfield investment*, also called *cross-border mergers and acquisitions* (the purchase of local firms by foreign multinationals). In recent years, the number of greenfield investments (GF) has been approximately 2.5 times larger than the number of cross-border mergers and acquisitions (M&A), whereas the values of these transactions are almost the same (UNCTAD, 2019). Although both modes of investment are economically important, policymakers seem to prefer GF over M&A: Only one-half of governments' investment promotion agencies solicit M&As, while around 90% of them target GF investors (UNCTAD, 2001).[2] Given that FDI policies focus on promoting GF investment, it is of first-order policy importance to understand

[1] This information comes from the OECD analytical AMNE database. I refer to the VOX EU CEPR column, "Multinational enterprises in the global economy: Heavily discussed, hardly measured," published on September 25, 2019.

[2] An investment promotion agency is a government agency that aims to attract FDI to its country. Each agency can promote either or both FDI modes.

how multinational firms decide whether to pursue a GF or M&A investment. Moreover, the current literature does not provide a rigorous framework to analyze this choice and its welfare consequences for host countries. To fill this gap, I examine the determinants of FDI mode (i.e., GF or M&A) and the policy implications of these decisions. In particular, I investigate two related questions: (1) how do firms choose between the two FDI entry modes and (2) how does the firm's choice of FDI mode affect the local economy? I study the first question in the first chapter and the second question in the second chapter.

In this chapter, I start with the premise that the key difference between GF and M&A is the role of intangible capital, such as a firm's brand name, intellectual property, and supplier network. One of the defining characteristics of intangible capital is its nonrivalness. That is, unlike physical capital, intangible capital can be used in multiple locations simultaneously. Because of this characteristic, intangible capital plays an important role in FDI (Markusen, 1995; Burstein and Monge-Naranjo, 2009; McGrattan and Prescott, 2010). If investing firms intensively use their own intangible capital, they are also likely to use those intangibles in foreign markets, thus relying less on M&A and more on GF. For example, multinational firms such as Walmart with established global brands—a type of intangible capital—will likely pursue GF investments (DePamphilis, 2019). Firms that do not have well-known brands or reputations will seek instead to acquire local brands.

To test this hypothesis, I empirically analyze how the amount of intangible capital stock affects a firm's choice of FDI mode. I construct a novel US firm-level dataset using financial information on US publicly listed firms (Compustat), data on GF projects (fDi Market), and the universe of M&A deals (SDC Platinum). Although my data focus only on publicly listed firms, this new dataset covers approximately 60% of US multinational firms. I measure the amount of firm's intangible capital following Peters and Taylor (2017) and Ewens et al. (2020). My regression analysis shows that firms with less intangible capital are more likely to choose M&A rather than GF. This result is consistent with the above hypothesis: Firms with low pre-FDI stocks of intangible capital benefit more from the extra intangible capital gained through M&A. I also find that firms are more likely to make GF investments instead of M&A if they invest in host countries with lower GDP per capita and longer distance from the US. This result reflects the fact that multinationals face difficulties in finding local firms to merge with if their host countries are less developed (because of fewer local target firms and institutional barriers to FDI) and distant (because of higher search costs and cultural differences).

Related Literature This chapter is primarily related to the literature on foreign market entry. For example, Helpman et al. (2004) develop a model with heterogeneous firms that self-select into exporting or investing abroad. Recent literature such as Ramondo and Rodríguez-Clare (2013) and Tintelnot (2017), extends Helpman's framework and allows foreign affiliates to export. Unlike these studies, which consider firms' exporting and FDI decisions, my research focuses on the firm's FDI mode choice—i.e., whether a multinational chooses GF or cross-border M&A when it makes FDI. While there are fewer studies on FDI mode choice compared with the extensive literature on FDI and exporting, the studies most relevant to my research are by Nocke and Yeaple (2007, 2008), who extend Helpman et al. (2004) by incorporating cross-border M&A. My study contributes to this literature in three ways. In the first chapter, I provide a comprehensive empirical analysis with a larger and more up-to-date dataset than Nocke and Yeaple (2008). In the second chapter, I construct an equilibrium search model of mergers that is consistent with salient empirical features from the data. Additionally, I quantitatively assess the model to analyze the welfare implications of equilibrium FDI patterns for host countries. This allows me to showcase a potential inefficiency in the laissez-faire equilibrium and propose a policy to address it.

My research also relates to other studies on firm FDI mode choice. For example, Davies et al. (2018) use global transaction-level data and show that geographical and cultural barriers affect firms' FDI mode decisions. Díez and Spearot (2014) focus on the matching of core competencies between acquirer and target firms, and Chan and Zheng (2019) consider the effect of migrant networks on firms' investment decisions. Unlike these studies, my dataset incorporates US firm financial data, which allows me to explore how firm-level heterogeneity drives FDI mode decisions.[3] Similarly, my research builds on a theoretical literature that aims to predict how FDI mode choice affects welfare (Norbäck and Persson, 2007; Kim, 2009; Bertrand et al., 2012). My study paper complements those studies by focusing on intangible capital stock as a key determinant of FDI modes.

In terms of the role of intangible capital in FDI, the first and second chapters of my dissertation relate to a broader literature that examines knowledge transfer and firm boundaries. Firm's knowledge and technology (i.e., intangible capital in this paper) can be shared across countries through FDI (Teece 1977; Dunning, 1981; Burstein and Monge-Naranjo, 2009; McGrattan and Prescott, 2010; Bloom et al., 2012; Arkolakis et al., 2018; Bilir and Morales, 2020). In particular, Burstein and Monge-Naranjo (2009) study knowledge transfer

[3] Other studies on firm's FDI mode choice focus on two GF ownership choices, whole ownership or a joint venture (Raff et al., 2012); vertical and horizontal FDI (Ramondo, 2016); and the impact of the FDI mode on total factor productivity in developed and developing countries (Ashraf et al., 2016).

from developed to developing countries via FDI and quantify the potential welfare gains by loosening foreign ownership restrictions. I contribute to this research by considering the differences between FDI modes, and find that M&A can increase welfare in developing countries because multinationals can improve local firms' productivity through M&As. Another relevant study is by Ramondo et al. (2016), who show that few foreign affiliates engaged in trade with their parent firms.[4] This empirical study supports the fact that multinational firms transfer intangible capital to their affiliates rather than tangible goods.

Finally, my research contributes to the corporate finance and macroeconomic literature on intangible capital. Researchers have documented that firms have become more intangible capital-intensive in recent years, especially in developed economies. For example, since 1992, US firms have invested more in intangible capital than they have in physical capital (Corrado and Hulten, 2010). Following Peter and Taylor (2017) and Ewens et al. (2020), I use the Compustat database to measure the amount of intangible capital of US firms. To my best knowledge, this is the first empirical analysis of the relationship between firms' FDI and intangible capital. I show that intangible capital is one of the important factors for firm's FDI mode choice, which provides additional insights into intangible capital.

The outline of this chapter is as follows. I explain the data in Section 2, report the empirical evidence in Section 3, and conclude in Section 4.

1.2 Data

I construct a novel dataset that links US firms' FDI deals and their financial characteristics between 2003 and 2018. I use three data sources to construct my US firm-level dataset: cross-border M&A deals (SDC Platinum), GF projects (fDi Market), and US firms' financial information (Compustat). In addition, I employ data that describe host country characteristics such as GDP per capita and distance. In this section, I first introduce each data source. I then provide a brief explanation of how to merge these data sources and also how I organize the merged data for regression analysis. Appendix A provides the further details.

1.2.1 Data Sources

(i) Greenfield Investment Projects: The greenfield investment data come from the fDi Markets database published by the Financial Times Ltd. This database is considered as one

[4] Atalay et al. (2014) also demonstrate that firms engage in intangible capital transfer rather than intra-firm trade using data on US multi-plant firms.

of the main data sources of global greenfield projects, and it is used in UNCTAD's World Investment Reports. The database provides information about all cross-border physical investments in new projects, expansion of existing projects, and joint ventures, since 2003. I extract only new investment projects made by US parent companies (that is, companies with headquarters in the US).[5] The most useful feature of this dataset is that the industry classification represents the specific operations of the new establishment, and the classification is not about the investing firm's main business.[6] Therefore, by merging with Compustat, which provides the parent firm's main industry classification, I can identify whether the firm made intra- or inter-industry FDI.

(ii) Cross-border M&A Deals: My cross-border M&A data come from SDC Platinum, produced by Thomson Reuters. This database covers both domestic and cross-border M&A deals globally. To match these M&A data to my greenfield investment database, I extract all cross-border projects involving US acquiring (parent) firms. I restrict my attention to deals involving acquisitions of more than 10% ownership.[7] The 10% cutoff is common in most of FDI studies to determine whether an acquiring firm has control over the target firm (Davies et al., 2018). For example, the Bureau of Economic Analysis (BEA) defines foreign affiliates as overseas business entities that are established by US direct investment and in which US firms own or control 10% or more of the voting shares. In addition, I delete deals involving investment funds such as hedge funds, sovereign wealth funds because these acquisitions are conducted based on speculative activities, not on seeking a new business in foreign markets.[8]

(iii) US Firms' Financial Information: I obtain financial information of publicly-listed US firms between 1980 and 2018 from Compustat. I measure US firms' intangible capital following the methodology of Peter and Taylor (2017) and Ewens et al. (2020) who also estimate the intangible capital stocks among firms in the Compustat database.[9] Intangible

[5] Unlike SDC Platinum below, I can sort only by headquarter location of parent firms (not the locations of investing firms) in the fDi Market database.

[6] For example, if a firm establishes its new research center to develop IT software, the industry sector of this project is classified to Software & IT Services, regardless what kind of primary business the firm operates.

[7] I only delete about 3% of all deals in this step.

[8] I delete deals if the target or acquirer's primary NAICS code is 523 (Securities, Commodity Contracts, and Other Financial Investments and Related Activities) or 525 (Funds, Trusts, and Other Financial Vehicles). See Appendix A about SDC Plantinum's unique NAICS codes.

[9] There are two types of intangibles: one is internally generated intangible capital, and the other is intangibles purchased externally by acquiring another firm. The latter is the sum of goodwill and other intangible assets, and both are shown in firm's financial sheets. Goodwill is the excess purchase price of an acquired firm and is often confounded with over-payment or under-payment in deals. In addition, the

capital created by an investing firm is defined as the sum of its *knowledge capital* and its *organizational capital*. Knowledge capital is any capital stock pertaining to R&D, while organizational capital includes human capital, branding, customer relationships, and distribution systems. I assume that a firm accumulates knowledge capital through R&D spending, and that organizational capital is accumulated through a part of selling, general, and administrative (SG&A) spending. The depreciation rates and the multiplier of SG&A spending are from Ewens, et al. (2020). I use a 33% depreciation rate for knowledge capital accumulation. I use 27% of SG&A spending and a 20% depreciation rate to accumulate organizational capital.[10] These depreciation rates of intangible capital are higher than the depreciation rate of physical capital. Intangible capital adjusts slowly compared with physical capital, which makes purchasing already-accumulated capital stock attractive.

(iv) Host Country Characteristics: I include variables describing host country characteristics in my regression analyses. I measure the level of development using GDP per capita (GDPPC) and the market size using population. These two variables are from the Penn World Table. I also measure the level of openness to trade using the ratio of the sum of exports and imports to GDP. These data come from the World Bank Database. The CEPII database gives the following information: distances from the US to host countries and whether English is the official language in a host country (i.e., if a host country has the common language with the US). I obtain the FDI Regulatory Restrictiveness Index (FDI index) from the OECD database.[11]

1.2.2 Merging the Firm Datasets

I merge both (i) cross-border M&A deals (SDC Platinum) and (ii) GF projects (fDi Market) with (iii) US listed firms' financial information (Compustat). I implement the data merging process in two steps. First, I exploit CUSIP (Committee on Uniform Security Identification Procedures) codes, which SDC Platinum reports for publicly-listed firms. I match 60% of

purchased intangible capital is amortized for approximately 5-10 years after its purchase and the amortization schedules vary depending on firms. Thus, I focus only on internally generated intangible capital in this study.

[10] My empirical results are robust to using alternative calculations of intangible capital with different depreciation rates and multiplier for SG&A spending. Alternate parameters are 20% or 40% (instead of 27%) for the SG&A multiplier, 15% or 25% (instead of 20%) for the depreciation rate of organizational capital, and 20% or 40% (instead of 33%) for the depreciation rate of knowledge capital.

[11] The FDI regulatory restrictiveness Index (FDI Index) measures institutional restrictions on FDI. The OECD looks at the following restrictions to create the index: foreign equity limitations, discriminatory screening or approval mechanisms, restrictions on the employment of foreigners as key personnel, and other operational restrictions including land ownership. The index ranges from 0 (open) to 1 (closed).

Table 1.1: Summary Statistics

	My data				Nocke & Yeaple	
	All industries		Manufacturing only			
Variable	mean	s.d.	mean	s.d.	mean	s.d.
M&A	0.417	0.493	0.415	0.493	0.435	0.496
Sales	21.809	2.287	22.037	2.227	15.37	1.61
SG&A/Sales	−2.964	0.858	−3.055	0.814	-	-
R&D/Sales	−3.100	1.407	−3.330	1.361	−0.389	1.32
Intangibles/Sales	−1.313	0.956	−1.255	0.858	-	-
GDPPC	10.048	0.841	10.011	0.853	9.81	0.723
Population	17.622	1.653	17.716	1.689	16.7	1.38
Openness	4.262	0.559	4.259	0.555	3.94	0.648
Distance	8.766	0.813	8.804	0.772	8.72	0.69
Language	0.380	0.485	0.346	0.476	-	-
FDI index	0.128	0.119	0.135	0.123	-	-
Number of obs	15,472		8,579		856	

[a] Nocke and Yeaple's data is from 1994 to 1998. I deflate the mean of sales in Nocke and Yeaple using the CPI for all urban consumers (FRED series CPIAUCSL).
[b] All continuous variables are in logs.
[c] M&A is equal to one if the firm made M&A investment.
[d] The number of observations for R&D/sales and FDI index are 10,375 and 13,737 in all industries, and 7,439 and 7,635 in manufacturing industries, respectively.

publicly-listed ultimate acquires with Compustat firms. Next, for the remaining 40% of the firms in SDC Platinum and all firms in fDi Market, I matched them with Compustat firms using company names and headquarters states. I also check firms that changed their names manually using the internet.

After merging the datasets, I obtain a dataset with 2,667 Compustat firms in total. During the sample period (2003 - 2018), 695 firms made only GF investments, while 789 firms made only cross-border M&As. 1,183 firms made investments using both FDI modes. In SDC Platinum, I match around 92% of deals made by publicly-listed ultimate acquires with Compustat firms. Unfortunately, I cannot identify which firms are listed in the fDi Market database. According to the BEA data, there are around 4,500 US multinational parents in 2014.[12] Therefore, my dataset covers roughly 60% of US multinational parents.

[12] According to the BEA's benchmark survey of US direct investment abroad, there are 2,541 (in 2004), 2,340 (in 2009), and 4,541 (in 2014) multinationals.

1.2.3 Data for Regressions

After merging the datasets, I aggregate firms' investments by firm-industry-destination. For firms that made more than one investment in the same industry and destination country, I extract the first FDI from the merged data.[13] I focus on a firm's first investment in a given industry-by-destination because my research question concerns market entry, not additional investments in existing subsidiaries. Additionally, a firm's first entry mode correlates strongly with its entry mode in any subsequent FDI deal. For example, Table A.1 shows that 84% of firms which made a GF investment in their first entry in a particular industry and country, made also GF investments in their subsequent FDIs in the same industry and country.

In Table 1.1, I compare my data to the BEA data in Nocke and Yeaple (2008).[14] Unlike my data spanning 2003-2018, Nocke and Yeaple (2008) only use data from 1994-1998. My data is similar to Nocke and Yeaple's especially with the share of M&A investment and country variables, but I have more observations. In addition, my data cover FDI activities in service industry, and interestingly share of M&A investment is similar both in manufacturing and service industry.

1.3 Empirical Evidence of FDI Entry Modes

Using my unique dataset, I find two main empirical facts: 1) firms with more intangible capital are more likely to make GF investments rather than M&A; and 2) more GF investments are made in less developed and distant countries.

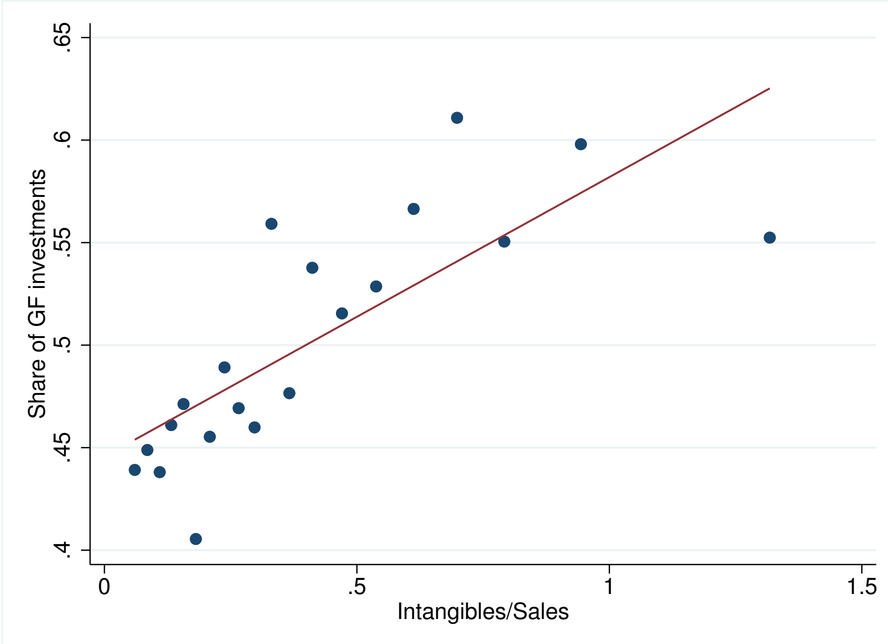
1.3.1 Intangible Capital

One of my main research questions is how investing firms choose between GF and M&A investment. Firms will obtain physical capital either through GF or M&A investment, but they can acquire existing intangible capital only through M&A. Thus, I hypothesize that M&A is the preferred market entry option for firms that seek to obtain existing intangible capital. Giving a glimpse of the detailed empirical analysis to be presented below, Figure 1.1 plots the relationship between firm intangible capital intensity (intangible assets divided by sales) and the share of FDI investments done through GF. The positive and statistically

[13]There is more than one investment in 27% of firm-industry-country cells.

[14]I aggregate the data in a slightly different way from Nocke and Yeaple (2008). For firms with more than one investment in a particular industry and country, Nocke and Yeaple (2008) consider firms that made M&As if and only if all investments made during the data period are through M&As.

Figure 1.1: Share of GF Investments and Intangible Capital



[a] The vertical axis shows the share of GF investment that each firm made (i.e., how many GF investments are made as a share of total number of investments), and the horizontal axis shows the ratio of intangible capital to sales.
[b] The figure is a binned scatter plot. The data space is partitioned into rectangular bins and compute the mean of the variables in the horizontal and vertical axes within each bin. I then create a scatter plot of these data points.
[c] I delete outliers (observations below the 5th percentile and ones above the 95th percentile).

significant correlation supports the hypothesis that firms with higher levels of intangible capital tend to pursue GF rather than M&A.

I test the hypothesis in a more rigorous way by estimating the following logit model:

$$\mathbb{1}[MA_{i,h,j,t} = 1] = \alpha \times intangibles_{i,t-1} + \beta \times sales_{i,t-1} + country_h + firm\text{-}industry_i \\ + affiliate\text{-}industry_j + year_t + \epsilon_{i,h,j,t},$$

where $\mathbb{1}[MA_{i,h,j,t} = 1]$ is an indicator for whether firm i uses M&A for its first FDI in market h and industry j in year t. All explanatory variables in regressions are in logs. Firm i's intangible capital in year $t-1$ is denoted by $Intangibles_{i,t-1}$. Using lagged explanatory variables prevents a potential endogeneity issue between firm's investment decisions and its financial status in the same data period.[15] In addition, I control for firm size using $sales_{i,t-1}$

[15] I refer to the empirical analysis in Spearot (2012) who studies firms' investment decisions between new (or greenfield) investment and M&A in the US, using the Compustat database.

Table 1.2: Logit Regressions of Firms' FDI Mode Choices

Dep var: $\mathbb{1}[MA_{i,h,j,t}=1]$	(1) Intangible	(2) Knowledge	(3) Organizational	(4) Physical
Capital	-0.220^{***}	-0.190^{***}	-0.102^{*}	-0.036
	(0.047)	(0.050)	(0.050)	(0.047)
Sales	0.108^{**}	0.101^{*}	0.004	-0.047
	(0.044)	(0.052)	(0.047)	(0.050)
Parent Industry FEs	Yes	Yes	Yes	Yes
Affiliates Industry FEs	Yes	Yes	Yes	Yes
Country FEs	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes
N	14805	8783	14805	14529
$PseudoR^2$	0.291	0.288	0.289	0.287

[a] Standard errors are clustered by parent firm. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
[b] All explanatory variables are in logs.

since I need to consider the importance of intangible assets in firms' business operations.[16] For example, Arrighetti et al. (2014) shows that larger firms have more intangible capital using the data on Italian manufacturing firms. Lastly, I also control for country, investing (or parent) firm industry, affiliate industry, and year using fixed effects.

Table 1.2 presents the results. In the first column, the coefficient on intangible capital is negative and statistically significant. This shows that probability of making a GF investment increases with the amount of intangible capital. These effects are driven both by the amount of knowledge capital and organizational capital (see the second and the third columns). The results mean that if firms have enough intangible capital, they invest via GF; otherwise they invest via M&A to benefit more from acquiring local intangibles. Interestingly, column 4 shows that the coefficient on physical capital is insignificant. This result supports my prediction that physical capital is not a significant determinant of an investment mode because firms establish their physical facilities abroad either through M&A or GF, and thus underlines the importance of intangible capital in FDI mode choice. Following Nocke and Yeaple (2008), I also use the log of value-added per employee (VADDPW) to the regressions as an additional measure of firm efficiency.[17] The results are in Table 1.3. The coefficients

[16] I include intangibles and sales separately, instead of using the ratio of intangible capital to sales, $(intangibles/sales)_{i,t-1}$. Using the ratio imposes an unnecessary restriction that the coefficients on *intangibles* and *sales* must be the same values.

[17] The value-added per employee is calculated as (gross profit)/(number of employees).

Table 1.3: Logit Regressions of Firms' FDI Mode Choices

Dep var: $\mathbb{1}[MA_{i,h,j,t} = 1]$	(1) Intangible	(2) Knowledge	(3) Organizational	(4) Physical
Capital	-0.220^{***}	$-\ 0.158^{***}$	-0.114^{**}	-0.069
	(0.050)	(0.055)	(0.055)	(0.048)
Sales	0.110^{**}	0.078	0.019	-0.006
	(0.047)	(0.056)	(0.050)	(0.054)
VADDPW	-0.106^{**}	-0.185^{***}	-0.141^{***}	-0.179^{***}
	(0.048)	(0.069)	(0.048)	(0.049)
Parent Industry FEs	Yes	Yes	Yes	Yes
Affiliates Industry FEs	Yes	Yes	Yes	Yes
Country FEs	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes
N	14476	8593	14476	14210
$PseudoR^2$	0.294	0.294	0.293	0.291

[a] Standard errors are clustered by parent firm. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
[b] All explanatory variables are in logs.

on VADDPW are negative and more strongly correlated with the firm's FDI mode choice, unlike sales. However, I still observe the same results in the coefficients on capital—firms with larger intangible capital are more likely to invest via GF, and physical capital is not correlated with the firm's investment mode choice.

Note that these results provide a new perspective on the literature studying the determinant of firms' FDI decision. For example, Nocke and Yeaple (2008) shows that more productive firms (i.e., firms with greater sales) are more likely to choose GF investment rather than M&A.[18] My results show that there is an additional determinant of firms' FDI decisions, in addition to firm's sales.

1.3.2 Country Characteristics

In addition to firm heterogeneity, the characteristics of destination countries are also important for firms' FDI decisions. Instead of country FEs, I include the following covariates describing the host country in the regressions: log of GDP per capita (GDPPC), log of population (POP), log of openness to trade (OPEN), log of distance (DIST), and common

[18] Table A.2 shows that I obtain the same results in the regressions analogous to Nocke and Yeaple (2008), using my dataset in 2003-2018.

Table 1.4: Logit Regressions of Firms' FDI Mode Choices with Country Variables

Dep var: $\mathbb{1}[MA_{i,h,j,t} = 1]$	(1) Intangibles	(2) Knowledge	(3) Organizational	(4) Intangibles
Capital	-0.196^{***}	-0.155^{***}	-0.093^{*}	-0.200^{***}
	(0.046)	(0.048)	(0.051)	(0.046)
GDPPC	0.857^{***}	0.967^{***}	0.860^{***}	0.907^{***}
	(0.046)	(0.063)	(0.046)	(0.051)
DIST	-0.466^{***}	-0.632^{***}	-0.466^{***}	-0.294^{***}
	(0.031)	(0.043)	(0.031)	(0.030)
POP	0.007	0.015	0.010	0.090^{***}
	(0.022)	(0.029)	(0.022)	(0.025)
OPEN	-0.689^{***}	-0.705^{***}	-0.687^{***}	-0.225^{***}
	(0.043)	(0.055)	(0.044)	(0.061)
LANG	0.458^{***}	0.443^{***}	0.460^{***}	0.614^{***}
	(0.044)	(0.058)	(0.044)	(0.050)
FDI_index				-1.905^{***}
				(0.265)
N	15016	9039	15016	13260
$Pseudo R^2$	0.2474	0.2319	0.2455	0.2467

[a] Standard errors are clustered by firm and country. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

[b] All explanatory variables are in logs. I control for firm size using sales in addition to industry and year FEs.

language (LANG).[19] The results are in Table 1.4. The positive coefficients on GDPPC show that there are more M&A investments in developed countries. Firms in countries with high GDPPC likely have more intangible capital on average, and thus investing firms can easily find target firms in these countries. In addition, the coefficients on distance are negative, while the coefficients on language are positive. These estimates indicate that American investing firms are less likely to make M&A investments in countries far from the US and

[19] Nocke and Yeaple (2008) use the first four variables in their regressions: GDP per capita, population, openness to trade, and distance. I use language and FDI index additionally. Unlike Nocke and Yeaple (2008), who use the US FDI data from 1994-1998, I obtain negative signs on DIST. The negative signs in my regressions correspond to the results in Davies et al. (2018), which uses more recent global transactions from 2003-2010. The authors conclude that there are fewer M&A investments as brriers between countries get larger because M&A relies on intra-firm integration.

in counties where English is not the most common language. I also study the effect of institutional restrictions on firms' FDI mode choices using the FDI regulatory restrictiveness Index (FDI_Index). Column 4 shows that tighter restrictions in a destination country deter firms from making M&A investments.[20,21] Overall, this analysis suggests that geographic, linguistic, and institutional barriers matter for multinationals in their search for partners with whom to conduct M&A. This could reflect the fact that there is a smaller matching probability between target and acquiring firms, as well as higher search costs, if the barriers between the US and a destination country get larger.[22]

1.4 Conclusion

In this chapter, I investigate the determinants of firm FDI entry mode choice. To do so, I construct a novel dataset using FDI investment deals, financial information of US investing firms, and country variables. I show that a firm with less intangible capital is more likely to make M&A investments, whereas one with more intangible capital is more likely to choose GF. The regressions also suggest that geographic, linguistic, and institutional barriers matter for investing firms when they decide which mode of investment to pursue. The empirical results I obtain in this chapter motivate me to build a model of multinationals' FDI choices and analyze the subsequent question: how does the FDI mode choice affect welfare in investment-receiving countries?

[20] I observe FDI restrictiveness in 66 out of 148 destination countries in my data. I also run regressions in which I use knowledge and organizational capital separately as outcome variables. Those results appear in Table A.3.

[21] Once I control for the FDI restrictiveness, coefficients on population (POP) become significant. Population represents the market size of a destination country. One of the benefits for firms conducting M&A is acquiring a sales network in the local market. China has some of the tightest FDI restrictions, and more than 80% of FDIs toward China are via GF. If the Chinese restrictions regarding foreign ownership were less severe, multinationals would be more likely to make M&A investments there to capture the larger market opportunity.

[22] Note that the negative coefficients on openness to trade show that there are fewer M&A deals in host countries that are more open to trade. Investing firms in these countries face greater market potential (i.e., easier to export) and also proceed their procurement (i.e., easier to import). Therefore, acquiring existing assets is less important when firms invest in countries with greater openness to trade.

Chapter 2

Model of Firm FDI Mode and Welfare in the Host Country

2.1 Introduction

In the first chapter, I show that firms with larger intangible capital are likely to invest via greenfield investment rather than via cross-border M&A. Motivated by this empirical result, I study how the firm's choice of FDI mode affects the local economy in this chapter.

First, I develop a general equilibrium search model of firm FDI choice. Expanding on Nocke and Yeaple (2007, 2008), I incorporate search and matching frictions in the merger market. In this framework, a multinational firm searches for a partner and chooses M&A if it matches with a local target firm; otherwise, it invests via GF. A multinational's production technology in the host country has two components: its productivity (TFP) and intangible capital. Both components of the production technology are completely transferable across countries, and the complementarity between these two technologies generates a trade-off in the multinational's M&A decision. In particular, if a multinational firm invests via M&A, it cannot use all of its own intangible capital at its new foreign affiliate, but obtains additional intangible capital from the acquired local firm and upgrades the acquired firm's intangibles by leveraging its higher productivity. The investing firm's optimal search effort depends on the attractiveness of M&A. The attractiveness of M&A, in turn, depends on the expected return from acquiring intangible capital, which is decreasing in the firm's own intangible capital stock. To focus on the role of intangible capital, I assume that multinationals are heterogeneous in intangible capital but have a uniform productivity, which exceeds the productivity of local firms. Because of this Melitz-type (2003) structure, there is a cutoff level of intangible capital below which multinationals prefer to invest via M&A. Multinationals with higher levels of intangible capital invest through GF, consistent with my empirical results.

The model suggests that equilibrium FDI patterns can be suboptimal from the host country's perspective. Therefore, there could be room for the local government to improve local welfare using FDI policies that incentivize one entry type over the other. To examine this possibility, I quantitatively assess the model and conduct counterfactual experiments. The optimal policy response differs between developed (i.e., the North) and developing countries (i.e., the South). Welfare in the North benefits more from GF than M&A, while the South would benefit from more M&A investment than they receive in equilibrium. Since the gap between the productivities of multinationals and local firms is larger in the South, policymakers there can increase welfare by incentivizing FDI through M&A. By allowing highly productive multinationals to use local intangible capital, this policy increases aggregate productivity more than the laissez-faire outcome. In counterfactual analyses, I evaluate the effect of subsidies on GF investments in the North and the effect of a tax on the profits of GF multinationals in the South. My findings suggest that if policymakers in the South seek to increase local welfare, they should restrict GF investments. By contrast, in the North, local welfare increases as a result of promoting GF investments.

This chapter is organized as follows. I present a model of FDI entry mode by multinational firms in Section 2.2. I match the model to the data in Section 2.3 and present the counterfactual analyses in Section 2.4. Section 2.5 concludes.

2.2 A Model of FDI Entry Mode

I develop a model to further investigate how intangible capital stock affects a firm's FDI mode choice. My model is static and builds upon Nocke and Yeaple (2007, 2008), in which firm's production efficiency consists of two exogenous parameters.[1] In my paper, two exogenous parameters are productivity and intangible capital. Along the lines of Nocke and Yeaple's study, firms can trade one of the parameters—intangible capital in my paper—in the merger market, which incentivizes firms to conduct M&As rather than greenfield (GF) investments.

To characterize the international merger market, I follow David (2021), who analyzes domestic M&A activity. In my model, a firm's outside option of conducting M&A is making a

[1] In Nocke and Yeaple (2007), two types of production efficiencies are *mobile capability*, such as technology, and *non-mobile capability*, such as marketing ability. In Nocke and Yeaple (2008), production efficiencies are characterized by an *entrepreneurial ability*, such as productivity, and *production division*, such as a manufacturing plant. The first paper focuses on industry heterogeneity, and the latter focuses on firm heterogeneity.

greenfield investment, and the merger gain and acquisition price are endogenously determined depending on the stock of intangible capital a firm holds.

One of this paper's main goals is to analyze how foreign investment policies affect multinationals' FDI decisions and welfare in investment-receiving countries. To analyze these effects, I construct a model of domestic general equilibrium in the host country. The model endogenously determines wage, and the volumes of M&A and GF investment that occur in the host country.

2.2.1 Basic Setup

Consider two types of firms in two countries: multinational firms (indexed by i) in source country s and local firms (indexed by j) in host country h. Both multinational and local firms produce intermediate goods, y. A final good is produced by combining the intermediate goods.

The mass of multinational firms is M in country s, and the mass of local firms is N in country h. All multinational firms in country s make foreign direct investment (FDI) in country h either through M&A or GF. Some of the multinationals search their M&A partners in h, while some of them conduct GF without searching. If multinationals search and find their partners, they can merge with local firms. Multinationals which do not search and also those which fail to search make GF investment and establish their own affiliates to produce.

I assume host country h is a small open economy, and labor is not mobile across countries.[2] Here, the final good, Y, is traded between s and h, but each intermediate good, y, is not traded. Part of the final good, Y, becomes the firm's wage bill and profit. Multinational firms are owned by foreign entities and the profits are shipped out to source country s, whereas local firms are owned by local entities. Consumer supply labor and consume final good.

[2] I study the effects of unilateral investment policies made by the host country, and analyze how these policies affect the multinationals' FDI entry mode as well as labor market outcomes in the host country. The small open economy setting is reasonable in this study because my focus is not on the economic outcomes of source country policies but rather on host country outcomes. See Demidova and Rodríguez-Clare (2013) and Haaland and Venables (2016) for a recent paper on the small open economy framework in the monopolistic competition setting.

Intermediate Good Firms

A multinational firm i in s produces a differentiated variety of good, y_i, using a Cobb-Douglas production technology:

$$y_i = \tilde{Z} K_i^{\alpha} \ell_i^{\beta},$$

where $\tilde{Z}$ is productivity, K_i is intangible capital, and ℓ_i is labor. Each multinational draws its intangible capital when it enters. I assume that the distribution of intangibles across multinationals follows a Pareto distribution. The cumulative distribution function is:

$$G(K) = 1 - K^{-\theta} \quad \text{with support} \quad [\underline{K}, \infty) \quad \text{for} \quad \underline{K} = 1 \quad \text{and} \quad \theta > 1, \tag{2.1}$$

where θ is a shape parameter. For simplicity, assume that productivity for multinational firm i is constant at the value $\tilde{Z}$.[3]

A local firm j in h produces a differentiated variety of good y_j with a Cobb-Douglas production technology:

$$y_j = \tilde{z} \kappa^{\alpha} \ell_j^{\beta},$$

where $\tilde{z}$ is productivity, κ is intangible capital, and ℓ_j is labor. The productivity of local firm j is constant at the value $\tilde{z}$ such that $\tilde{z} \leq \tilde{Z}$. A firm's level of intangible capital is homogeneous and it is given as κ.[4]

Merger Market

The rate at which an searching firm matches with its target is determined by a matching technology. Let the number of matches that is created be $v(N, n)$, where n is the measure of searching multinational firms. I assume the matching function:[5]

$$v(N, n) = \frac{Nn}{(N^{\rho} + n^{\rho})^{1/\rho}},$$

[3] This setting is analogous to the probability distribution in Eaton et al. (2011) who consider that the measure of multinationals with productivity at least z is $\mu^z(z) = Tz^{-\theta}$, where T is an exogenous technology parameter.

[4] I choose this assumption because I don't observe the local firm's intangible capital in the data. Interesting potential extensions are to (i) making local-firm intangible capital to be heterogeneous capital and (ii) making the local capital investment to be endogenous.

[5] This functional form follows Den Haan et al. (2000) and is also used in Coşar et al. (2016). The benefit of this functional form, compared to Cobb-Douglas matching technology, is that this form guarantees matching probabilities are between 0 and 1.

where $\rho > 0$. The probability that a multinational finds an M&A partner in host country h is denoted as $\mu(n) \in (0, 1)$. When n multinational firms search, $\mu(n)n$ multinationals find their targets, and therefore $\mu(n)n$ local firms are acquired. Assume that the number of local firm, N is sufficiently large so that $N > \mu(n)n$. With the above functional form, the matching probability $\mu(n)$ is:

$$\begin{aligned}\mu(n) &= \frac{v(N,n)}{n} \\ &= \left(\frac{1}{1+(n/N)^{\rho}}\right)^{\frac{1}{\rho}}.\end{aligned} \tag{2.2}$$

Because $\mu'(n) < 0$, when more multinationals search, the matching probability falls (i.e., there is congestion in search). I assume that when a multinational firm searches, it incurs a search cost $\psi > 0$. After searching and matching with a local firm, if a multinational decides to make an M&A investment, it needs to pay the price of acquisition, P.

Foreign Direct Investment (FDI)

After multinationals make FDI, the following three types of firms exist in the host country.

(i) Greenfield Firms: Multinational firm i which either did not search or failed to find a target conducts a greenfield investment (GF). This assumption is reasonable within this model, as we see below that the multinational firm can receive a positive net return from the GF investment. Unlike physical capital, both productivity, $\tilde{Z}$, and intangible capital, K_i, can easily replicated and be transferred into the new market. Thus, a GF multinational can operate with the same level of production technology as it had before FDI in a host country.[6]

The production function for GF firm g is

$$y_g = \tilde{Z} K_i^{\alpha} \ell_g^{\beta}.$$

Let the amount of intangibles of the GF firm g be $k_g \equiv K_i$, and its productivity be $\tilde{Z}_g \equiv \tilde{Z}$.

(ii) Merged Firms: When multinational firm i is merged with a local firm, it can take advantage of the acquired firm's intangibles, κ, in producing. This is in line with the fact

[6] This setting is the same as Nocke and Yeaple (2008) and McGrattan and Prescott (2010). They assume that a subsidiary of a multinational operates with the same productivity as the parent firm.

that M&As improve the acquirer's productivity (e.g., Schoar 2002; Li 2013; Dimopoulos and Sacchetto 2017). I assume that the merged firm inherits the acquirer's productivity $\tilde{Z}$. The production function for merged firm m is

$$y_m = \tilde{Z}(\kappa + \eta K_i)^\alpha \ell_m^\beta,$$

where $\eta \in (0, 1)$. In post-merger integration process, a multinational will not be able to transfer all of its intangible to the new foreign affiliate. Some of the business segment is duplicated with its target firm, and a multinational uses some part of target firm's intangible (instead of its intangible capital) to benefit it in the local market.[7] This imperfect "scalability" in M&A investments is represented by η. Note that the formulation here highlights the difference between technology and intangible capital: technology does not have an additive property (for example, a better management practice prevails within a firm) whereas intangible capital can accumulate within a firm (patents can have independent values; local network and brand name can have separate effects). Let the amount of intangible capital of the merged firm m be $k_m \equiv (\kappa + \eta K_i)$, and its productivity be $\tilde{Z}_m \equiv \tilde{Z}$.

(iii) Local Firms: If local firm j does not merge with multinational i, it operates alone. The production function for a local producer a is

$$y_a = \tilde{z}\kappa^\alpha \ell_a^\beta.$$

Let the amount of intangible capital of the local firm a be $k_a \equiv \kappa$, and its productivity be $\tilde{Z}_a \equiv \tilde{z}$.

Final Good Producer

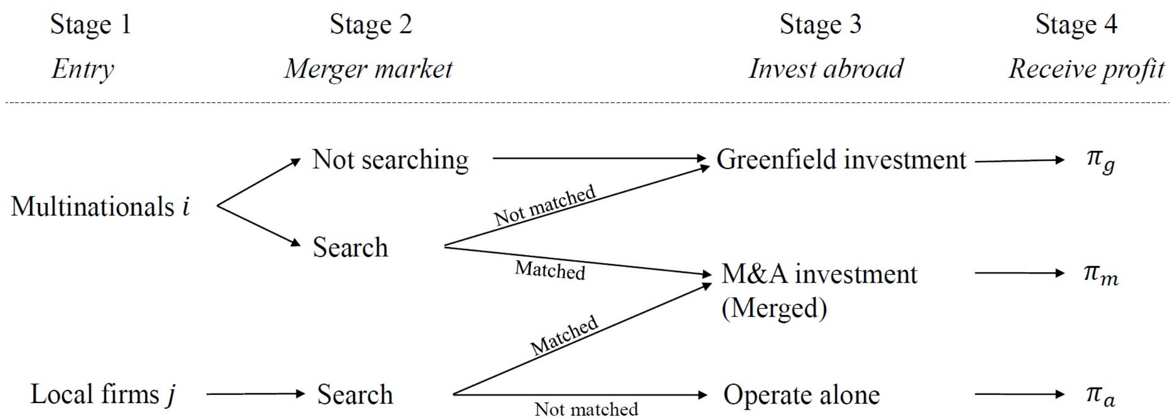
I assume there is a final good producer that aggregates three types of outputs: y_m, y_g, and y_a. I index firms in the host country after investment by ω. Each firm, ω, is assigned to one of the firm types: M&A firm, m, GF firm, g, and local firm, a. Ω is the set of all of the firms, $\omega \in \Omega$.

The final-good production function is:

$$Y = \left[\int_\Omega y_\omega^{\frac{\sigma-1}{\sigma}} d\omega\right]^{\frac{\sigma}{\sigma-1}}, \tag{2.3}$$

[7]For example, when Walmart acquired a Japanese supermarket, Seiyu sold Walmart's products under Seiyu's name. This is one example of how merged multinationals gave up some part of their own intangibles.

Figure 2.1: Timing of the Model



where $\sigma > 1$ is the elasticity of substitution.[8]

Households

There is a measure of representative households, L, in host country h and they maximize utility by consuming final good, C. The households supply labor, L, at wage, w. The households earn income, I, from the wage payment, wL, profits of local firms, and acquisition transfer, P. Both households' consumption and income payments are done in the final good, Y.

Timing

I summarize the timing of the model over the following 4 stages:

Stage 1: Multinationals in s and local firms in h enter.

Stage 2: Multinationals decide if they search for their M&A partners in the merger market, or make GF investment without searching.

Stage 3: Multinationals which do not search make GF investments in h. If multinationals search for their partners and find them, they will make M&As in h. Otherwise, they will make GF investments.

Stage 4: Firms hire workers, produce, and receive profits. Households consume.

[8]We can consider that each firm, ω, produces its differentiated variety, y_ω given the other firms' production, Y. We can call Y "the other firms' production" since one firm is negligible with a continuum of firms.

2.2.2 Model Solution

I solve the model backwards according to the timing given in section 2.2.1.

Profit Maximization (Stage 4)

After multinationals invest in stage 3, three types of intermediate good firms exist in country h: merged multinationals, m, greenfield multinationals, g, and local firms which operates alone, a. In stage 4, a final good is produced and each intermediate good firm maximizes its profit given the three types of production function, defined in section 2.2.1.

First, the final-good producer minimizes its expenditure:

$$\min_{y_\omega} \int_\Omega p_\omega y_\omega d\omega \qquad \text{subject to equation (2.3).} \tag{2.4}$$

The unit price of the final output us $\Xi = [\int_\Omega p_\omega^{1-\sigma} d\omega]^{1/(1-\sigma)}$. The final good market is perfectly competitive, and a final good producer can sell any amount of good, Y, at the market price, Ξ. I use the final good as a numéraire, and normalize Ξ to one.[9] The inverse demand function for good ω is

$$p_\omega = \left(\frac{Y}{y_\omega}\right)^{1/\sigma}. \tag{2.5}$$

Given the CES demand function, firm ω solves the maximization problem for its profit:

$$\max_{\ell_\omega, p_\omega, y_\omega} p_\omega y_\omega - w\ell_\omega \qquad \text{subject to equations (2.3) and (2.5).}$$

w is the wage in the host country. I assume that $\alpha = \sigma/(\sigma-1) - \beta$ (with $0 < \beta \leq 1$). Note that the amount of intangibles, K, is determined exogenously. This assumption is without a loss of generality in the setting here, as one can always change the unit of measurement for K by a monotonic transformation, so that α satisfies this relationship.[10]

[9] The optimization in the final good sector yields the Constant Elasticity of Substitution (CES) demand function. One can, instead, directly assume that the consumers have CES preferences. Here, the representative consumers receive local firms' profits and merger payments which are endogenously determined in the model. The advantage of the current formulation (setting the price index equal to one and also using the final good sector) is that profit transfer and merger payments can be made internationally in the final good unit, so that the final good can serve as "dollars". Also, it is easier to clarify what is traded and what is not traded—I am explicit that the intermediate goods are non-tradables and the final good is used for the international transactions.

[10] Note that the distribution $G(K)$ is for the post-transformed value of K. Additionally, this assumption would not be without loss of generality if the multinational firm i chooses K_i by investment, for example, as the unit of measurement also affects the form of investment cost function.

Solutions for the labor demand, ℓ_ω, are:

$$\begin{cases} \ell_m(K_i; w, Y) = \tilde{\Theta}(w,Y)Z(\kappa + \eta K_i) & \text{for merged multinationals,} \\ \ell_g(K_i; w, Y) \ = \tilde{\Theta}(w,Y)ZK_i & \text{for GF multinationals, and} \\ \ell_a(w, Y) \ = \tilde{\Theta}(w,Y)z\kappa & \text{for non-merged local firms.} \end{cases} \tag{2.6}$$

where $\tilde{\Theta}(w,Y) \equiv \left[\frac{Y^{1/\sigma}}{w}(1 - \frac{\sigma-1}{\sigma}\alpha)\right]^{\frac{\sigma}{\alpha(\sigma-1)}}$. For notational simplicity, let $Z \equiv \tilde{Z}^{1/\alpha}$ and $z \equiv \tilde{z}^{1/\alpha}$.

The profits of each type of entities are:

$$\begin{cases} \pi_m(K_i; w, Y) = \Theta(w,Y)Z(\kappa + \eta K_i) & \text{for merged multinationals,} \\ \pi_g(K_i; w, Y) \ = \Theta(w,Y)ZK_i & \text{for GF multinationals, and} \\ \pi_a(w, Y) \ = \Theta(w,Y)z\kappa & \text{for non-merged local firms.} \end{cases} \tag{2.7}$$

Here, $\Theta(w,Y) \equiv w\left(\frac{\alpha(\sigma-1)}{\sigma-\alpha(\sigma-1)}\right)\tilde{\Theta}(w,Y)$. The expression of firms' profits is analogous to the ones in Nocke and Yeaple (2007, 2008): the profit depends on two types of production efficiency, productivity (Z and z) and intangible capital (K and κ), as well as the wage in the host country w.[11]

Gain from Mergers (Stage 3)

In stage 3, a multinational firm decides whether to pursue M&A or GF investment after it matches with its target. All analyses in stage 3 and stage 2 are for a given (w, Y). Thus in these two stages, I omit the dependence on (w, Y) to simplify the notation. For example, I use Θ in place of $\Theta(w,Y)$. The combined gain (surplus) from the merger (i.e., "synergy" from mergers), Σ, for multinationals which match with local firms is given by:

$$\begin{aligned} \Sigma(K_i) &= \pi_m(K_i) - \pi_g(K_i) - \pi_a \\ &= \Theta Z(\kappa + \eta K_i) - \Theta Z K_i - \Theta z\kappa \\ &= \Theta\left[(Z - z)\kappa - Z(1-\eta)K_i\right]. \end{aligned} \tag{2.8}$$

Multinationals consummate mergers so long as they have positive merger gain. The gains are the profit of the merged firm, π_m, less the profit that the multinational would have earned

[11] Although I set the levels of productivity, Z and z, are constant in this study, if I make the productivity heterogeneous across firms, I can also state that the profit functions show the complementary between two production technologies (i.e., $\frac{\partial^2\pi}{\partial Z \partial K} > 0$), similarly to Nocke and Yeaple (2008).

through GF, π_g (the multinational's outside option), and the pre-merger profit of the local firm, π_a (the target's outside option).

Note that multinationals face a tradeoff between conducting M&A and GF investments: M&A firms can leverage the difference in productivity between multinational and local firms, $(Z - z)$, and upgrade local firms' intangibles, κ; but they would lose some part of their intangibles, K_i, at rate $Z(1-\eta)$. The gains from merging are decreasing in a multinational's intangible capital, K_i, because $\eta \in (0, 1)$. This tradeoff implies that multinationals with smaller intangible capital stock observe larger marginal benefits from obtaining additional intangibles through M&As, and have a greater incentive to merge. One can also see that the gains from merging are higher if the multinational firm can transfer a larger fraction of its intangible capital (i.e., if η is higher).

If a multinational consummates a merger (i.e., gain from merging $\Sigma > 0$), it pays a price of acquisition. The purchase price, $P(K_i)$, is determined through Nash bargaining between the multinational and the local firm. I set the local firm's bargaining power as $\chi \in (0, 1)$, and the multinational's bargaining power as $1 - \chi$. The acquisition price (i.e., the merger gains of local firms) is sum of the profit of the local firm, π_a, and the target's share of the combined gain, $\chi\Sigma$:

$$P(K_i) = \pi_a + \chi\Sigma(K_i).$$

Using equation (2.8) and (2.7),

$$P(K_i) = \Theta z\kappa + \chi\Theta\left[(Z - z)\kappa - Z(1 - \eta)K_i\right]. \tag{2.9}$$

Search Decision (Stage 2)

In stage 2, a multinational firm decides whether it will (i) try to find a target firm by undertaking a search effort or (ii) not undertake a search effort. Multinational i participates in the merger market if it satisfies the following condition,

$$\mu(n)\left[\pi_m(K_i) - P(K_i)\right] + (1 - \mu(n))\pi_g(K_i) - \psi \geq \pi_g(K_i), \tag{2.10}$$

that is, its expected (net) profit from searching (left-hand side) must be higher than its profit from making a GF investment (right-hand side).

Using (2.9) and (2.7), inequality (2.10) can be rewritten as

$$(1 - \chi)\mu(n)\underbrace{\Theta\left[(Z - z)\kappa - Z(1 - \eta)K_i\right]}_{\text{gain from merger, } \Sigma} \geq \psi. \tag{2.11}$$

There are two findings of note. First, the left-hand side of the above inequality is decreasing in K_i. This means that a multinational firm with a lower level of intangible capital K_i is more likely to search for an M&A partner. Second, if the above inequality holds, a searching multinational will always obtain positive gains from merging, which means $\Sigma \geq 0$. Thus, if a multinational firm searches and finds a target firm, it always conducts M&A. These two findings lead the following proposition:

Proposition 1 *Given (w, Y), there exists a threshold, K^*, such that a multinational firm with $K_i < K^*$ will search and pursue M&A, and one with $K_i \geq K^*$ make a GF investment. The threshold level of intangible capital K^* satisfies the following equation:*

$$(1-\chi)\hat{\mu}(K^*)\Theta\left[(Z-z)\kappa - Z(1-\eta)K^*\right] = \psi. \tag{2.12}$$

Proof. See Appendix B.

Recall that the multinational's intangible capital is distributed across firms with a cumulative distribution function $G(K)$. In equilibrium, the fraction $G(K^*)$ of the mass of multinationals will search and conduct M&As, and the fraction $1-G(K^*)$ of multinationals will make GF investments without searching in the merger market. I denote the matching probability $\mu(n)$ as $\hat{\mu}(K^*)$ because the mass of searching multinationals is now $n = MG(K^*)$. The matching probability, $\hat{\mu}(K^*)$, is a decreasing function of K^*.

One of the main objectives of this chapter is to investigate how multinational firms choose their modes of FDI depending on their levels of intangible capital stock. The model shows that, under reasonable assumptions, firms with less intangible capital are more likely to choose M&A investments. This prediction is consistent with the empirical results shown in section 1.3.

Measures of Firms

Using the matching probability, $\hat{\mu}(K^*)$, I define the measures of the three types of firms which exist after multinationals invest. The measure of multinational firms which make M&As is:

$$E_m = \hat{\mu}(K^*)MG(K^*). \tag{2.13}$$

The measure of multinational firms which make GF investments is:

$$E_g = [1-\hat{\mu}(K^*)]MG(K^*) + M(1-G(K^*)), \tag{2.14}$$

where the first term represents the multinationals which failed to find an M&A partner, and the second term represents the multinationals which chose GF without searching.

If E_m multinationals conduct M&As, the same number of firms are acquired in country h. The remaining firms, the mass of $N - E_m$, continue to operate independently. The measure of these local firms is:

$$E_a = N - E_m = N - \hat{\mu}(K^*)MG(K^*).$$

From the viewpoint of a local firm, the probability of being acquired is:

$$\lambda(K^*) = \frac{E_m}{N} = \frac{\hat{\mu}(K^*)MG(K^*)}{N}. \tag{2.15}$$

2.2.3 Characterization of the Equilibrium

I consider the equilibrium in the host country in this section. I first show output and labor demand for each type of firm. I then state conditions satisfied in the equilibrium. The equilibrium is characterized by the wage level, w, and the cutoff in the level of multinational's intangibles, K^*.

Intermediate Good Firm Outcomes

In section 2.2.2, the cutoff level of intangible capital for M&A, K^*, is pinned down for a given (w, Y). To compute the aggregate output and the aggregate labor demand, I organize the output, y_ω, and labor demand, ℓ_ω, for each type of firm, $\{m, g, a\}$, using (K^*, w, Y) as below:

(i) For M&A firms which successfully match with local firms with probability, $\hat{\mu}(K^*)$ $\rightarrow y_m(K_i; w, Y)$ and $\ell_m(K_i; w, Y)$ where $K_i \in [\underline{K}, K^*]$.

(ii) For GF firms which search and fail to match with local firms with probability, $1-\hat{\mu}(K^*)$ $\rightarrow y_g(K_i; w, Y)$ and $\ell_g(K_i; w, Y)$ where $K_i \in [\underline{K}, K^*]$.

(iii) For GF firms which decide to make GF investment without searching $\rightarrow y_g(K_i; w, Y)$ and $\ell_g(K_i; w, Y)$ where $K_i \in [K^*, \infty]$.

(iv) For local firms that operate alone with probability, $\lambda(K^*)$ $\rightarrow y_a(w, Y)$ and $\ell_a(w, Y)$.

Using the above description, I now consider the intermediate goods market, the labor market clearing conditions.

Intermediate Goods Market

There are three unknowns in the equilibrium, (w, K^*, Y). First, using the production function (2.3), I show that Y can be represented as a function of (w, K^*). From equation (2.3),

$$
\begin{aligned}
Y &= \left[\int_{\Omega} y_{\omega}^{\frac{\sigma-1}{\sigma}} d\omega\right]^{\frac{\sigma}{\sigma-1}} \\
&= \Bigg[\hat{\mu}(K^*)M \int_{\underline{K}}^{K^*} y_m(w, K, Y)^{\frac{\sigma-1}{\sigma}} dG(K) \\
&\quad + (1-\hat{\mu}(K^*))M \int_{\underline{K}}^{K^*} y_g(w, K, Y)^{\frac{\sigma-1}{\sigma}} dG(K) \\
&\quad + M \int_{K^*}^{\infty} y_g(w, K, Y)^{\frac{\sigma-1}{\sigma}} dG(K) \\
&\quad + (1-\lambda(K^*))N \; y_a(w)^{\frac{\sigma-1}{\sigma}}\Bigg]^{\frac{\sigma}{\sigma-1}}.
\end{aligned}
$$

The right-hand side is a function of (w, K^*, Y). Thus, one can solve this equation for Y and represent Y as a function of (w, K^*). The solution for Y is

$$
\begin{aligned}
Y = \left[\frac{1}{w}\left(1 - \frac{\sigma-1}{\sigma}\alpha\right)\right]^{\frac{\beta}{1-\beta}} \Bigg\{&\hat{\mu}(K^*)MZ \int_{\underline{K}}^{K^*} k_m \; dG(K) + (1-\hat{\mu}(K^*))MZ \int_{\underline{K}}^{K^*} k_g \; dG(K) \\
&+ MZ \int_{K^*}^{\infty} k_g \; dG(K) + (1-\lambda(K^*))Nzk_a\Bigg\}^{\frac{\sigma\alpha}{\alpha(\sigma-1)-\beta}}.
\end{aligned}
$$

This shows that the aggregate output, Y, is a function of (w, K^*). Appendix B provides the detailed derivation. For graphical analyses, now I characterize equilibrium conditions using two unknowns (w, K^*). Below, I use the notation $\tilde{\Theta}(w, K^*)$ and $\Theta(w, K^*)$ in place of $\tilde{\Theta}(w, Y)$ and $\Theta(w, Y)$.

Cutoff Condition

In sections 2.2.2 and 2.2.2, I showed that K^* can be solved for a given (w, Y). Restating the cutoff condition, equation (2.12), using the notation $\Theta(w, K^*)$ instead of Θ,

$$
(1-\chi)\hat{\mu}(K^*)\Theta(w, K^*)\left[(Z-z)\kappa - Z(1-\eta)K^*\right] = \psi. \tag{2.16}
$$

Labor Market

The labor market in the host country is cleared by equating the labor supply to the aggregate labor demand. I compute the aggregate labor demand using the cutoff level K^* shown in section 2.2.3, and equating it to the labor supply, L:

$$
\begin{aligned}
L = \hat{\mu}(K^*)M & \int_{\underline{K}}^{K^*} \ell_m(w, K)dG(K) \\
& + [1 - \hat{\mu}(K^*)]M \int_{\underline{K}}^{K^*} \ell_g(w, K)dG(K) \\
& + M \int_{K^*}^{\infty} \ell_g(w, K)dG(K) \\
& + [1 - \lambda(K^*)]N\ell_a(w, K^*).
\end{aligned}
$$

Inserting equation (2.1), (2.6) and (2.15) to the right-hand side of this equation, the expression for the aggregate labor demand below:

$$
\begin{aligned}
L = \hat{\mu}(K^*)M\tilde{\Theta}(w, K^*)Z & \left[\kappa(\underline{K}^{-\theta} - K^{*-\theta}) + \frac{\eta\theta}{\theta - 1}(\underline{K}^{1-\theta} - K^{*1-\theta})\right] \\
& + [1 - \hat{\mu}(K^*)]M\tilde{\Theta}(w, K^*)Z\frac{\theta}{\theta - 1}\left[\underline{K}^{1-\theta} - K^{*1-\theta}\right] \\
& + M\tilde{\Theta}(w, K^*)Z\frac{\theta}{\theta - 1}K^{*1-\theta} \\
& + \tilde{\Theta}(w, K^*)z\kappa\left[N - \hat{\mu}(K^*)MG(K^*)\right].
\end{aligned} \tag{2.17}
$$

Equilibrium

Now I am ready to state the domestic equilibrium in host country h.

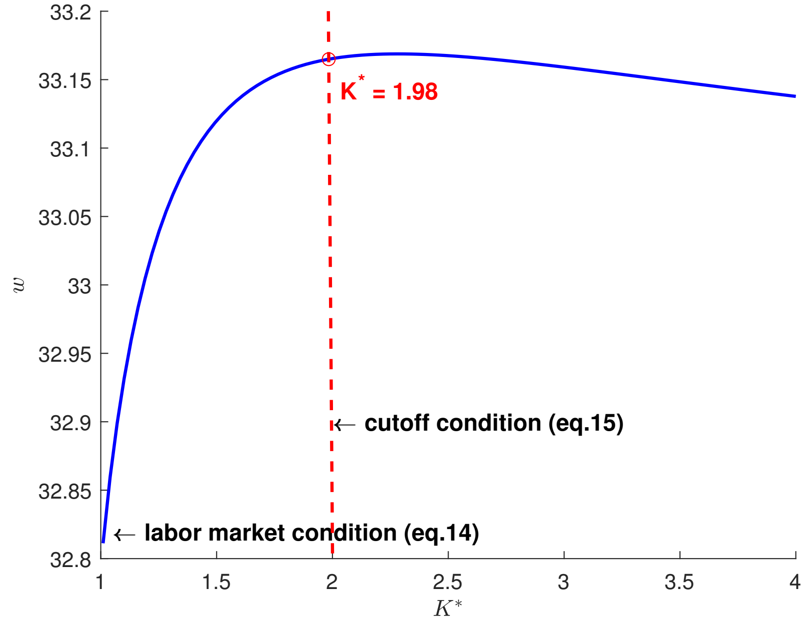
Definition 1 *Given parameters* $\{Z, z, \kappa, \underline{K}, \theta, \chi, \eta, \sigma, \beta, N, M, L, \psi, \rho\}$*, the domestic equilibrium is characterized by the equilibrium wage,* w*, and the cutoff in the level of intangibles,* K^**, satisfying*

(i) The labor market condition in equation (2.17).

(ii) The cutoff condition in equation (2.16).

There are three markets in host country h: the final-good market, the intermediate-goods market, and the labor market. The intermediate good market clears such that p_ω and y_ω satisfy the firm's profit maximization problem and the intermediate good demand curve in

Figure 2.2: Equilibrium Conditions



[a] The lines in this figure show the K^* and w which satisfy the labor market condition (equation 2.17 is shown as the blue curved line) and the cutoff condition (equation 2.16 is shown as the red dashed line). I use the parameters in Table 2.3.

equation (2.5), and the labor market clears when equation (2.17) is satisfied. From Walras' Law, the final-good market automatically clears.[12]

The system of two equations—the labor market condition (equation 2.17), and the cutoff condition (equation 2.16)—has a unique solution. In Figure 2.2, I plot the equilibrium wage level, w, and the threshold level of intangible capital, K^*, which satisfy each of the conditions. The cutoff condition is strictly decreasing, while the labor market condition is a concave function.

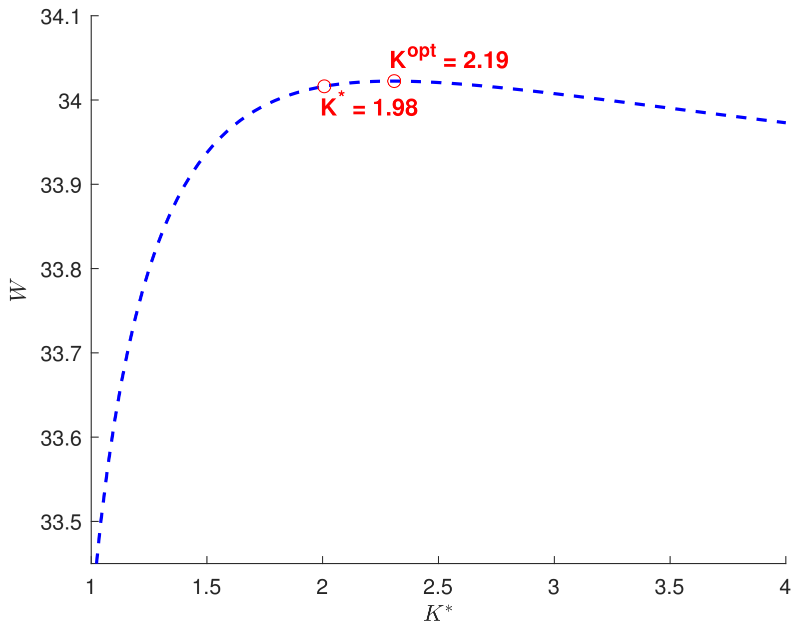
Welfare

The representative household's income, I, is equal to its consumption of final good, C, which is defined as an index of welfare. The welfare of the representative household is the sum of wage payments, profits of local firms, and acquisition transfers:

$$W(w, K^*) = wL + (1 - \lambda(K^*))N\pi_a(w, K^*) + \hat{\mu}(K^*)M \int_{\underline{K}}^{K^*} P(w, K)dG(K) \tag{2.18}$$

[12] Final-market clearing condition is in Appendix B.

Figure 2.3: Socially Optimal K^*



[a] The lines in this figure show the welfare level which satisfy the labor market condition (equation 2.17). I use the parameters in Table 2.3. K^{opt} is the threshold level of intangible capital which maximizes welfare in the local economy.

I assume local firms are owned by local consumers, whereas M&A and GF firms are foreign-owned. All firms earn profits and pay wage bills. When multinationals search, they incur search costs, and if they acquire local firms, they make acquisition payments. All payments are made in terms of the final good, Y. The representative household's consumption is also denominated in terms of Y.

The socially optimal threshold level of intangibles maximizes welfare in the host country subject to the labor market clearing condition. The following problem gives the socially optimal K^{opt}:

$$\max_{w,K^*} W \quad \text{subject to the labor market condition (equation 2.17).}$$

Figure 2.3 shows that there is a cutoff level of multinationals' intangibles, K^{opt}, which maximizes welfare, W. Interestingly, the equilibrium threshold level of intangible, K^*, can be different from the optimal level, K^{opt}. Externalities are generated during search and matching. Multinational and local firms bargain over a merger gain, after a match is made. Firms are not likely to take the search cost of those still unmatched into consideration. In my model, the threshold level of intangible capital determines the types of investment that the host country receives. The equilibrium FDI patterns can be suboptimal from the host country's perspective, meaning that there is a certain level of greenfield or M&A investment that maximizes local welfare. If policymakers seek to maximize welfare, W, they would like to pursue a policy that leads to the optimal threshold level, K^{opt}. For example, suppose there is a country for which $K^* > K^{opt}$. In this case, policymakers restrict M&As to lower the value of K^*. This model prediction motivates me to conduct experiments regarding FDI policies by an investment-receiving country.

2.3 Quantitative Analyses

I match the model to the data in order to quantitatively assess how a multinational firm's intangible capital relates to their FDI decisions and to the welfare in the local country. I also analyze how these relationships differ between developed and developing countries. I then use the resulting parameters for policy experiments in section 6.

2.3.1 Distribution of Intangible Capital

First, I analyze the distribution of intangible capital among US investing firms. The firm's intangible capital is assumed to have a Pareto distribution, and it's cumulative distribution function is $G(K)$ as defined in equation (2.1). A large number of studies suggest that distribution of firm sizes, measured by sales and the number of employees, can be characterized by a Pareto distribution.[13] Arrighetti et al. (2014) uses the data on Italian manufacturing firms and shows that the probability of investing in intangibles depends on a firm's size. In my US firm-level data, the distribution of firms' intangibles is also skewed right (Figure 2.4).[14]

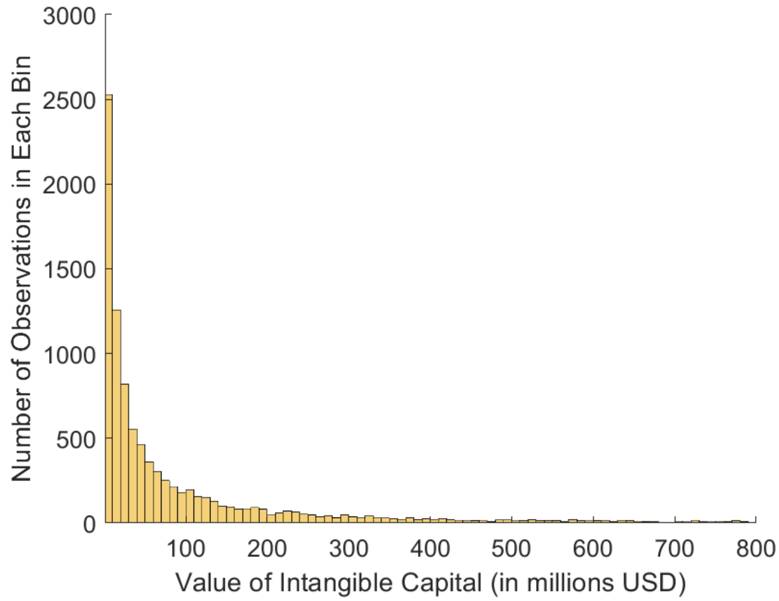
I estimate the value of the shape parameter, θ, following Axtell (2001) and Helpman et al. (2004). First, I rank firms in descending order, according to their amount of intangible capital (i.e., the firm with the largest intangible capital is ranked first). I then plot the logarithms of the ranking and the firm's intangible capital. Following the existing literature, I focus on the upper tail of the distribution when estimating the shape parameter. I consider firms within the top 1 percentile of intangibles.[15] This log-log plot (Figure 2.5) is known as

[13] See Simon and Bonini (1958) and Axtell (2001) as examples of studies that introduce the fact that a firm's size distribution follows a Pareto distribution.

[14] Figure B.1 in Appendix B shows the quantile plots of intangible capital and sales. The figures shows that the shapes of both distribution are the same.

[15] For example, Eaton et al. (2011) consider the top 1% of firms in their dataset. By the assumption of the

Figure 2.4: Distribution of Firms' Intangible Capital



[a] This figure shows the histogram of US firm's intangible capital. Each bin has a width of 10 million dollars. The vertical axis shows the number of observations that fall in each bin.

Table 2.1: Estimated Shape Parameter in $G(K)$

Estimated θ	Adjusted R^2
1.951 (0.055)	0.924

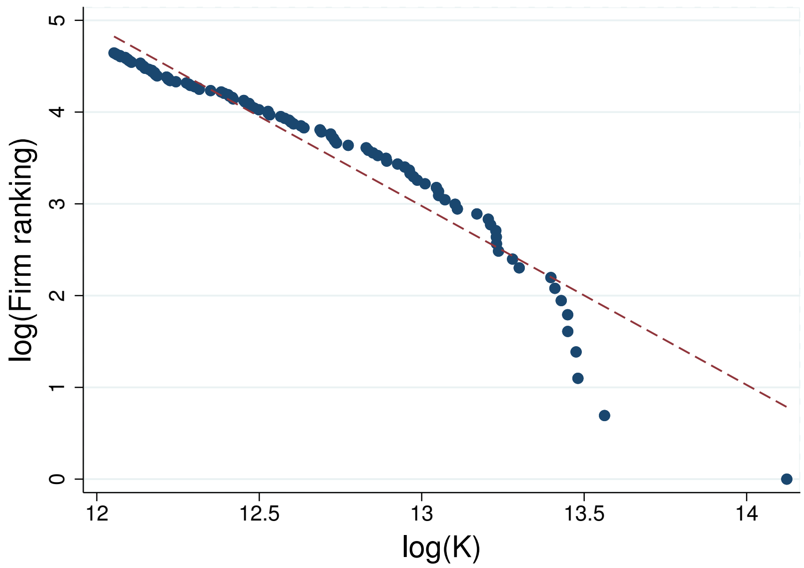
[a] Standard error of the estimated parameter is shown in the parenthesis.

a Zipf plot. We expect to observe a negative linear relationship in the Zipt plot if the data follow a Pareto distribution. Finally, I estimate the slope of the line using OLS. Consider the survival function, $\bar{G}(K) = K^{-\theta}$. If I take logs on both sides, I obtain $\ln(\bar{G}(K)) = -\theta \ln(K)$. The slope of the log-log plot corresponds to $-\theta$. Thus, the absolute value of the coefficient is equivalent to the shape parameter, θ. I normalize the data by setting the lowest value of intangibles equal to one since I set the scale parameter $\underline{K} = 1$. I set $\theta = 1.95$ from the regression result (Table 2.1).[16]

Pareto distribution, the shape parameter does not depend on the level of the cutoff (further references can be found in footnote 26 in Helpman et al. (2004) and footnote 7 and 8 in Eaton et al. (2011)). In my data, I obtain a similar coefficient ($\theta \approx 2$) using the other cutoffs at around the 99th percentile of the data.

[16]The Pareto distribution has an infinite variance if $\theta \leq 2$. This means that the moment will not converge as the sample size goes to infinity. This is not a problem in this paper since the variance exists in a finite sample.

Figure 2.5: Zipf Plot: Firm's Intangible Capital



[a] The horizontal axis is the amount of intangible capital, and the vertical axis is the ranking of the firms. Both values are in logs. I normalize the value of intangibles by setting the lowest value of intangibles to one. The dotted line is the fitted OLS line. Regression results are shown in Table 2.1.

2.3.2 Baseline Parameters

I set parameters using moments that are obtained from my data. The cutoff condition (equation 2.12) and the labor market clearing condition (equation 2.17) are functions of the cutoff level of intangible capital $K^*(w, \theta, \rho, \kappa, \eta, \psi; X)$ and the real wage in the host country $w(K^*, \theta, \rho, \kappa, \eta, \psi; X)$. The shape parameter of the Pareto distribution, θ, is estimated in the previous subsection 2.3.1. ρ is the elasticity of the matching function, κ is the intangible capital of local firms, η is the friction parameter (i.e., the degree of incomplete transfer of intangibles), and ψ is the search cost. X indicates other parameters that are exogenously determined. The details of these parameters are shown in Table 2.3. In this subsection, I include all FDI deals in my sample, regardless of their destination country.

I pin down four parameters, ρ, κ, η, and ψ, using the following four moments in addition to the two equilibrium conditions for $K^*(w, \theta, \rho, \kappa, \eta, \psi; X)$ and $w(K^*, \theta, \rho, \kappa, \eta, \psi; X)$: (i) the share of multinational firms that make M&A investments, (ii) the productivity difference between acquiring and target firms, (iii) the average merger premium, and (iv) the threshold level of intangible capital.

Table 2.2: Moments

Moment	All FDIs (baseline)		FDIs to the North		FDIs to the South	
	Data	Model	Data	Model	Data	Model
$\frac{\overline{K}_{MA}}{\overline{K}}$	0.6490	0.6490	0.7730	0.7732	0.5700	0.5701
$\frac{E_m}{E_m+E_g}$	0.4170	0.4168	0.5560	0.5561	0.2050	0.2053

[a] $\frac{\overline{K}_{MA}}{\overline{K}}$ is the ratio of the average intangibles of M&A firms to that of all firms. $\frac{E_m}{E_m+E_g}$ is the share of M&A investments out of total investments (both M&A and GF). I show the numbers from both the data and the calibrated model.

(i) The share of M&A multinationals

Using equations (2.13) and (2.14), the share of multinational firms that make M&A investments is:

$$\frac{E_m}{E_m + E_g} = \hat{\mu}(K^*)G(K^*). \tag{2.19}$$

The share is 0.42 in the data (Table 1.1). The matching function $\hat{\mu}$ (equation 2.2) is a function of K^* and other parameters: the elasticity of the matching function ρ, the number of multinationals M, the number of local firms N, and the shape parameter, θ. I fix M and N so that ρ has only one unknown, K^*. In my data, the average number of FDI projects across destination countries is 630. As a measure of local firms, N—which is unobservable—I use the US as a baseline. I assume that N is equal to the number of US local firms times the ratio of local GDP to US GDP. I weight by the total number of investments and compute the weighted average across destination countries. I calculate that $M = 630$ and $N = 3430$.[17]

(ii) The productivity difference between acquiring and target firms

I use the fact that the average profitability of US acquirers is 7.5 times that of US target firms (David, 2021). I assume this same ratio applies to international acquisitions as well. This assumption is consistent with research showing that foreign acquirers are more productive than their domestic targets (Guadalupe et al., 2012). This moment is represented in the

[17] The total number of firms is not available in each destination country, but I can see the number of listed firms in the World Bank data. Since there is a strong relationship between the number of listed firms and GDP (correlation is 0.97), I project the number of local firms in each destination country using GDP. I use the number of US firms with more than 250 employees (of which there are 26,225, according to the Census). Around 90% of US multinationals in my dataset have more than 250 employees. Since acquirers usually buy targets of a similar size, I focus on target firms with more than 250 employees.

Table 2.3: Baseline Parameters

Parameters	Definition	Value
estimated/ calibrated		
θ	Shape parameter of $G(K)$	1.95
ρ	Elasticity of the matching function	0.55
κ	Intangible capital of local firms	1.09
η	M&A friction	0.80
ψ	Search cost	0.00030
exogeneously determined		
Z	Technology level in the US	1
z	Technology level in host countries	0.5
M	Number of multinationals (FDI projects)	630
N	Number of local firms	3430
σ	Elasticity of substitution	6
β	Labor share of the production function	0.7
χ	Bargaining power of local firms	0.5
L	Labor force size	1

[a] This table shows the parameters I set for the analysis when I use all US investing firms.

model as:

$$\frac{\pi_m(\overline{K}_{MA})}{\pi_a} = \frac{Z\overline{K}_{MA}}{z\kappa} = \frac{Z(1-K^{*1-\theta})}{z\kappa} = 7.5.$$

In the above equation, κ, the intangible capital of local firms, is a function of K^* and the two technology parameters—the technology level in the US, Z, and the technology in host countries, z. The two technology parameters are exogenously determined using productivity per hour worked.[18] In the data, the labor productivity in the US (61.056) is double the average across destination countries (30.174). I normalize the technology level of US firms, Z, to one, and set the level of the target firms, z, to 0.5.

(iii) The average merger premium

The average merger premium gives the relationship between the M&A friction parameter, η, the cutoff level of intangible capital, K^*, and the real wage in the host country, w. According to a report by Thomson Reuters (2018), the average world M&A premium ranges from 20%

[18]The data come from Our World in Data, a project by Oxford University. The data are based on Feenstra et al. (2015) and the Penn World Table. I take the average values during my data period (https://ourworldindata.org/grapher/labor-productivity-per-hour-pennworldtable, last accessed on Sep 17, 2020).

to 26%. I define the average merger premium as

$$\frac{P(\overline{K}_{MA}) - \pi_a}{\pi_a} = 0.25,$$

where $P(\overline{K}_{MA})$ is the acquisition price of a firm with the mean level of intangibles among M&A firms, and π_a is the profit of the local firm. The average merger premium is a function of (η, K^*, w, Z, z, β, σ, χ). In addition to Z and z, I take the last three parameters, β, σ, and χ, from the existing literature and other data sources, and therefore η can be represented a function of two unknowns, K^* and w. I take the elasticity of substitution, σ, from Broda and Weinstein (2006), and the bargaining power of target firms from David (2021): $\sigma = 6$ and $\chi = 0.5$. I also set the labor share in the Cobb-Douglas production function, β, to 0.7.

(iv) The threshold level of intangible capital

An investing firm with intangible capital lower than the cutoff ($K_i \leq K^*$) chooses M&A investment rather than GF. I calculate the mean of M&A firms' intangibles, and divide by the overall mean of intangibles. In my model, the relationship is

$$\frac{\overline{K}_{MA}}{\overline{K}} = \frac{[\int_{\underline{K}}^{K^*} K dG(K)]/G(K^*)}{\int_{\underline{K}}^{\infty} K dG(K)} = \frac{1 - K^{*1-\theta}}{1 - K^{*-\theta}},$$

where $\overline{K}_{MA}$ is the mean of M&A firms' intangibles, and $\overline{K}$ is the mean of all firms' intangibles. The value in the data is 0.65. This moment describes how much the mean of intangibles among M&A firms deviates from that of all firms.[19] As the moment gets larger, firms with larger intangible capital make more M&A investments.

As I showed in section 2.2.3, the equilibrium can be characterized by two endogenous variables, K^* and w. The first three moments, (i) the share of multinational firms that make M&A investments, (ii) the productivity difference between acquiring and target firms, and (iii) the average merger premium, provide the relationships between parameters, ρ, κ, and η, and the two endogeneous variables, K^* and w. The last moment, (iv), the threshold level of intangible capital, determines the search cost, ψ through the cutoff condition (equation

[19] I use the mean of M&A firms' intangibles rather than that of GF firms. In the model, if a searching firm i with $K_i \leq K^*$ fails to find a target, it chooses GF. Thus, the moments relating to GF firms represent not only the firms with $K_i > K^*$, but also firms with $K_i \leq K^*$. The matching outcome does not depend on the level of intangible capital that firms exogenously received before investing (i.e., random search). Therefore, the moments relating to M&A firms can be used to analyze the firms only with $K_i \leq K^*$.

2.12). I set $\rho = 0.55$, $\kappa = 1.09$, $\eta = 0.80$, and $\psi = 0.00030$. I pin down the threshold level of intangible capital, $K^* = 1.98$, and the wage level, $w = 33.17$. I normalize the labor force size to one to apply the labor market clearing condition (equation 2.17). Table 2.2 shows that the calibrated model produces moments similar to the data.[20]

2.3.3 Different Types of Host Countries (FDIs in the North or the South)

In this subsection, I split the FDI projects by destination. As I discuss in section 1.3.2, developed countries have received more M&A investments than developing countries. Therefore, the relationship between the cutoff level of intangibles and wages would differ across these two types of destinations. Moreover, recent global policies are polarized in the preference of receiving M&As. There are more restrictions on M&A in developed countries than developing countries. Analyzing the difference between developed and developing countries could provide the insight regarding recent trend in M&A policies. To investigate the difference in FDI across different host countries, I repeat the analysis under two different parameter values. I use country classifications released by the IMF to categorize host countries. They divide the economy into two groups: "advanced economies", and "emerging and developing economies." I call the former the North, and the latter the South. Below, I look at how the firm's FDI decisions differ if it invests in the North or in the South.

I set parameters using the same procedures as used for the baseline case. The resulting parameters are reported in Table 2.4. M&A firms investing in the North have a higher level of $\frac{\overline{K}_{MA}}{\overline{K}}$ than those investing in the South (Table 2.2). Reflecting this difference, I find that firms investing in the North face a higher level of cutoff K^*. I set $K^* = 3.73$ for firms investing in the North, and $K^* = 1.33$ for firms investing in the South. Firms with intangibles larger than the cutoff will invest via GF without searching for their M&A partners. The cutoff in the North is 2.5 times larger than that in the South. Therefore, firms making GF in the North have a larger amount of intangible capital than those in the South.

I pin down the matching function parameter, ρ, is 0.71 in the North and 0.35 in the South. More occurrence of M&As means higher matching probability in the M&A market in the North. Thus, the matching function parameter, ρ, is higher for those firms. The average labor productivity in the North is 43.92, while that in the South is 14.93. Compared to the labor productivity in the US which is 61.06, I set the exogenous technology parameter of

[20]The calibrated model replicates the profit of each type of firm and the acquisition price. Table B.1 shows the average of each type of profits.

Table 2.4: Parameters (by Destination)

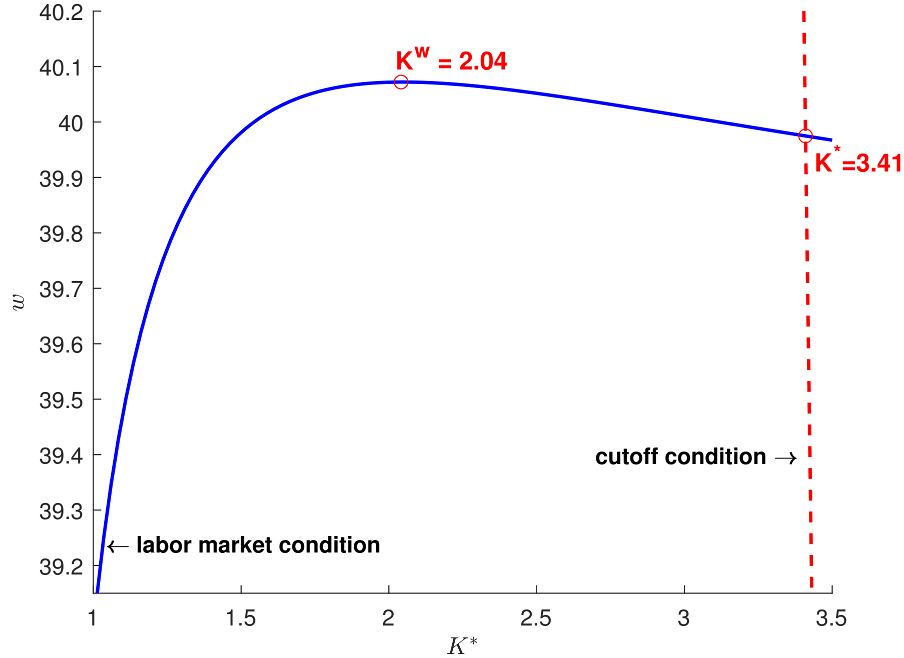
Parameter	Definition	Value	
		North	South
ρ	Elasticity of the matching function	0.71	0.35
M	Number of multinationals (FDI projects)	1023	576
N	Number of local firms	3081	5303
Z	Technology level in the US	1	1
z	Technology level in host countries	0.72	0.24
κ	Intangible capital of local firms	1.11	1.08
η	M&A friction	0.92	0.68
ψ	Search cost	0.00016	0.0018

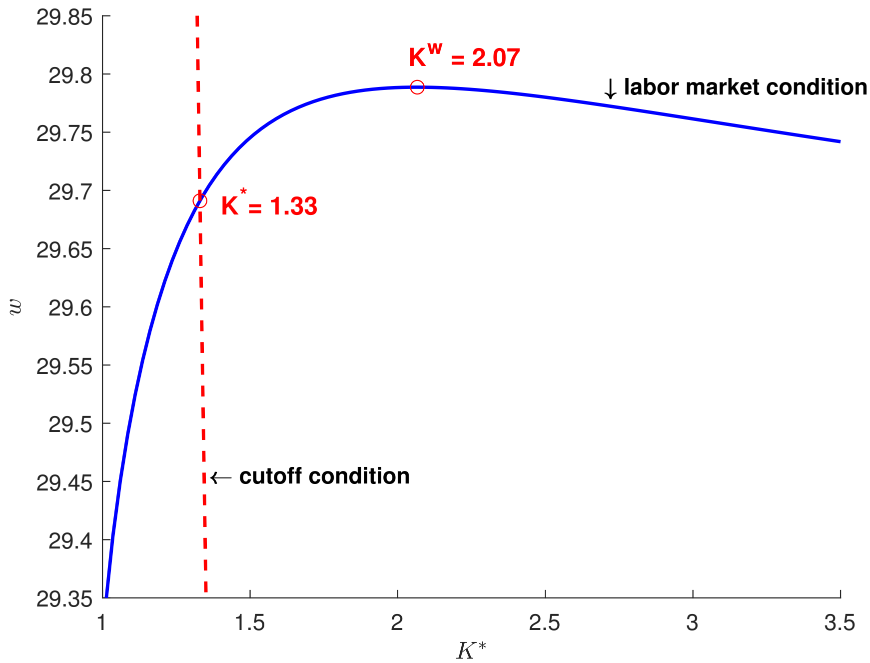
[a] This table shows parameters I set when I analyze US investments by destination countries. Only the parameters that differ from the baseline model are presented here.

local firms, z, to 0.72 for firms investing in the North, and 0.24 for firms investing in the South (again, $Z = 1$ for US firms). US acquirers have more opportunity to leverage the difference in productivity between acquirers and targets when they are making M&As in the South (i.e., $Z - z = 0.28$ in the North, while $Z - z = 0.76$ in the South). The larger gain from mergers and the lower probability of matching create a much higher search cost, and discourage firms from searching for M&A partners in the South. To set the M&A friction parameters, η, I consider the fact that cultural barriers and communication costs affect the quality of post-acquisition integration. Thus, I assume the distance between host countries and the US governs the M&A friction parameter, and use the number of investments to compute a weighted average of the distance. The ratio of the average distance in the South to that of the North is 1.35.[21] Considering the baseline value $\eta = 0.80$, I set the M&A friction parameter to 0.92 in the North and 0.68 in the South. Using the labor market clearing condition (equation 2.17), I obtain the equilibrium wage, w^*, in the North is 39.97 and 29.68 in the South. Interestingly, the cutoff level of intangibles achieving the highest wage, K^w, is smaller than the current cutoff, K^*, in the North, while it is larger in the South (Figure 2.6). This difference suggests that policymakers in the South and the North would take opposite actions toward M&A restrictions. I discuss this policy implication in the next section.

[21] The weighted average distances are 6962 km in the North and 9405 km in the South.

Figure 2.6: K^* and K^w ([top] the North, [bottom] the South)





[a] The lines in this figure show the K^* and w which satisfy the labor market condition (equation 2.17 is shown as the blue curved line) and the cutoff condition (equation 2.16 is shown as the red dashed line). I use the parameters in Table 2.4. K^w is the cutoff maximizing real wages in the local economy.

2.4 Counterfactual Experiments

In this section, I evaluate the impact of FDI policies on welfare in host countries. As I show in the previous section, the optimal policy response differs in the North and the South. In the North, if policymakers would like to increase real wages, they should promote GF investments. Conversely, if policymakers in the South would like to increase real wages, they should restrict GF investments.

2.4.1 Tax on GF investments in the South

First, I consider the effects of a tax on the profits of GF multinationals in the North. A change in firms' profits affects the cutoff condition which determines the minimum level of intangible capital whether a multinational firm needs to make an M&A search worthwhile. Consider a τ% tax on GF profits. the profits of a GF multinational with intangible capital K_i are given by:

$$(1-\tau)\pi_g(w, Y, K_i) \ = (1-\tau)\Theta(w, Y) Z K_i, \tag{2.20}$$

where $\tau > 0$. The cutoff condition (equation 2.16) becomes

$$(1-\chi)\hat{\mu}(K^*)\Theta(w, K^*)\left[(Z-z)\kappa - Z((1-\tau)-\eta)K^*\right] = \psi.$$

Figure 2.7 shows that if there is a tax on GF profits, the cutoff condition shifts to the right. The equilibrium level of intangible capital, K^{**}, is larger than the previous cutoff level, K^*. When multinationals decide whether to search for an M&A target, they compare their expected profits from M&A and GF investments. Lower expected profits from choosing GF investments encourage multinationals to instead try to find an M&A partner, resulting in more M&A deals and fewer GF investments.

The local welfare consists of four parts: wage payment, local profits, acquisition transfer, and tax transfer. Table 2.5 shows that, if the government taxes GF multinationals, wages and acquisition transfers both increase (by 0.037% and 3.44%, respectively, for a 1% tax). By contrast, local firms' profits decline (by 0.12%). Thus, the net welfare effect of the tax is positive: the increases in wages and acquisition transfers more than offset the decrease in local profits. Since more local firms will be acquired, households will receive lower profit dividends from local firms. However, the increase in wages and the additional acquisition transfers more than offset this loss, and thus the net effect on welfare will be positive. The government transfers all tax revenue to households.

Table 2.5: Welfare Change: Tax on Profits of GF Multinationals in the South

Welfare	baseline	0.5% tax		1%tax	
	value	value	change (%)	value	change (%)
Wage payment	29.678	29.683	0.019	29.689	0.037
Profits of local firms	26.368	26.335	−0.062	26.210	−0.123
Acquisition transfer	1.102	1.120	1.716	1.139	3.436
Tax transfer	0	0.100	–	0.964	–
Total	57.148	57.256	0.189	57.363	0.377

[a] This table shows how welfare changes when there is a 1% and 5% tax on profits of GF multinationals in the South.

2.4.2 Subsidy on GF investments in the North

I next consider the effects of state subsidies on GF multinationals in the North. Figure 2.7 shows that if governments subsidize GF profits (i.e., $\tau < 0$ in equation 2.20), the cutoff condition shifts to the left. The equilibrium level of intangible capital, K^{**}, is smaller than the previous cutoff level, K^{*}. Higher expected profits from making GF investments discourage multinationals from searching for their M&A partners, and thus fewer M&As occur.

Table 2.6 shows how welfare in the host country changes when it increases subsidies by 0.5% and 1%. When the host country receives more GF investments, both wage payments and total profits of local firms increase. Although the representative consumer receives lower total acquisition receipts and needs to pay taxes to cover the subsidies, there is a positive net effect on welfare. There are two key findings to note. First, FDI policies that subsidize GF investments increase total welfare, but the net effect is small. Second, my counterfactual analysis shows that if policymakers would like to increase wage payments, they can restrict M&As even though total welfare does not increase by much. An increase in foreign M&A activity can bring objections from the public in the North because it endangers local jobs (Katitas, 2020). My model suggests that those concerns on the part of workers might be well-founded.

2.5 Conclusion

I study how firm FDI mode choice affects welfare in investment-receiving countries. To do so, I develop a model of firm FDI choice based on the empirical results that I obtain in the

Table 2.6: Welfare Change: Subsidy to Profits of GF Multinationals, in the North

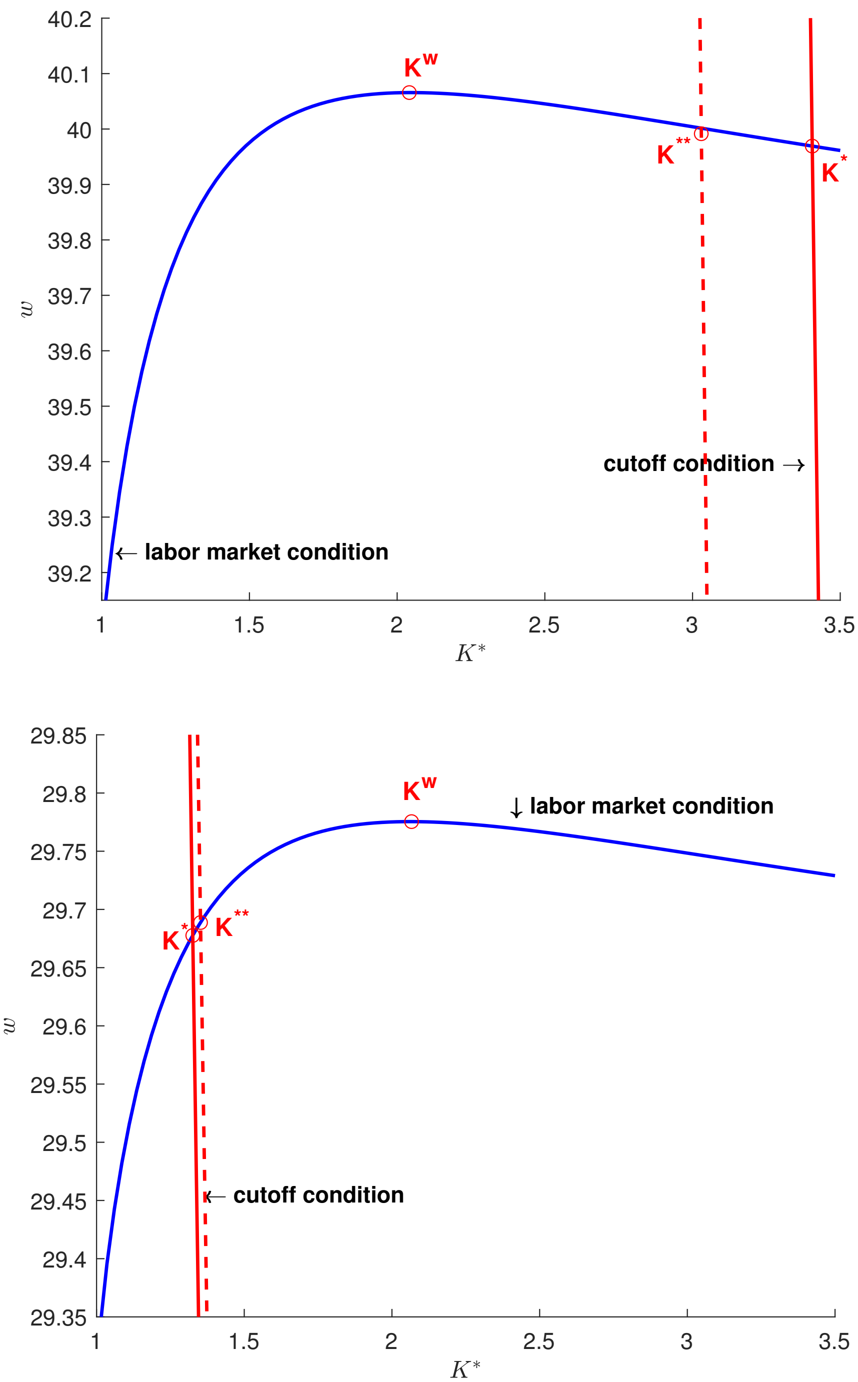
Welfare	baseline	0.5% subsidy		1% subsidy	
	value	value	change (%)	value	change (%)
Wage payment	39.969	39.986	0.043	40.002	0.081
Profits of local firms	29.106	29.149	0.148	29.197	0.313
Acquisition transfer	7.305	7.247	−0.794	7.185	−1.643
Tax Payment	0	−0.087	–	−0.177	–
Total	76.380	76.382	0.003	76.383	0.004

[a] This table shows how welfare changes when a government subisidies on GF multinationals in the North.

first chapter. In the model, firms' intangible capital levels determine which mode of FDI they pursue. Under a reasonable set of assumptions, I show that firms with lower intangible capital tend to choose GF, which is consistent with the empirical results. Moreover, I show that equilibrium FDI patterns can be suboptimal from the host country's perspective, which implies that there is a certain level of GF investment that maximizes local welfare. This allows me to assess the welfare effects of various policies in investment-receiving countries through changes in FDI. In particular, I find that the effects of FDI policies differ between a developed economy (i.e., the North) and a developing economy (i.e., the South). In the South, policies that restrict GF investments raise total welfare. By contrast, in the North, I find that policies that promote GF decrease total welfare.

The local firm's intangible capital is constant in my model because of data limitations. However, the recent M&A literature considers heterogeneous targets and assortative matching. A possible extension of my model is to make the local firm's intangibles κ heterogeneous and consider sorting between multinationals and locals (i.e., a high-K multinational may look for a high-κ local firm). Another possible extension is to endogenize multinational firms' intangibles K and local firms' intangibles κ. This extension would reveal potential sources of additional inefficiencies (e.g., over/under-investment) and further room for policy intervention. Lastly, my model can help in analyzing other policy interventions. For example, future work could investigate the possibility of a government's levying taxes on the costs of M&A (i.e., acquisition transfer or search costs) and distributing the tax revenue to GF multinationals as an investment incentive.

Figure 2.7: [top] Subsidy on GF Profits in the North, [bottom] Tax on GF Profits in the South



[a] The lines in this figure show the K^* and w which satisfy the labor market condition (equation 2.17 is shown as the blue curved line) and the cutoff condition (equation 2.16 is shown as the a red straight line). I use the parameters in Table 2.4.

[b] [top] The dashed line is the cutoff condition when there is a 1% subsidy on profits of GF multinationals.

[b] [bottom] The dashed lines are the conditions when there is a 1% tax on profits of GF multinationals.

Chapter 3

FDI and the Local Labor Market: Japanese Automobile Plant Openings in the 1980s

3.1 Introduction

I studied the determinants of FDI mode (i.e., GF or M&A) and the policy implications of these decisions in the first two chapters. In this chapter, I examine the effect of FDI on local labor markets, focusing on the investment by Japanese automotive firms in the US in the 1980s.

In the 1970s, the rapid growth of Japanese automobile exports to the US had a serious impact on the US automotive labor market. Japanese auto imports, combined with a recession, forced around 40% of the workers in automobile-related industries to be temporarily laid off in late 1981.[1] Under political pressure from the United States, Japan imposed a voluntary export restraint (VER) and restricted the quantity of automobiles exported to the US in 1981. Additionally, the US government also requested that Japanese automotive companies invest in the US in order to offer new employment opportunities to their unemployed automotive workers. Because of this political pressure, Japanese automotive firms made their first investments in the US in the 1980s. Starting with new assembly plants opened by Honda and Nissan, more than 250 plants for automobile parts were built in the US by 1988 (Mair et al. ,1998). These Japanese new assembly plants added at least 35,000 jobs,

[1] In addition, although the exact number of job losses is difficult to estimate, membership in the United Auto Workers (UAW) labor union declined by one third, from 1.5 million in 1979 to 1 million in 1987.

and other automobile-related plants, including those for bodies and parts, created around 337,600 additional jobs by 1998 (Sturgeon and Florida, 2004). This large job creation seems to have a large impact on the US labor market, but the effect of Japanese FDI on the US local labor market has not been investigated in the existing literature. Therefore, in this chapter, I study how much Japanese automobile assembly plants contributed to increases in auto industry wages over the 1980s.

I use a difference-in-differences estimation strategy to analyze the impact of new Japanese plant openings on local wages.[2] I use US Census data for 1980 and 1990, and the local labor markets are defined by *conspumas*, which are groups of counties. I control for workers' characteristics, such as age, race, and educational attainment, in addition to the ratio of union membership in the state. I do not find any effects of Japanese plant openings on all workers once I control for state-level variation. But I do find significant *declines* in wages among Black auto workers: Japanese plant openings decreased Black auto workers' wages by 9.3%. This finding is consistent with the fact that Japanese automakers hired fewer Black workers than US automakers (Cole and Deskins, 1998). In fact, in the West, where Japanese firms (specifically, Toyota) did hire a relatively large share of Black workers, I find that Japanese plant openings had no effect on Black earnings.

However, Japanese firms' location decisions are likely nonrandom. In particular, firms that pursued brownfield investments—buying existing, idled plants—had a narrower choice set than firms that pursued greenfield investments—building a new plant from scratch. Greenfield investors can choose any location to build a plant, whereas brownfield investments only occur in locations that were (endogenously) chosen and (also endgenously) idled by American companies. This selection bias could impact my estimates. Therefore, I consider an alternative specification in which I focus on greenfield investments. Following Greenstone et al., (2010), I compare wages in locations that received greenfield investments from Japanese auto firms to those that were final contenders for investment, but were ultimately passed over. The likely similarity between these winning and losing locations likely minimizes selection bias. In this sample, I find similar effects to those above: overall, Japanese plant openings had no impact on wages, but among Black workers, Japanese investments decreased wages. Additionally, I analyze if the wages of the treatment and control groups follow the same trend before the 1980s. I run a regression with the census data for 1970 and

[2]Japanese firms are only the foreign firms that invested in new locations to produce during the 1980s. Volvo built a new plant in October 1987, but it was in the same city where they previously had their plant. Renault opened a plant in June 1982, but it was based on an existing plant they took over and closed in December 1988.

1980 instead of the data for 1980 and 1990 and show there is no trend on county-level wages before 1980.

My research is related to the literature concerning the impact of FDI on labor markets. For example, Feliciano and Lipsey (2006) investigate how an increase in foreign-owned establishments affects the US labor market, and they find no significant employment effects in the manufacturing or non-manufacturing sectors. While the authors focus on changes in average wages across industries and states, I expand on their research by using individual-level wage data. This enables my regression to control for workers' demographics and skill level and to see the effects more precisely within detailed geographical units. Another related study is Greenstone et al. (2010) that measure the spillover effects of million-dollar plant openings in the 1980s and 1990s. They focus on firms' investment in all manufacturing industries and show the million-dollar plant openings increased local wages by 2.7%. In comparison, my paper focuses on a well-known case in a single industry.

This study also contributes to the literature concerning the Japanese auto industry during the 1980s. For example, Feenstra (1984) and Berry et al. (1999) study how much VER raised the prices of imported Japanese cars and how this policy affected the US consumer welfare. My research instead focused on the Japanese firms' investment caused by VER. Additionally, Smith and Florida (1994) examine the location choice of Japanese auto-related firms.[3]

Focusing on Japanese investment in the US has a unique empirical advantage in the labor market analysis. Political pressure primarily drove Japanese automobile investments in the 1980s, and thus these investments are independent of firms' investment timing decisions. In general, firms analyze their business environments and decide to invest when they can anticipate their future profitability. However, econometricians cannot observe all of the factors driving the timing of firms' investment decisions. Therefore, Japanese auto firms' investments are ideal for local labor market analysis since the timing of investments can be regarded as exogenous. For example, documentation in Toyota Motor Corporation suggests that, at the time of investment, Toyota's managers did not know whether or not their US plant would turn a profit.[4] This example shows that the driving factor behind their investment was mainly political pressure, and thus I can analyze the impact on the local labor market without considering endogenous investment timing decisions.

The third chapter is organized as follows. Section 2 shows the characteristics of Japanese

[3]While they do not focus on the automobile industry, Head et al. (1995, 1999) and Woodward (1992) also analyze the location choices behind Japanese investments.

[4]Source: Toyota Motor 75 Years' History https://www.toyota.co.jp/jpn/company/history/75years/ (in Japanese)

Table 3.1: Japanese Automobile Investments in the 1980s

Company	Date of Opened	Date of Announced	Place	New Plant (Greenfield)	Employees	Union	Company Investment (million USD)	Incentive[b] Package (million USD)	Projected Capacity (cars/year)
Honda	1982. Nov	1980. Jan	Marysville, OH	Yes	5,300	No	1,300	20	360,000
Nissan	1983. Jun	1980. Oct	Smyrna, TN	Yes	4,300[c]	No	760	239	440,000[d]
Toyota	1984. Dec	1983. Feb	Fremont, CA	No	4,500	Yes	150	-	300,000
Mazda	1987. Sep	1984. Nov	Flat rock, MI	No	3,500	Yes	750	80	240,000
Toyota	1988. May	1985. Dec	Georgetown, KY	Yes	5,000	No	800	296	200,000
Mitsubishi	1988. Sep	1985. Oct	Normal, IL	Yes	3,100[b]	Yes	500-700	139	240,000
Subaru-Isuzu	1989. Sep	1986. Dec	Lafayette, IN	Yes	1,900	No	500	111	120,000
Honda	1989. Dec	1987. Sep	East Liberty, OH	Yes	1,800	No	410	78	150,000

[a] Source: Robert (2017) except the amount of incentive package, and the information of company investment and projected capacity of the Toyota's plant in Fremont, CA. This information comes from Jacob (2015).

[b] The values of incentive packages is different across different sources. For example, Robert (2017) gives smaller numbers compared to Jacob (2015).

[c] The number is as of 1992.

[d] The number includes trucks.

automobile investment. Section 3 introduces the data source and summary statistics. Section 4 provides a regression model. Section 5 shows the results. Section 6 discusses the robustness. Section 7 concludes.

3.2 Japanese Automobile Investment in the 1980s

There are eight automakers in Japan and seven among them invested in the US during the 1980s. Table 3.1 shows the details of these investments. The first three investments were made by the largest three Japanese automakers (Honda, Nissan, and Toyota) and later by the other four automakers (Mazda, Mitsubishi, Subaru, and Isuzu).[5] The main purpose of VER was to reduce the imports by the largest three automakers, but this policy also urged the other relatively small auto firms to invest in the US. Those smaller automakers got only limited allocations of all Japanese car exports to the US by the Japanese government due to their smaller sales share in Japan (Jacobs, 2015). While the largest three automakers established their production facilities by themselves, the other four firms invested through joint ventures (i.e., a 50/50 share) with American or Japanese firms. Mitsubishi and Mazda jointly invested with American firms—the former with Chrysler and the latter with Ford. Subaru and Isuzu, two Japanese auto firms, cooperated to invest.

Some companies built plants in completely new places (greenfield investment), while others (Toyota in Fremont, California, and Mazda) reopened plants that were previously operated by US companies (brownfield investment). Both types of investments come with pros and cons. Most of the firms with greenfield investments had the advantage of being able to hire non-union workers, who could get accustomed to the Japanese management system relatively easily. However, these greenfield investors had to construct their business environments from scratch. For example, there was no water supply or sewage system in place when Honda and Toyota made their greenfield investments. By contrast, investing in existing facilities enabled Japanese companies to start up their businesses smoothly. In particular, the firms benefited from procurement systems and other know-how developed by the previous companies. However, they were sometimes subjected to restrictions imposed by allied companies which previously owned their plants. For example, Toyota established a joint venture with General Motors (GM) in Fremont, California, and agreed to rehire workers laid off from the former GM plant.

Firms that made greenfield investments hired new workers to operate their new facilities,

[5] Suzuki opened its production facility in Ontario, Canada in April 1989 through a joint venture with GM.

Table 3.2: Motor Vehicle Sector Employment and Relative Wages

Year	Share of the US Auto Workers (%)		Wages (US=100)	
	East South	Great Lake	East South	Great Lake
1970	5.7	69.4	78.9	104.9
1975	6.8	68.7	72.9	106.8
1980	9.4	64.1	73.1	109.3
1985	12.5	60.9	73.5	111.9
1990	15.6	59.4	75.2	112.8
1992	16.7	59.1	79.1	110.8

Source: Sturgeon and Florida (2004, Table 3.6)

and that contributed directly to local labor demand. Although some Japanese firms used plants that US firms previously operated and even hired the same people, their investments provided additional employment opportunities in the local labor markets. For example, Mazda operated a plant that Ford had previously run and closed four years earlier. Mazda not only provided employment to the people who were made unemployed by Ford's closure, but they improved the facility and built additional assembly lines. Toyota in Fremont, California, is another example. GM employed 6,800 hourly workers in 1978, and the number declined to around 3,000 when they closed the plant in 1982 (Adlar, 1993). Toyota's investment in this GM plant helped the unemployed who previously worked at the plant. In addition, Toyota made another investment in 1990 and hired 650 more employees. These case studies show how Japanese investments in existing US facilities may have also increased labor demand in the local labor markets.

Japanese automobile companies invested both within the traditional Midwestern auto corridor as well as in adjacent states such as Kentucky and Tennessee. Japanese auto firms that invested in the South sought access to growing markets, cheaper land and operating costs, and labor supplies with fewer union ties. The automobile industry in the South was undeveloped compared to that in the Midwest, and therefore, the impact on the local labor markets was quite large. As we can see from Table 3.2, the regional share of the US automotive sector employment and relative wages have dramatically increased in the East South region after 1980. In contrast, the share in the Great Lakes region decreased by 5 percentage points between 1980 and 1992.

In addition to the effect on employment, there were large infrastructure investments made in tandem with the Japanese investments. Most of the infrastructure investments were supported by subsidies offered by state and local governments. For example, Nissan and Mazda received \$239 million and \$80 million, respectively, from state and local governments for improving highway connectivity, local tax exemptions, and training employees. The improved infrastructure benefited not only car production but also people living around the cities in which Japanese firms operated plants.

3.3 Data Source and Summary Statistics

I use the US Census' 5% sample for 1980 and 1990, which is publicly available through IPUMS-USA (Steven et al., 2021). I select male Black or White workers aged less than 65, who are employed in the automobile industry and report a positive total pre-tax wage and salary income in the year before the census.[6] The industry categorization corresponds to "351-Motor vehicles and motor vehicle equipment." This includes not only workers who are working in car plants but also those who manufacture motor vehicle parts and components in local factories. Japanese car manufacturers built just-in-time supplier relations in the US. According to Kenney and Florida (1993), more than 40% of suppliers for Japanese automakers were located within a 2-hour drive shipping radius and around 80% of suppliers meet just-in-time delivery requirements in their survey. New car plant openings can affect not only workers in the new plants but also surrounding auto parts suppliers, therefore it is reasonable to use the industry category includes motor vehicle equipment.

In addition to wage and salary income (hereafter, I refer to this variable as simply "wages"), I obtain workers' personal characteristics, such as sex, age, race, and educational attainment. Following Batistich and Bond (2019), I restrict the data to male workers to deal with the issue of changing female labor force participation across time. I also create four categories in the educational level: high school dropout, high school graduate, some college, and college graduate. I treat geographic areas in the census data, named *conspumas* (Consistent Public Use Microdata Areas), as the local labor markets. These are consistently defined between 1980 and 1990. Each conspuma consists of counties, and conspumas do not cross state lines. I use samples only in the continental United States, which has 539 different conspumas. I also include a control for unionization in my regression. Since I do not have the union membership status for each individual in the census data, I obtain the ratio of wage and salary workers who are union members in each state from the CPS's Union Membership

[6] I adjust the wage and salary income to 1999 dollars amount using the Consumer Price Index adjustment factors. Source: Consumer Price Index adjustment factors https://cps.ipums.org/cps/cpi99.shtml

Table 3.3: Summary Statistics

Variable	Mean	SD	Min	Max	Observation
Individual level					
wage	46,684.09	24,494.74	2.69	265935.90	86,276
age	39.71	11.30	16	64	86,276
black	0.11	0.32	0	1	86,276
high school dropouts	0.22	0.42	0	1	86,276
high school graduates	0.44	0.50	0	1	86,276
some college	0.27	0.44	0	1	86,276
college graduates	0.07	0.26	0	1	86,276
State level					
union membership ratio (%)	16.24	6.37	4.6	32.5	92

The sample consists only of the workers who are in the automobile industry. 67,387 samples in 1980 and 56,603 samples in 1990. The number of union membership ratio is 49 in each year.

and Coverage Database.[7] The data about union membership is at the state level, not at the individual level.[8]

Table 3.3 shows descriptive statistics of the control variables. The sample contains 86,276 workers who are in the automobile industry in 1980 or 1990. Only 11% of workers are Black and 66% of workers do not have a college education. Union membership varies across states and time, while 16% of total workers are union members on average. Table 3.4 shows the average union membership rates by region. Most states in the South already adopted right-to-work laws by 1980, and therefore the average union membership rate in the South is lower than in other regions. This lower union membership rate was one of the drivers behind Japanese automobile investment in the South, such as Toyota investing in Kentucky (with an 18% union membership rate) and Nissan investing in Tennessee (with a 15% union membership rate). The Japanese companies avoided unexpected disputes with workers by investing in these lower unionized areas. In contrast, states in the traditional Midwestern auto corridor had higher percentages of unionized workers. For example, 30% of workers were union members in Michigan.

[7]Since the state-level data are available only from 1983, I use 1983 data to describe samples in the 1980 census. The URL for the union membership and coverage database: https://www.unionstats.com/.

[8]Using the CPS data is another possibility, but they have individual union membership status only from 1990.

Table 3.4: Percentage of Workers with Union Membership in Total Employees

in 1983			in 1990		
Rank:	Region	Union Membership (%)	Rank:	Region	Union Membership (%)
1	Northeast	22	1	Northeast	19
2	Midwest	20	2	Midwest	17
3	West	19	3	West	16
4	South	14	4	South	11
Total average		18	Total average		15

Source: Union Membership and Coverage Database from the CPS (http://unionstats.com/)

3.4 Econometric Model

I estimate the effect of Japanese automobile investment on local wages from 1980 to 1990. There were no Japanese automobile investments before 1980, and thus I conduct a difference-in-differences estimation at the conspuma level. I compare changes in individual wages among the treatment group to changes in wages of those in the control group. The treatment group consists of workers who live in conspumas where Japanese automobile plants opened. The control group consists of workers who do not live in conspumas where Japanese plants opened. Individuals reported the wages that they earned in the year before the census, which means that the wages in the data are from 1979 and 1989. I treat auto workers in the conspumas where plants opened before 1989 (i.e., the first six plants in Table 3.1) as the treatment group, and auto workers in the other conspumas as the control group.

I use the following regression equation:

$$\log(wage_{i,j,t}) = \alpha \; plant_{ij} + \beta \; year90_t + \gamma \; (plant_{ij} \times year90_t) + \theta \; X_{i,j,t} + \varepsilon_{i,j,t}. \tag{3.1}$$

The dependent variable, $\log(wage_{i,j,t})$, is the log of individual i's wages at time t in consupuma j. A treatment dummy, $plant_{ij}$, indicates whether an individual i lives in conspuma j which obtains a new Japanese plant. A post-treatment dummy, $year90_t$, is equal to 1 if the observation is in the 1990 census and 0 otherwise. The coefficient on $(plant_{ij} \times year90_t)$ is a difference-in-differences estimator which compares the change in the treatment group to the change in the control group. I include individual demographics, $X_{i,j,t}$, which are similar to those in Greenstone et al. (2010). The covariates include age, age-squared, education, and race (Black or white). There are three education dummies: high school graduate, some college, and college graduate. Additionally, I control for either union membership rates or state fixed effects to capture the state-level variation that might be confounding my estimates.

There could be a sorting effect between wages and plant locations—that is, the local wage level could attract investors to some particular areas. I argue that there is little concern for the sorting effect because the exiting literature and anecdotes suggest that the local wage level was not a primary factor for Japanese companies to decide their investing locations. For example, Woodward (1992) analyzes location choices made by Japanese companies in the East North Central and the East South Central divisions where almost all Japanese auto plants are located. Their county-level study shows that the coefficient on wages is insignificant and it has a positive sign. Instead, other factors such as interstate connectivity and educational attainment are important for the choice of the investment locations. Japanese automobile companies may have prioritized the skill level of workers to maintain the quality of products. Some of the companies, such as Honda and Toyota, planned to export their cars to Japan, and therefore the quality of their workforce is key for their business. In fact, according to the case studies, the wage rate is not in the criteria that the three largest Japanese auto firms used to choose the investment locations (Inabetsu, 1998; Kusunoki, 2004; Oshikawa, 1992).

Although the wage level was not the main factor for the Japanese firms' location decisions, I address concerns about the potential endogeneity following Greenstone et al. (2010). The authors focus on an investor's location choice process. They identify winning counties that received investment and losing counties that did not receive investment but were on the final list of potential investment locations. They treat winning counties as a treatment group and losing counties as a control group, assuming that counties in both groups have similar trends before the investment. Unfortunately, I do not observe finalist sites at the county level for Japanese auto investors in the 1980s. However, I observe the states that were finalists for Japanese auto investments in the 1980s, using data provided by Robert (2017).

Echoing Greenstone et al. (2010), I perform a difference-in-differences analysis using just individuals in states that received investment from Japanese auto firms (my treatment group) and those in states that were finalists for investment, but were ultimately passed over (my control group). I argue that these states likely share similar trends in pre-investment wages and unobservable determinants of automotive sector employment, and thus that, within this sample, any bias stemming from endogenous firm location decisions will be minimized. These results serve as a robustness check for my analysis using the full sample of workers from all US conspumas.

Table 3.5: Winning and Losing States for Japanese Greenfield Auto Investment

Firm	Year Opened	Winning State	Losing States
Honda	1982	Ohio	Arizona, Indiana, Kentucky, Missouri
Nissan	1983	Tennessee	Georgia, South Carolina
Toyota	1984	Kentucky	Georgia, Indiana, Kansas, Missouri, Tennessee
Mitsubishi	1988	Illinois	Indiana, Michigan, Ohio

Source: Robert (2017, Table 3.1)

Recall that Japanese auto firms pursued two types of investment, greenfield and brownfield. In this analysis in which I restrict my sample to finalist states, I focus only on greenfield investments. Brownfield investment opportunities are endogenous, a function of previous (US) auto firm location decisions that I cannot observe. Greenfield investment decisions, by contrast, do not directly depend upon previous choices made by American automotive firms. The choice set of greenfield firms is also larger than that of brownfield firms. For example, Toyota first received offers from thirty-six states and narrowed them down to the six states—Kentucky, Georgia, Kansas, Missouri, and Tennessee—as the finalist sites before choosing Kentucky as their final choice (Jacobs, 2015). The winning and losing states for Japanese greenfield auto firms are shown in Table 3.5.

3.5 Results

I mainly use two samples to analyze the effect of Japanese plant openings on local wages. In the first subsection, I consider all Japanese plants opened before 1989 and treat auto workers who live in conspumas with the new Japanese plants as a treatment group. I treat other auto workers as a control group. In the second subsection, I focus only on greenfield investments (i.e., plants newly build by Japanese firms). The sample consists of auto workers who live in winning states—states that obtained Japanese greenfield investment—and losing states—states that did not receive Japanese investment but were considered as the finalist sites.

3.5.1 Baseline Regressions

In my baseline specification, I do not distinguish between greenfield and brownfield investments and include workers from all conspumas. The results are in Table 3.8. The coefficients on plant×year90 represent the effects of new Japanese plant openings on local wages. The coefficient of interest is statistically significant at the 1% level on the regression in column 1. This shows that wages in the automobile industry increased by 4.1% in conspumas where Japanese assembly plants opened. However, the coefficients become insignificant once I control for state variation using either unionization rates (column 2) or state fixed effects (column 3). This means that I would overestimate the positive effect if I did not control for union membership. Union membership has the effect of increasing wages by 1.9%, and the coefficient is statistically significant at the 1% level. Without controlling for this state characteristic, the plant dummy is the only variable that varies across locations for similar workers. The plant dummy divides samples only into two groups—whether an individual lives in a conspuma that gains a new Japanese automobile plant—and this does not offer much variation. Additional variation at the state level is quite important in accounting for regional wage differences.

Columns 4 and 5 in Table 3.8 show the results of regressions by separating individuals to Black or white workers. Interestingly, the effects are different by race: Black workers see negative impacts on their wages. Column 5 shows that wages of Black workers in conspumas where Japanese assembly plants opened decreased by 9.3%, and the coefficient is statistically significant at the 1% level. Cole and Deskins (1998) argue that Japanese firms offered fewer employment opportunities to Black workers by locating their plants in areas with lower Black population ratios and hiring less Black workers.[9] They also show that Japanese automakers, especially Honda, Nissan, and Mazda, employed fewer Black workers compared to other US automakers. Based on their findings, my regression shows that Black auto workers experienced a wage decline and saw fewer gains from the Japanese plant openings.

I explore heterogeneity by region. Table 3.7 shows estimates for autoworkers in the West; results from the Southern and the Midwestern samples are in Appendix C. The Northeast is omitted since there was no Japanese automobile investment in that region. In the West, Toyota's plant is only the Japanese assembly plant opened during the 1980s. Toyota established a joint venture with GM and renovated the idled plant in Fremont, California where GM closed in October 1982, and started its production in December 1984. Column 1, Table 3.7 shows that wages in the automobile industry increased by 8.2% in the consupuma where the Toyota-GM plant is located. The coefficients of interest are still significant after controlling for unionization rates (column 2) and state fixed effects (column 3). The effect on local wages is larger in the West compared to the result from the whole sample. This large effect in the West reflects the fact that Ford and GM closed almost all of their assembly plants on

[9] In addition to Japanese firms, the authors argue that Volkswagen's plant in Pennsylvania (which opened in April 1978 and closed in July 1988) also hired few Black workers.

Table 3.6: Regression Results using All State Sample

Dependent variable: ln(wage)	(1) All	(2) All	(3) All	(4) White	(5) Black
plant×year90	0.041***	0.016	0.006	0.020	-0.093**
	(0.014)	(0.021)	(0.021)	(0.020)	(0.038)
unionization rate[c]		0.019***			
		(0.001)			
state FEs	No	No	Yes	Yes	Yes
N	86276	86276	86276	76505	9769
R^2	0.240	0.269	0.282	0.297	0.179

[a] Standard errors in parentheses and are clustered by conspuma. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
[b] Regressions control for age, age^2, black (not in the regression (4) and (5)), and educational level.
[c] Unionization rate is a state-level variable.

the West coast from 1970 to 1990 (Sturgeon and Florida, 2004). It is likely that the impact on the conspuma with the Toyota-GM plant stands out because of the low automotive labor demand in the other conspumas. Unlike the previous regression, I do not observe the negative and significant effect on the wage of Black workers in the West. Toyota rehired the United Auto Workers (UAW) labor union members who were laid off from the former GM plant, and their share of Black workers to the total employees (23%) is larger compared to the average of Japanese automakers (12.8%) (Cole and Deskins, 1998).[10] Toyota hired more Black workers than other Japanese automakers, and therefore there is no significant wage decrease among the Black workers near the Toyota-GM plant.

In addition to the impact of new plant openings, my analysis also captures regional differences in union membership. The results show that the state unionization rate has a larger impact on individual wages in the Midwest than in the South and the West. A 1 percentage point increase in the unionization rate raises the average wage by 0.024% in the Midwest (column 2, Table C.1), 0.015% in the South (column 7, Table C.1), and 0.009% in the West. There are more union workers in the Midwest compared to the South and the West. The coefficient on the union membership ratio is higher in the Midwest potentially because a higher unionization rate gives all union workers more bargaining power over their working contracts.

[10] Toyota-GM's, Nissan's, Honda's, Mazda's plants in the authors' sample.

Table 3.7: Regression Results using Western State Sample

Dependent variable: ln(wage)	(1) All	(2) All	(3) All	(4) White	(5) Black
plant×year90	0.082**	0.086**	0.082**	0.075*	0.004
	(0.041)	(0.042)	(0.041)	(0.039)	(0.065)
unionization rate[c]		0.009**			
		(0.003)			
state FEs	No	No	Yes	Yes	Yes
N	4592	4592	4592	4341	250
R^2	0.267	0.264	0.267	0.272	0.194

[a] Standard errors in parentheses and are clustered by conspuma. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
[b] Regressions control for age, age^2, black (not in the regression (4) and (5)), and educational level.
[c] Unionization rate is a state-level variable.

3.5.2 Regressions with Winning and Losing States

In this subsection, I show the results of regressions using auto workers only in winning and losing states. The data consist of the workers who live in states shown in Table 3.5. I first pool all of the workers and run difference-in-differences regressions. The results in Table 3.8 are similar to the results using the whole sample shown in Table 3.6. The coefficient on plant×year90 is positive and significant, but it becomes insignificant once controlling for state variation. The regression in column 5 also shows the negative and significant coefficient on plant×year90 for Black workers.

Next, I run regressions by each of the Japanese plant openings to compare the effects on wages only within winner and losing state pairs. Results for Nissan's case are in Table 3.9, and results for the other three cases (Honda, Toyota, and Mitsubishi) are in Appendix C.[11] I find a positive effect of Nissan's new plant opening on local wages. The coefficients on plant×year90 are still significant even when I control for state variation using unionization rates and state fixed effects (columns 2 and 3 in Table 3.9). Nissan's car plant had the largest capacity among all Japanese assembly plants (Table 3.1), and therefore the impact on the local labor market might be larger compared to the other plants. Additionally, I observe that the wage differential between white and Black workers is more pronounced in

[11]Results in the other three cases are similar to the results with all winning and losing state samples. The coefficients on plant×year90 are insignificant with state fixed effects. Regressions also show Black workers who lived in conspumas with new Honda's and Mitsubishi's plants experienced a wage decrease.

Table 3.8: Regression Results using Winning and Losing States

Dependent variable: ln(wage)	(1) All	(2) All	(3) All	(4) White	(5) Black
plant×year90	0.031*	-0.000	0.016	0.031	-0.102***
	(0.016)	(0.020)	(0.024)	(0.023)	(0.032)
unionization rate[c]		0.019***			
		(0.002)			
state FEs	No	No	Yes	Yes	Yes
N	60650	60650	60650	53531	7118
R^2	0.233	0.255	0.258	0.277	0.123

[a] Standard errors in parentheses and are clustered by conspuma. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

[b] Regressions control for age, age^2, black (not in the regression (4) and (5)), and educational level.

[c] Unionization rate is a state-level variable.

Nissan's case. The coefficients of interest are significant both in the white and Black worker samples and there is a large difference in the effects on these two groups (columns 4 and 5). Black workers who live in the conspuma where Nissan's plant opened experience a 31% wage decrease compared to Black workers in other conspumas. Conversely, white workers who are in the conspuma with the new Nissan's plant experience a 11% wage increase compared to white workers in other conspumas.

3.6 Pre-Trend Analysis

The key assumption for the difference-in-differences estimation is that the wages of the treatment and control groups follow the same trend before the 1980s. Without this assumption, it is possible that the economies in the areas where new plants opened had been thriving before the plants were built. If this is the case, then the wages of the treatment group would already have started rising before the 1980s, and thus the difference-in-differences estimation may just capture the pre-trend which is likely caused by other factors. To check the validity of this assumption, I run a placebo regression. The equation is almost the same as the one shown in Section 3.4, except that I use the census data for 1970 and 1980 instead of the data for 1980 and 1990. Thus, I investigate the average wage change from 1970 to 1980 instead of the change from 1980 to 1990. This exercise is similar to the ones conducted by Autor et

Table 3.9: Regression Results using Nissan's Winning and Losing States

Dependent variable: ln(wage)	(1) All	(2) All	(3) All	(4) White	(5) Black
plant×year90	0.104***	0.112***	0.083***	0.113***	-0.309***
	(0.026)	(0.029)	(0.025)	(0.028)	(0.053)
unionization rate[d]		-0.014*			
		(0.008)			
state FEs	No	No	Yes	Yes	Yes
N	3943	3943	3943	3257	686
R^2	0.246	0.249	0.257	0.270	0.150

[a] The sample consists of individuals who live in Tennessee (Nissan's winning state), and Georgia, South Carolina (Nissan's losing states).

[b] Standard errors in parentheses and are clustered by conspuma. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

[c] Regressions control for age, age^2, black (not in the regression (4) and (5)), and educational level.

[d] Unionization rate is a state-level variable.

al. (2013) and Hakobyan and McLaren (2015).

In order to proceed with the placebo test, I use the 1970 and 1980 1% metro samples of US Census data. I observe county groups as the geographical unit, instead of conspumas. Ideally, it is best to use the conspumas as in the original difference-in-differences estimation. However, conspumas are not available in the 1970 data, and moreover, the definitions of the county groups are not consistent between the 1970 census and the 1980 census. To ensure consistency, I use crosswalks made by Wiltshire (2021).[12] Similar to commuting zones in Autor et al. (2013), the crosswalks enable researchers to map observations from county groups in the 1970 and 1980 1% metro samples to the 1970 counties using adjusted person's weights. I limit the sample following the same criteria as I discuss in Section 3.3, but I do not restrict the sample to workers in the automotive industry because the auto industry was undeveloped before the Japanese investments in most of the greenfield locations.

I use the following regression equation to conduct a placebo analysis:

$$\log(wage_{i,t}) = \alpha\ plant_j + \beta\ year80_t + \gamma\ (plant_j \times year80_t) + StateFEs_j + \varepsilon_{i,t}, \qquad (3.2)$$

where $\log(wage_{j,t})$ is the mean log wage in county j at time t. Unlike equation 3.1, a post-

[12] The crosswalks are available in the author's website https://justinwiltshire.com/research-1

Table 3.10: Placebo Regressions

	Manufacturing Industry		All Industries	
	(1)	(2)	(3)	(4)
	All Plants	Only GF	All Plants	Only GF
plant×year80	0.059	0.083	0.032	0.045
	(0.045)	(0.061)	(0.054)	(0.079)
state FEs	Yes	Yes	Yes	Yes
N	6134	6134	6134	6134
R^2	0.862	0.862	0.902	0.902

[a] Standard errors in parentheses and are clustered by county. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

treatment dummy is now changed to $year80_t$ and the regression is at the county level, not at the individual level. I assign one to the variable, $plant_j$, if Japanese investment occurred in county j in the 1980s, otherwise I assign zero. I expect the coefficient on $(plant_j \times year80_t)$ to be insignificant, which means that there is no wage premium before 1980 in the counties where Japanese assembly plants open in the 1980s.

I first restrict my sample to the workers who are in the manufacturing industry and calculate the county-level mean log wage. While I assign one to $plant_j$ for all plant locations built before 1989 (results are in column 1), I only include the greenfield (GF) locations in the second regression (results are in column 2). Both coefficients on $(plant_j \times year80_t)$ are insignificant. This means that manufacturing workers in the areas where new plants opened in the 1980s did not experience a significant wage increase in the 1970s. Therefore, I also do not detect any pre-trend in the county-level mean log wage.

I also check for pre-trends in wages among all workers. Column 3 and column 4 of Table 3.10 show that the coefficient of interest is still insignificant in the regression with samples including all industries. Once again, I do not detect any pre-trend before plants opened in the 1980s.

3.7 Conclusion

I use US Census data and examine the effects of Japanese automobile firms' investments on US local labor markets during the 1980s. I do not find a significant effect in the whole sample. However, I find a significant and negative effect in the sample of Black workers.

Black workers who lived in areas with new Japanese plants saw their wages decline by 9.3%. This result is in line with the argument by Cole and Deskins (1998) that Japanese auto firms hired fewer Black workers compared to US automakers and were not likely to contribute to the rise in demand for Black workers. My results also show regional differences in the effects of the labor demand increase. Autoworkers in the South benefited from higher wage gains compared to those in other areas.

There are two possible future research questions regarding the wage decrease of Black auto workers. First, Batistich and Bond (2021) show that Black workers were negatively affected by the Japanese import surge during the late 1970s. It could be that this negative effect worsened because of the new Japanese investment during the 1980s. Second, I am interested in looking at whether this negative effect on Black workers persisted and, more broadly, how foreign investment affects the racial wage differential in the long term. The Japanese investments in the 1980s are the first overseas horizontal investment by Japanese automakers, and they were not familiar with overseas production and management process at that time. As Japanese firms get used to the US business environment, it may be possible that they hire more Black workers.

Bibliography

[1] Arkolakis, Costas, Natalia Ramondo, Andrés Rodríguez-Clare, and Stephen Yeaple. "Innovation and production in the global economy." *American Economic Review* 108, no. 8 (2018): 2128-73.

[2] Arrighetti, Alessandro, Fabio Landini, and Andrea Lasagni. "Intangible assets and firm heterogeneity: Evidence from Italy." *Research Policy* 43, no. 1 (2014): 202-213.

[3] Ashraf, Ayesha, Dierk Herzer, and Peter Nunnenkamp. "The effects of Greenfield FDI and cross-border M&As on total factor productivity." *The world economy* 39, no. 11 (2016): 1728-1755.

[4] Atalay, Enghin, Ali Hortaçsu, and Chad Syverson. " Vertical integration and input flows." *American Economic Review* 104, no. 4 (2014): 1120-48.

[5] David, H., David Dorn, and Gordon H. Hanson. "The China syndrome: Local labor market effects of import competition in the United States." *American Economic Review* 103, no. 6 (2013): 2121-68.

[6] Batistich, Mary Kate, and Timothy Bond. "Stalled racial progress and Japanese trade in the 1970s and 1980s." (2019).

[7] Berry, Steven, James Levinsohn, and Ariel Pakes. "Voluntary export restraints on automobiles: Evaluating a trade policy." *American Economic Review* 89, no. 3 (1999): 400-430.

[8] Bertrand, Olivier, Katariina Nilsson Hakkala, Pehr-Johan Norbäck, and Lars Persson. "Should countries block foreign takeovers of R&D champions and promote greenfield entry?" *Canadian Journal of Economics* 45, no. 3 (2012): 1083-1124.

[9] Bilir, L. Kamran, and Eduardo Morales. "Innovation in the global firm." *Journal of Political Economy* 128, no. 4 (2020): 1566-1625.

[10] Bloom, Nicholas, Raffaella Sadun, and John Van Reenen. “Americans do IT better: US multinationals and the productivity miracle.” *American Economic Review* 102, no. 1 (2012): 167-201.

[11] Broda, Christian, and David E. Weinstein. “Globalization and the Gains from Variety.” *The Quarterly journal of economics* 121, no. 2 (2006): 541-585.

[12] Burstein, Ariel T., and Alexander Monge-Naranjo. “Foreign know-how, firm control, and the income of developing countries.” *The Quarterly Journal of Economics* 124, no. 1 (2009): 149-195.

[13] Chan, Jackie M.L., and Huanhuan Zheng. “FDI on the Move: Cross-border M&A and Migrant Networks. ScholarBank@NUS Repository (2019).

[14] Cole, Robert E., and Donald R. Deskins Jr. “Racial factors in site location and employment patterns of Japanese auto firms in America.” *California Management Review* 31, no. 1 (1988): 9-22.

[15] Corrado, Carol A., and Charles R. Hulten. “How do you measure a “technological revolution”?” *American Economic Review* 100, no. 2 (2010): 99-104.

[16] Coşar, A. Kerem, Nezih Guner, and James Tybout. “Firm dynamics, job turnover, and wage distributions in an open economy.” *American Economic Review* 106, no. 3 (2016): 625-63.

[17] David, Joel M. “The Aggregate Implications of Mergers and Acquisitions” *Review of Economic Studies* 88, no. 4 (2021): 1796-1830.

[18] Davies, Ronald B., Rodolphe Desbordes, and Anna Ray. “Greenfield versus merger and acquisition FDI: Same wine, different bottles?” *Canadian Journal of Economics* 51, no. 4 (2018): 1151-1190.

[19] Den Haan, Wouter J., Garey Ramey, and Joel Watson. “Job destruction and propagation of shocks.” *American economic review* 90, no. 3 (2000): 482-498.

[20] Demidova, Svetlana, and Andres Rodríguez-Clare. “The simple analytics of the Melitz model in a small economy.” *Journal of International Economics* 90, no. 2 (2013): 266-272.

[21] DePamphilis, Donald. “Mergers, acquisitions, and other restructuring activities: An integrated approach to process, tools, cases, and solutions.” Academic Press, 2019.

[22] Díez, Federico J., and Alan C. Spearot. “Core competencies, matching and the structure of foreign direct investment.” *Canadian Journal of Economics/Revue canadienne d'économique* 47, no. 3 (2014): 813-855.

[23] Dimopoulos, Theodosios, and Stefano Sacchetto. “Merger activity in industry equilibrium.” *Journal of Financial Economics* 126, no. 1 (2017): 200-226.

[24] Dunning, John H. *International production and the multinational Enterprise (RLE international business).* Routledge, 1981.

[25] Ewens, Michael and Peters, Ryan H and Wang, Sean. “Acquisition Prices and the Measurement of Intangible Capital.” *NEBR working paper* 25960 (2019).

[26] Feenstra, Robert C. “Voluntary export restraint in us autos, 1980-81: Quality, employment, and welfare effects.” Baldwin, Robert E. and Krueger, Anne O. eds., The structure and evolution of recent US trade policy, University of Chicago Press, 35-66, 1984.

[27] Feenstra, Robert C., Robert Inklaar, and Marcel P. Timmer. “The next generation of the Penn World Table.” *American economic review* 105, no. 10 (2015): 3150-82.

[28] Feliciano, Zadia M., and Robert E. Lipsey. “Foreign ownership, wages, and wage changes in US industries, 1987–92.” *Contemporary Economic Policy* 24, no. 1 (2006): 74-91. bibitemGreenstone et al. (2010) Greenstone, Michael, Richard Hornbeck, and Enrico Moretti. “Identifying agglomeration spillovers: Evidence from winners and losers of large plant openings.” *Journal of Political Economy* 118, no. 3 (2010): 536-598.

[29] Guadalupe, Maria, Olga Kuzmina, and Catherine Thomas. “Innovation and foreign ownership.” *American Economic Review* 102, no. 7 (2012): 3594-3627.

[30] Haaland, Jan I., and Anthony J. Venables. “Optimal trade policy with monopolistic competition and heterogeneous firms.” *Journal of International Economics* 102 (2016): 85-95.

[31] Hakobyan, Shushanik, and John McLaren. “Looking for local labor market effects of NAFTA.” *Review of Economics and Statistics* 98, no. 4 (2016): 728-741.

[32] Head, Keith, John Ries, and Deborah Swenson. "Agglomeration benefits and location choice: Evidence from Japanese manufacturing investments in the United States." *Journal of international economics* 38, no. 3-4 (1995): 223-247.

[33] Head, C. Keith, John C. Ries, and Deborah L. Swenson. "Attracting foreign manufacturing: Investment promotion and agglomeration." *Regional Science and Urban Economics* 29, no. 2 (1999): 197-218.

[34] Helpman, Elhanan, Marc J. Melitz, and Stephen R. Yeaple. "Export versus FDI with heterogeneous firms." *American economic review* 94, no. 1 (2004): 300-316.

[35] Inabetsu, Masaharu. Honda's local management in the U.S. Bunshind, Tokyo, 1998. (in Japanese)

[36] Jacobs, Andrew James. The new domestic automakers in the United States and Canada: History, impacts, and prospects. Lexington Books, 2015.

[37] Katitas, Ayan. "Foreign Direct Investment Neutralizes Perceived Economic Threat: Evidence From Chinese Investment in the U.S." Working paper (2020).

[38] Kenney, Martin, and Richard L. Florida. "Beyond mass production." Oxford University Press, 1993.

[39] Kim, Young-Han. "Cross-border M&A vs. greenfield FDI: Economic integration and its welfare impact." *Journal of Policy Modeling* 31, no. 1 (2009): 87-101.

[40] Kusunoki, Kanetoshi. Challenge and Leap - Start up the Toyota's North American Business. Chubu Keizai Shinbun Sha, Tokyo, 2004. (in Japanese)

[41] Li, Xiaoyang. "Productivity, restructuring, and the gains from takeovers." *Journal of Financial Economics* 109, no. 1 (2013): 250-271.

[42] Mair, Andrew, Richard Florida, and Martin Kenney. "The new geography of automobile production: Japanese transplants in North America." *Economic geography* 64, no. 4 (1988): 352-373.

[43] Markusen, James R. "The boundaries of multinational enterprises and the theory of international trade." *Journal of Economic perspectives* 9, no. 2 (1995): 169-189.

[44] McGrattan, Ellen R., and Edward C. Prescott. "Technology capital and the US current account." *American Economic Review* 100, no. 4 (2010): 1493-1522.

[45] Melitz, Marc J. "The impact of trade on intra-industry reallocations and aggregate industry productivity." *Econometrica* 71, no. 6 (2003): 1695-1725.

[46] Nocke, Volker, and Stephen Yeaple. "Cross-border mergers and acquisitions vs. greenfield foreign direct investment: The role of firm heterogeneity." *Journal of International Economics* 72, no. 2 (2007): 336-365.

[47] Nocke, Volker, and Stephen Yeaple. "An assignment theory of foreign direct investment." *The Review of Economic Studies* 75, no. 2 (2008): 529-557.

[48] Norbäck, Pehr-Johan, and Lars Persson. "Investment liberalization—why a restrictive cross-border merger policy can be counterproductive." *Journal of International Economics* 72, no. 2 (2007): 366-380.

[49] Oshikawa, Akira. Global strategies of Toyota, Nissan, and Honda. Sannou Daigaku Shuppan, Tokyo, 1992. (in Japanese)

[50] Peters, Ryan H., and Lucian A. Taylor. "Intangible capital and the investment-q relation." *Journal of Financial Economics* 123, no. 2 (2017): 251-272.

[51] Raff, Horst, Michael Ryan, and Frank Stähler. "Firm productivity and the foreign-market entry decision." *Journal of Economics & Management Strategy* 21, no. 3 (2012): 849-871.

[52] Ramondo, Natalia. "FDI Entry Mode and the Activity of Affiliates of Multinational Firms." Working paper, Asian Development Bank. (2016).

[53] Ramondo, Natalia, and Andrés Rodríguez-Clare. "Trade, multinational production, and the gains from openness." *Journal of Political Economy* 121, no. 2 (2013): 273-322.

[54] Ramondo, Natalia, Veronica Rappoport, and Kim J. Ruhl. "Intrafirm trade and vertical fragmentation in US multinational corporations." *Journal of International Economics* 98 (2016): 51-59.

[55] Perrucci, Robert. Japanese auto transplants in the heartland: corporatism and community. Routledge, 2017.

[56] Schoar, Antoinette. "Effects of corporate diversification on productivity." *The Journal of Finance* 57, no. 6 (2002): 2379-2403.

[57] Florida, Richard. "Agglomeration and industrial location: An econometric analysis of Japanese-affiliated manufacturing establishments in automotive-related industries." *Journal of urban economics* 36, no. 1 (1994): 23-41.

[58] Spearot, Alan C. "Firm heterogeneity, new investment and acquisitions." *The Journal of Industrial Economics* 60, no. 1 (2012): 1-45.

[59] Steven Ruggles, Sarah Flood, Sophia Foster, Ronald Goeken, Jose Pacas, Megan Schouweiler and Matthew Sobek. IPUMS USA: Version 11.0 [dataset]. Minneapolis, MN: IPUMS, 2021. https://doi.org/10.18128/D010.V11.0

[60] Sturgeon, Timothy, and Richard Florida. "Globalization, deverticalization, and employment in the motor vehicle industry." *Locating global advantage: Industry dynamics in the international economy.* (2004): 52-81.

[61] Thomson Reuters. "Mergers & Acquisitions Review" (2018).

[62] Teece, David J. " Technology transfer by multinational firms: The resource cost of transferring technological know-how." *The economic journal* 87, no. 346 (1977): 242-261.

[63] Tintelnot, Felix. "Global production with export platforms." *The Quarterly Journal of Economics* 132, no. 1 (2017): 157-209.

[64] UNCTAD. "The world of investment promotion at a glance: a survey of investment promotion practices." UNCTAD/ITE/IPC3, ASIT advisory studies No.17 (2001).

[65] UNCTAD. *World investment report 2019.* (2019).

[66] Wiltshire, Justin C. "Crosswalks from 'County Groups' to Counties for the 1970 and 1980 US Decennial Census Metro Samples." (2021).

[67] Woodward, Douglas P. "Locational determinants of Japanese manufacturing start-ups in the United States." *Southern economic journal* (1992): 690-708.

Appendix A

Data Appendix for Chapter 1

I provide the detailed explanation on the main three datasets that I described in Section 1.2.

Cross-border M&A Deals (SDC Platinum)

- There are mainly two dates concerning completed M&A deals: one is "date announced" and the other is "date effective" (i.e., completion date). fDi Market provides "project date" which indicates the month when the GF project has started, and does not provide information when the GF project has been completed. In line with the fDi Market database, I use "date announced" in SDC Platinum as the date when the M&A project has been started.

- If a firm acquired a particular target in multiple times, I gathered these deals and aggregated these ownership shares. I keep the year when the firm made a first acquisition for this particular target.

- The information of the share of acquisition is missing in 11.6% of the total deals. For these deals, I check if an acquirer owned the majority of its target's shares using the information of "form of transactions" (code in SDC: FORM). If the deals are with the following codes, I keep the transactions:

  - MERGER: A combination of business takes place or 100% of the stock of a public or private company is acquired.
  - ACQUISITION: deal in which 100% of a company is spun off or split off is classified as an acquisition by shareholders.

- ACQ OF MAJORITY INTEREST: the acquirer must have held less than 50% and be seeking to acquire 50% or more, but less than 100% of the target company's stock.
- ACQ OF REMAINING INTEREST: deals in which the acquirer holds over 50% and is seeking to acquire 100% of the target company's stock.

- There are special NAICS codes in SDC Platinum data. I replace the following codes in accordance with 2007 NAICS to merge the SDC data with Compustat:
  - BBBBBA: Internet Service Providers (such as Comcast Corporation) → NAICS code: 517911
  - BBBBBB: Web Search Portals (such as Alphabet Inc.) → NAICS code: 518210

Greenfield Projects (fDi Market)

- The database provides source and destination locations at the city level. If a company made more than one investments in several cities (in the same country) on the same project date, these investments are recorded as different investments in the fDi Market database. I aggregated these investments by country-date.
- I assign unique NAICS 2007 code to each sub-sector by referring to the cross-work the vendor, the Financial Times, provided.

US firms' Financial Data (Compustat)

- I downloaded firms' financial data from Compustat North America—Annual Updates. The data period is from 1980 to 2018 in firms' fiscal year. I use "data date" if the fiscal year is missing.
- I restricted firms only in the US by deleting 1) firms that report their financial statements in Canadian dollars, and 2) firms that have their headquarters outside the US.
- Following Peter and Taylor (2017), I deleted firms with negative sales.
- In order to accumulate intangible capital using sufficient financial information, I deleted firms with the information in less than six-year period.

- Since the industry classification both in SDC Platinum and fDi Market databases are NAICS 2007, I changed NAICS codes in Compustat from 2017 NAICS to 2007 NAICS using historical NAICS codes (Compustat item *naicsh*). If the historical codes are missing, I checked their NAICS 2007 codes manually.
- Compustat assigns industry codes 9999 (unclassified establishment) to some firms and the code 9999 does not exist in NAICS classification. In my dataset, there are around 20 firms with NAICS 9999. I assigned new industry codes to these firms using acquirers' NAICS codes in SDC Platinum if the firms made M&A investments. If those firms did not make M&As, I referred to the NAICS codes in their SEC filing.

Subsequent Investments

This table shows the relationship between the entry mode in the first FDI and that in the subsequent FDIs made in the same country and industry. There are 9,163 first GF deals, and 6,595 first M&A deals in firm-affiliate industry-country. 96% of GF investments never followed up by M&A, and 95% of M&A investments never followed up by GF.

Table A.1: Entry Modes in Additional Investments

	Subsequent FDIs				
First FDI	GF	M&A	Both	None	Total
GF	**1,923**	189	166	6,885	9,163
M&A	225	**814**	99	5,457	6,595

Additional Empirical Results

This table shows the results of regressions analogues to Nocke and Yeaple (2008). Same as Nocke and Yeaple (2008), I find negative coefficients both on sales (SALE) and value added per worker (VADDPW).

Table A.2: Logit Regressions Analogous to Nocke and Yeaple (2008)

Dep var:	(1)	(2)	(3)	(4)
MA= 1 vs GF = 0	SALE	VADDPW	SALE	VADDPW
efficiency	-0.083^{***}	-0.212^{***}	-0.104^{***}	-0.195^{***}
	(0.020)	(0.077)	(0.020)	(0.040)
emp		-0.079^{***}		-0.103^{***}
		(0.024)		(0.023)
gdppc			0.877^{***}	0.890^{***}
			(0.164)	(0.165)
pop			0.009	0.011
			(0.069)	(0.071)
open			-0.685^{***}	-0.684^{***}
			(0.173)	(0.174)
dist			-0.509^{***}	-0.507^{***}
			(0.100)	(0.100)
FE: Parent Ind	Yes	Yes	Yes	Yes
FE: Affiliate Ind	Yes	Yes	Yes	Yes
FE: Year	Yes	Yes	Yes	Yes
FE: Country	Yes	Yes	No	No
N	14805	14479	15019	14690

[a] Standard errors are clustered by firm (same as in Nocke and Yeaple, 2008). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. All explanatory variables are in logs.

This table shows the results of regressions including the FDI index. The positive coefficients on the FDI index reflect the fact that multinationals are difficult to conduct M&A investment if a destination country has sever FDI restrictions such as a regulation on foreign ownership. Once I control for the FDI restriction, coefficients on population become significant.

Table A.3: Logit Regressions of Firms' FDI Mode Choices with Country Variables

Dep var: $\mathbb{1}[MA_{i,h,j,t} = 1]$	(1) Intangibles	(2) Knowledge	(3) Organizational
Capital	-0.200^{***}	-0.162^{***}	-0.095^{*}
	(0.046)	(0.049)	(0.052)
GDPPC	0.907^{***}	1.021^{***}	0.910^{***}
	(0.051)	(0.067)	(0.051)
DIST	-0.294^{***}	-0.400^{***}	-0.294^{***}
	(0.030)	(0.040)	(0.030)
POP	0.090^{***}	0.106^{***}	0.093^{***}
	(0.025)	(0.032)	(0.025)
OPEN	-0.225^{***}	-0.147^{*}	-0.226^{***}
	(0.061)	(0.077)	(0.061)
LANG	0.614^{***}	0.633^{***}	0.617^{***}
	(0.050)	(0.063)	(0.050)
FDI_index	-1.905^{***}	-2.010^{***}	-1.902^{***}
	(0.265)	(0.347)	(0.264)
N	13260	7996	13260
$Pseudo R^2$	0.2467	0.2333	0.2447

[a] Standard errors are clustered by firm and country. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

[b] All explanatory variables are in logs. I control for firm size using sales in addition to industry and year FEs.

Appendix B

Detailed Calculations and Parameters for Chapter 2

Proof for Equation (2.12)

Let H is the left-hand side of equation (2.12).

$$\frac{\partial H}{\partial K^*} = (1-\chi)\Theta\frac{\partial \hat{\mu}(K^*)}{\partial K^*}\left[(Z-z)\kappa - Z(1-\eta)K^*\right] - (1-\chi)\Theta\hat{\mu}(K^*)\left[Z(1-\eta)\right]$$

Since $\frac{\partial \hat{\mu}(K^*)}{\partial K^*} < 0$, the left-hand side of equation (2.12) is decreasing in K^* (i.e., $\frac{\partial H}{\partial K^*} < 0$). The right-hand side of equation (2.12) is constant as ψ, therefore there is one unique solution of K^*.

If multinational's intangible capital, K_i, is larger than the cutoff, K^*, search condition, equation (2.11), holds. Also, such multinational obtains the positive merger gain. Thus, a multinational firm with $K_i < K^*$ will search and consummate the M&A.

Solution for Y

From equation (2.3): $Y = \left[\int_\Omega y_\omega^{\frac{\sigma-1}{\sigma}} d\omega\right]^{\frac{\sigma}{\sigma-1}}$,

$$\begin{aligned}
Y^{\frac{\sigma-1}{\sigma}} &= \int_\Omega y_\omega^{\frac{\sigma-1}{\sigma}} d\omega \\
&= \hat{\mu}(K^*)M \int_{\underline{K}}^{K^*} y_m(w,K,Y)^{\frac{\sigma-1}{\sigma}} dG(K) \\
&\quad + (1-\hat{\mu}(K^*))M \int_{\underline{K}}^{K^*} y_g(w,K,Y)^{\frac{\sigma-1}{\sigma}} dG(K) \\
&\quad + M \int_{K^*}^{\infty} y_g(w,K,Y)^{\frac{\sigma-1}{\sigma}} dG(K) \\
&\quad + (1-\lambda(K^*))N \; y_a(w,Y)^{\frac{\sigma-1}{\sigma}} \\
&= \hat{\mu}(K^*)MZ\left[\frac{1}{w}\left(1-\frac{\sigma-1}{\sigma}\alpha\right)\right]^{\beta/\alpha} Y^{\beta/\sigma\alpha} \int_{\underline{K}}^{K^*} k_m \; dG(K) \\
&\quad + (1-\hat{\mu}(K^*))MZ\left[\frac{1}{w}\left(1-\frac{\sigma-1}{\sigma}\alpha\right)\right]^{\beta/\alpha} Y^{\beta/\sigma\alpha} \int_{\underline{K}}^{K^*} k_g \; dG(K) \\
&\quad + MZ\left[\frac{1}{w}\left(1-\frac{\sigma-1}{\sigma}\alpha\right)\right]^{\beta/\alpha} Y^{\beta/\sigma\alpha} \int_{K^*}^{\infty} k_g \; dG(K) \\
&\quad + (1-\lambda(K^*))NZ\left[\frac{1}{w}\left(1-\frac{\sigma-1}{\sigma}\alpha\right)\right]^{\beta/\alpha} Y^{\beta/\sigma\alpha} \; k_a.
\end{aligned}$$

This becomes

$$\begin{aligned}
Y^{\frac{\sigma-1}{\sigma}-\frac{\beta}{\sigma\alpha}} = \left[\frac{1}{w}\left(1-\frac{\sigma-1}{\sigma}\alpha\right)\right]^{\beta/\alpha} \Bigg\{ & \hat{\mu}(K^*)MZ\int_{\underline{K}}^{K^*} k_m \; dG(K) + (1-\hat{\mu}(K^*))MZ\int_{\underline{K}}^{K^*} k_g \; dG(K) \\
& + MZ\int_{K^*}^{\infty} k_g \; dG(K) + (1-\lambda(K^*))NZk_a \Bigg\}.
\end{aligned}$$

Thus,

$$\begin{aligned}
Y = \left[\frac{1}{w}\left(1-\frac{\sigma-1}{\sigma}\alpha\right)\right]^{\frac{\beta}{1-\beta}} \Bigg\{ & \hat{\mu}(K^*)MZ\int_{\underline{K}}^{K^*} k_m \; dG(K) + (1-\hat{\mu}(K^*))MZ\int_{\underline{K}}^{K^*} k_g \; dG(K) \\
& + MZ\int_{K^*}^{\infty} k_g \; dG(K) + (1-\lambda(K^*))Nzk_a \Bigg\}^{\frac{\sigma\alpha}{\alpha(\sigma-1)-\beta}}.
\end{aligned}$$

This shows that the aggregate output, Y, is a function of w and K^*.

Total Expenditure

I assume local firms are owned by local consumers, whereas M&A and GF firms are foreign-owned. All firms earn profits and pay wage bills. When multinationals search, they incur search costs, and if they acquire local firms, they make acquisition payments. All payments are made in terms of the final good, Y. The representative household's consumption is also denominated in terms of Y.

The income of the representative household, $I(w, K^*)$, is the sum of wage payments, profits of local firms, and acquisition transfers:

$$I(w, K^*) = wL + (1 - \lambda(K^*))N\pi_a(w, K^*) + \hat{\mu}(K^*)M \int_{\underline{K}}^{K^*} P(w, K^*, K)dG(K) \tag{B.1}$$

The final good market clears such that:

$$\begin{aligned} Y(w, K^*) = I(w, K^*) &+ \mu(K^*)M \int_{\underline{K}}^{K^*} \pi_m(w, K^*, K)dG(K) \\ &+ [1 - \mu(K^*)]M \int_{\underline{K}}^{K^*} \pi_g(w, K^*, K)dG(K) \\ &+ M \int_{K^*}^{\infty} \pi_g(w, K^*, K)dG(K) \\ &+ MG(K^*)\psi, \end{aligned} \tag{B.2}$$

where $I(w, K^*)$ is defined in equation (B.1). The second, third, and fourth terms represent the profits of M&A and GF firms, and they are repatriated to source country s. The last term is search costs.[1]

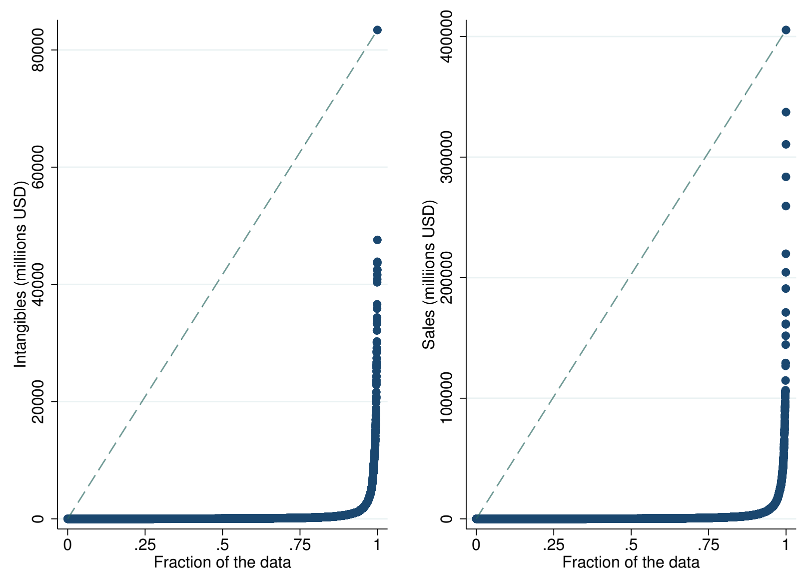
Additional Figures and Tables in Section 2.3

Figure B.1 shows the quantile plot of intangible capital and sales of Compustat firms. The distribution of intangible capital is skewed to the right same as the distribution of sales.

Table B.1 shows the average of each type of profits. The calibrated model replicates the profits of each type of firm and the acquisition price. I use these numbers to set the third moment, (iii) average merger premium, in subsection 2.3.2.

[1] I assume for simplicity that host country h only exports the final good Y to sources country s, and does not import anything s in return. Searching multinationals finance acquisition prices and search costs using IOU. Because there are no imports, there are no gains in h from diversifying product varieties. The host country's gains from openness mainly come from technology transfer through FDIs. In this static model, host country h runs a trade surplus.

Figure B.1: Quantile Plots: Intangible Capital (left) and Sales (right)



[a] Both intangible capital and sales are yearly average over the sample period in 2003-2018, and based on the Compustat database.
[b] In quantile plot, each value is plotted according to the fraction of the data. Both distributions are right skewed since all points are below the reference line.

Table B.1: Profits with the Baseline Parameters

Level of K	Profit	Definition (all values are in average)	Value
	$\pi_m(\overline{K}_{MA})$	M&A profits (in gross)	0.0157
$\overline{K}_{MA}$	$P(\overline{K}_{MA})$	Acquisition price	0.0050
	$\pi_g(\overline{K}_{MA})$	GF profits (firms which have searched)	0.0098
$\overline{K}_{GF}$	$\pi_g(\overline{K}_{GF})$	GF profits (firms which have not search)	0.0298
κ	π_a	Local firm's Profits	0.0040

[a] Numbers are replicated with the parameters shown in Table 2.3. $\overline{K}_{MA}$ is the mean of M&A firms' intangibles, $\overline{K}_{GF}$ is the mean of GF firms' intangibles, and κ is local firms' intangibles (this value is constant). $\overline{K}_{MA} = 1.33$, $\overline{K}_{GF} = 4.07$, and $\kappa = 1.09$.

Appendix C

Additional Results for Chapter 3

This chapter shows additional regression results in Chapter 3. Table C.1 shows the results of regression with autoworkers in the Midwest and the South. Unlike the result using a whole sample in Table 3.6, the coefficient of white autoworkers in the Midwest is significant. Coefficients with autoworkers in the South have the same signs as those in Table 3.6, but they are not statistically significant.

Table C.2, C.3, and C.4 show the results of regression focusing on winning and losing states for Honda, Toyota, and Mitsubishi plants respectively. I observe the negative and significant impact of an assembly plant opening on Black autoworkers with Honda's and Mitsubishi's plants.

Table C.1: Regression Results using the Midwestern and the Southern State Samples

Dependent variable:	Midwest				
ln(wage)	(1)	(2)	(3)	(4)	(5)
	All	All	All	White	Black
plant×year90	0.012	0.009	0.012	0.025**	-0.117***
	(0.014)	(0.020)	(0.014)	(0.012)	(0.022)
unionization rate[c]		0.024***			
		(0.003)			
state FEs	No	No	Yes	Yes	Yes
N	58908	58908	58908	52439	6469
R^2	0.246	0.241	0.246	0.269	0.092
	South				
	(6)	(7)	(8)	(9)	(10)
	All	All	All	White	Black
plant×year90	0.057	0.062	0.057	0.083	-0.188
	(0.070)	(0.070)	(0.070)	(0.077)	(0.117)
unionization rate[c]		0.015***			
		(0.004)			
state FEs	No	No	Yes	Yes	Yes
N	13846	13846	13846	11712	2133
R^2	0.248	0.234	0.248	0.254	0.176

[a] Standard errors in parentheses and are clustered by conspuma. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

[b] Regressions control for age, age^2, black (not in the regression (4) and (5)), and educational level.

[c] Unionization rate is a state-level variable.

Table C.2: Regression Results using Honda's Winning and Losing States

	Honda				
Dependent variable:	(1)	(2)	(3)	(4)	(5)
ln(wage)	All	All	All	White	Black
plant×year90	-0.004	-0.032***	-0.016	-0.008	-0.109***
	(0.012)	(0.011)	(0.011)	(0.012)	(0.030)
unionization rate[d]		0.024***			
		(0.004)			
state FEs	No	No	Yes	Yes	Yes
N	22549	22549	22549	20633	1915
R^2	0.222	0.231	0.235	0.256	0.077

[a] The sample consists of individuals who live in Ohio (Honda's winning state), and Arizona, Indiana, Kentucky, and Missouri (Honda's losing states).
[b] Standard errors in parentheses and are clustered by conspuma. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
[c] Regressions control for age, age^2, black (not in the regression (4) and (5)), and educational level.
[d] Unionization rate is a state-level variable.

Table C.3: Regression Results using Toyota's Winning and Losing States

Dependent variable:	(1)	(2)	(3)	(4)	(5)
ln(wage)	All	All	All	White	Black
plant×year90	0.094	0.071	0.101	0.115	-0.123
	(0.070)	(0.067)	(0.067)	(0.077)	(0.116)
unionization rate[d]		0.014***			
		(0.003)			
state FEs	No	No	Yes	Yes	Yes
N	15098	15098	15098	13620	1478
R^2	0.243	0.253	0.258	0.270	0.157

[a] The sample consists of individuals who live in Kentucky (Toyota's winning state), and Georgia, Indiana, Kansas, Missouri, Tennessee (Toyota's losing states).
[b] Standard errors in parentheses and are clustered by conspuma. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
[c] Regressions control for age, age^2, black (not in the regression (4) and (5)), and educational level.
[d] Unionization rate is a state-level variable.

Table C.4: Regression Results using Mitsubishi's Winning and Losing States

Dependent variable:	(1)	(2)	(3)	(4)	(5)
ln(wage)	All	All	All	White	Black
plant×year90	0.012	-0.008	0.007	0.021	-0.129***
	(0.014)	(0.016)	(0.015)	(0.013)	(0.017)
unionization rate[d]		0.021***			
		(0.005)			
state FEs	No	No	Yes	Yes	Yes
N	51670	51670	51670	45745	5925
R^2	0.221	0.227	0.230	0.252	0.083

[a] The sample consists of individuals who live in Illinois (Mitsubishi's winning state), and Indiana, Michigan, and Ohio (Mitsubishi's losing states).

[b] Standard errors in parentheses and are clustered by conspuma. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

[c] Regressions control for age, age^2, black (not in the regression (4) and (5)), and educational level.

[d] Unionization rate is a state-level variable.