Greenfield or Brownfield?
FDI Entry Mode and Intangible Capital

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Abstract

When a firm invests abroad, it either establishes a new facility in its host country or purchases a local firm. These two modes of foreign direct investment (FDI) are known as greenfield investment (GF) and brownfield investment (cross-border mergers and acquisitions, M&A). Using newly constructed US firm-level data, I show that M&A investment is the preferred market entry option for firms seeking to obtain existing intangible capital. Motivated by this empirical fact, I develop a structural model that describes how firms choose between M&A and GF. The model simulation shows that the effects of FDI policies are different between developed and developing economies. In particular, policymakers in a developed economy can maximize local wages by restricting acquisitions of domestic firms, while those in a developing economy can maximize local wages by easing foreign ownership restrictions. These results provide economic justification for recent FDI policy-making trends—developed countries have restricted M&As, whereas developing countries have liberalized M&As.

Keywords: FDI, Cross-border M&A, Greenfield FDI, Intangible capital

JEL Classification: F14, F21, F23

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1 Introduction

Sales of foreign affiliates have increased fourfold since 1990, and they were equivalent to 30% of global GDP in 2018 (UNCTAD, 2019a). In light of the growing importance of foreign affiliates, many governments have offered subsidies and tax incentives to attract foreign direct investment (FDI). Host countries can receive two types of FDI—one is *greenfield investment* (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). According to UNCTAD (2000), most governments used to prefer receiving greenfield investment (GF) to cross-border mergers and acquisitions (M&A).[1] However, there has been a recent divergence in FDI policies between developed and developing countries (UNCTAD, 2019b). In particular, the preference towards GF has become more prevalent in developed countries, as they would like more control over M&A investments. Conversely, most developing countries have liberalized FDI policies and seem open to both M&A and GF.

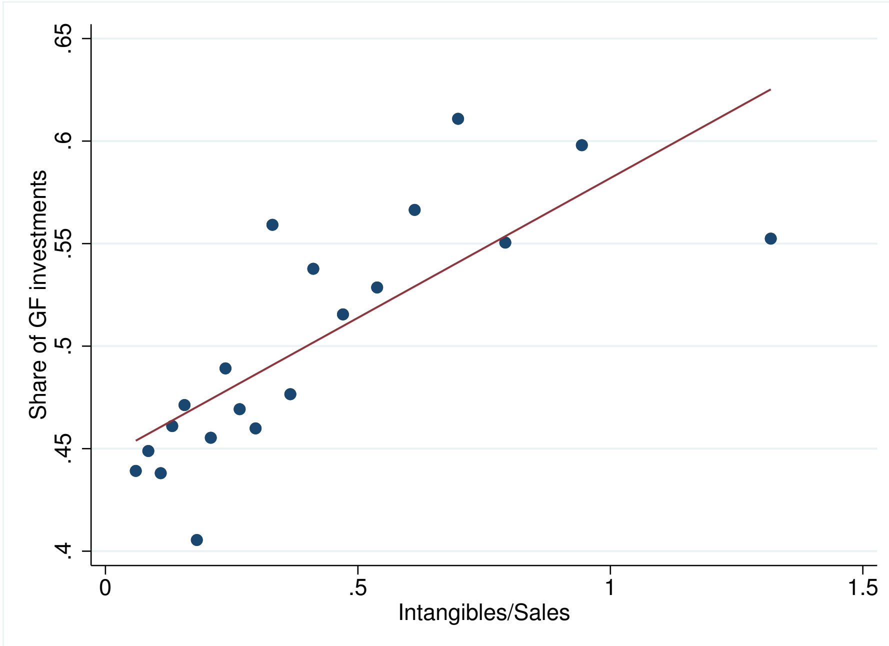
Given that developed and developing countries are adopting different FDI policies, it is of first-order policy importance to understand how multinational firms decide whether to pursue GF or M&A investments. Current theory does not provide a rigorous framework for analyzing how multinationals' FDI decision affects the local economy. As such, this paper analyzes the determinants of FDI mode 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 hypothesize that intangible capital—such as customer base, supplier network, and intellectual property—plays an important role in determining firms' FDI decisions. Given that both GF and M&A involve the purchase of physical capital, the difference between the two investment modes lies in whether the investing firm acquires intangible capital as a result of the FDI. One can infer, therefore, that M&A would tend to be the dominant mode of FDI when intangible capital is important. For example, multinational firms such as McDonalds or Coca-Cola with established, global brands–a type of intangible capital–will likely pursue GF investments. Firms that do not have well-known brands or reputations will seek to acquire local brands instead (DePamphilis 2019).

To further motivate this logic, I plot the relationship between firm intangible capital intensity (intangible assets divided by sales) and the share of FDI investments done through

[1] For example, according to the UNCTAD's extensive survey, only half of investment promotion agencies solicit M&As, while around 90% of them target GF investors (UNCTAD, 2000).

Figure 1: Share of GF Investments and Intangible Capital



[a] The vertical axis shows the share of GF investment 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. I partition the data space 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).

GF. Figure 1 shows that this correlation is significant and positive, which supports my hypothesis that firms with greater levels of intangible capital tend to pursue GF rather than M&A. The figure draws on a unique US firm-level dataset that I construct using US firm financial information (Compustat), data on GF projects (FDI Market), and M&A deals (SDC Platinum).

Motivated by the empirical evidence, I develop a structural model of firm FDI choice, expanding on Nocke and Yeaple (2007, 2008). In my model, an investing firm searches for a partner, and chooses M&A if it matches with a target firm; otherwise, the firm invests via GF. The investing firm's 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 intangible capital stock. I assume investing firms are heterogeneous in intangible capital. Similar to Melitz (2003), in which firms are heterogeneous in productivity, a cutoff in the level of intangible capital exists, whereby an investing firm with a larger level of intangible capital than the cutoff will make GF. One of the key features of my model is that the resulting equilibrium differs from the point where the real wage is maximized in the host country. This means that the market equilibrium might be suboptimal in that it will not maximize local workers' welfare. Therefore, there is room for a social planner to improve local welfare using FDI incentive programs.

I then match the model to the data to conduct counterfactual experiments. Interestingly, the relationship between multinationals' investment decisions and the equilibrium wage is different for developed (i.e., the North) and developing countries (i.e., the South). In particular, the North would like to receive more GF rather than M&A to maximize its welfare, while the South would like to receive more M&A than GF because its initially low intangible stock means it faces high marginal returns to intangible capital. In counterfactual analyses, I evaluate how welfare in an investment-receiving country changes with respect to recent FDI policies on M&A investment, i.e., the restrictions in the North and the liberalization in the South. My finding supports the current FDI policies. The restrictions on M&A investments increase local wages in the North, while the local wages in the South increases by liberalizing M&A policies.

My research relates to the literature on patterns of FDI. The most relevant study is Nocke and Yeaple (2007, 2008), which extends Helpman et al. (2004) by incorporating cross-border M&A. They consider the role of assets which are more difficult to transfer internationally. I operationalize this theory by identifying intangible capital to be these immobile assets. My research contributes to their study by empirically testing their model predictions and conducting the welfare analyses.

Another related literature focuses on how firms choose over FDI modes. For instance, Davies et al. (2018) use transaction-level FDI data and show that geographical and cultural barriers affect firms' cross-border M&A activities. My dataset incorporates US firm financial data, which allows me to explore how firm-level heterogeneity drives FDI mode decision. Similarly, my research builds upon a theoretical literature which tries to predict how FDI mode choice affects welfare (Norbäck and Persson, 2007; Kim, 2009; Bertrand et al., 2012). This paper complements to these studies by focusing on intangible capital stock as a key determinant of FDI investment modes.

Finally, this research relates to the corporate finance and macroeconomic literature on intangible capital. Many researchers have documented that firms have become more intangible capital intensive in recent years, especially in developed economies. For example, US firms have invested more into intangible capital than they have into tangible capital since 1992 (Corrado and Hulten, 2010). Intangible capital also adjusts slowly compared with physical capital (Peter and Taylor, 2017), which makes purchasing already-accumulated capital stock attractive. The fact that intangible capital is becoming more and more important is in line with the rapid increase in M&A in recent years, a pattern that my model incorporates.

The plan for this paper is as follows. I explain the data in the next section. I show the empirical evidence in section 3. I present the model in section 4, and match the model to the data in section 5. Section 6 shows the counterfactual analyses, and section 7 concludes.

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.

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 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).[2] 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.[3] 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.

[2]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.

[3]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.

(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.[4] 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.[5]

(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.[6] Intangible 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.[7]

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

[5] 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.

[6] 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 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.

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

(iv) Host Country Characteristics: I also 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. Distances from the US to host countries come from the CEPII database.

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 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.[8] Therefore, my dataset likely to cover roughly 60% of US multinational parents.

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.[9] I focus on a firm's first investment in a given industry-by-destination because my research question concerns market entry, not additional

[8] 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.

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

Table 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
Number of obs	15,475		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 are 10,375 in all industries, and 7,439 in manufacturing industries.

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 Table 1, I compare my data to the BEA data in Nocke and Yeaple (2008).[10] 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.

[10] 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.

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.

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.

I test this hypothesis 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 time t. All explanatory variables in regressions are in logs. $Intangibles_{i,t-1}$ is firm i's intangible capital in year $t-1$. Using lagged explanatory variables prevents a potential endogeneity issue between firm's investment decisions and its financial status in the same data period. In addition, I control for firm size using $sales_{i,t-1}$ since I need to consider the importance of intangible assets in firms' business operations.[11] 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 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

[11] 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.

Table 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)	(0.048)	(0.050)	(0.051)
Sales	0.108^{**}	0.101^{*}	0.004	-0.047
	(0.051)	(0.056)	(0.047)	(0.060)
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 firm and country. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
[b] All explanatory variables are in logs.

shows that the coefficient on physical capital is insignificant. This 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.

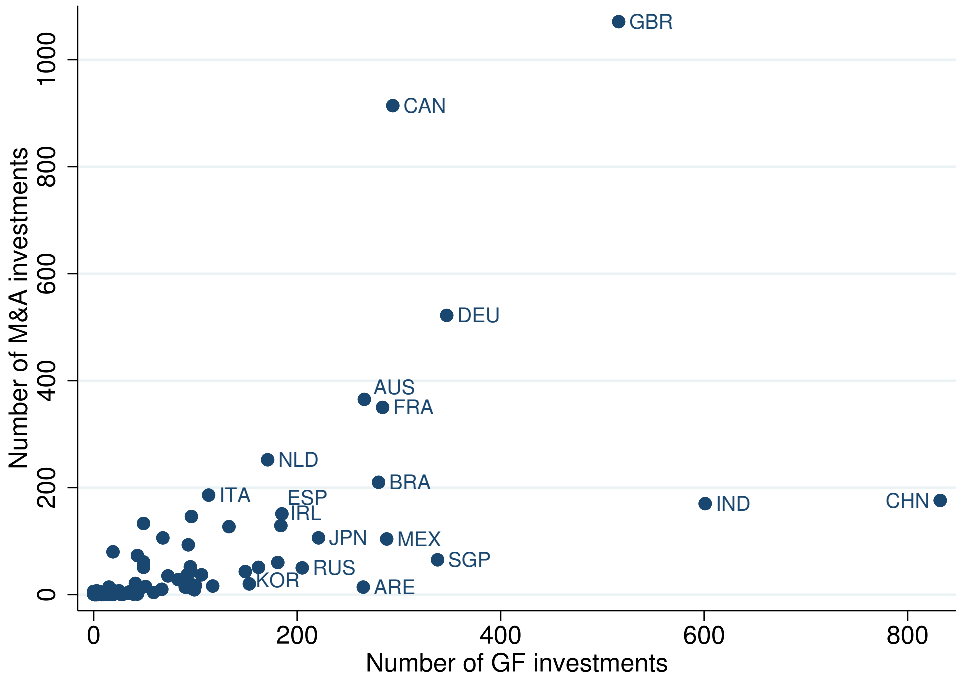
Note that these results provide a new perspective on the literature studying the determinant of firms' FDI decision. For example, Nocke and Yeaple (2008) shows that more productive firms (i.e., firms with greater sales) are more likely to choose GF investment rather than M&A.[12] My results show that there is an additional determinant of firms' FDI decisions, in addition to firm's sales.

3.2 Country Characteristics

In addition to firm heterogeneity, variations in destination countries are also matters for firms' FDI decisions. Figure 2 plots the number of M&A and GF investments that each host country had received from US listed firms during the data period. This figure shows that more M&A investments are made in developed country such as Canada, the UK, and Germany; while more GF investments are made in less-developed countries such as India, China, Brazil, and Mexico. In addition, the destinations of GF investments are more distant than those of M&A investments.

[12] 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.

Figure 2: Number of M&A and GF Investment by Host Country



[a] This figure shows the total number of cross-border M&As (in the vertical axis) and the total number of GF investments (in the horizontal axis) that each host country received from US listed firms in 2003-2018. There are 148 countries in my dataset

Table 3 shows that these predictions are still robust to controlling for firm and industry heterogeneity. Instead of country FEs, I include covariates describing the host country: GDP per capita (GDPPC), population (POP), openness to trade (OPEN), and distance (DIST).[13] The positive coefficients on GDPPC show that there are more M&A investments in more developed countries. There are more firms with greater intangible capital in countries with higher GDPPC, thus acquiring existing assets is more attractive for firms that invest in these countries. 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. Lastly, the negative coefficients on distance show that there is a smaller matching probability between target and acquiring firms if the investing countries are more distant. Investing firms are less likely to make M&A investments in distant countries since there are higher search costs.

[13] I refer to Nocke and Yeaple (2008) to select country variables.

Table 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^{***}	-0.159^{***}	-0.097^{*}
	(0.045)	(0.048)	(0.049)
GDPPC	0.869^{***}	0.964^{***}	0.872^{***}
	(0.027)	(0.044)	(0.027)
POP	0.003	0.002	0.006
	(0.005)	(0.009)	(0.005)
OPEN	-0.688^{***}	-0.708^{***}	-0.687^{***}
	(0.029)	(0.041)	(0.030)
DIST	-0.510^{***}	-0.664^{***}	-0.510^{***}
	(0.010)	(0.018)	(0.010)
N	15019	9039	15019
$Pseudo R^2$	0.242	0.227	0.240

[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 FEs.

4 A Model of FDI Entry Mode by Multinational Firms

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.[14] 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 (forthcoming), who analyzes domestic M&A activity. In my model, a firm's outside option of conducting M&As is making greenfield investments, and the merger gains and acquisition prices 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

[14] In Nocke and Yeaple (2007), two types of production efficiencies are *mobile capability*, such as technology, and *immobile capability*, such as marketing ability. In Nocke and Yeaple (2008), production efficiencies are characterized by an *entrepreneur 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.

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.

4.1 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.[15] 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 foreign countries, whereas local firms are owned by local entities. Consumer supply labor and consume final good.

4.1.1 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

[15] 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.

multinationals follows a Pareto distribution. The cumulative distribution function is:

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

where θ is a shape parameter. For simplicity, assume that productivity for multinational firm i is constant at the value $\tilde{Z}$.[16]

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.[17]

4.1.2 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 functional form:[18]

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

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

[16] 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.

[17] 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.

[18] 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.

matching probability $\mu(n)$ is:

$$\mu(n) = \frac{v(N,n)}{n} = \left(\frac{1}{1+(n/N)^{\rho}}\right)^{\frac{1}{\rho}}. \tag{2}$$

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.

4.1.3 Foreign Direct Investment (FDI)

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

(i) 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 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 $\eta \in (0,1)$. η reflects the imperfect "spillover" from the multinational firm's intangible capital, K_i, i.e., imperfect translation of the acquiring firm's intangible capital (branding, for instance) into the new market. In post-merger integration process, a multinational will lose some part of its intangibles because some of the business segment is duplicated with its target firm. 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 $\tilde{Z}_m \equiv \tilde{Z}$.

(ii) Greenfield Firms: The multinational firms which either failed to find a target or did not search 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. I assume that, unlike M&A acquiring firms, GF firms can use all of their intangible assets since there is no "duplication" in the contents of intangibles.

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 $\tilde{Z}_g \equiv \tilde{Z}$.

(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 $\tilde{Z}_a \equiv \tilde{z}$.

4.1.4 Final Good Producer

I assume there is a final good producer that aggregates three types of outputs: y_m, y_g, and y_a. The final-good production function is:

$$Y = \left[\int_{\Omega} y_{\omega}^{\frac{\sigma-1}{\sigma}} d\omega \right]^{\frac{\sigma}{\sigma-1}}, \tag{3}$$

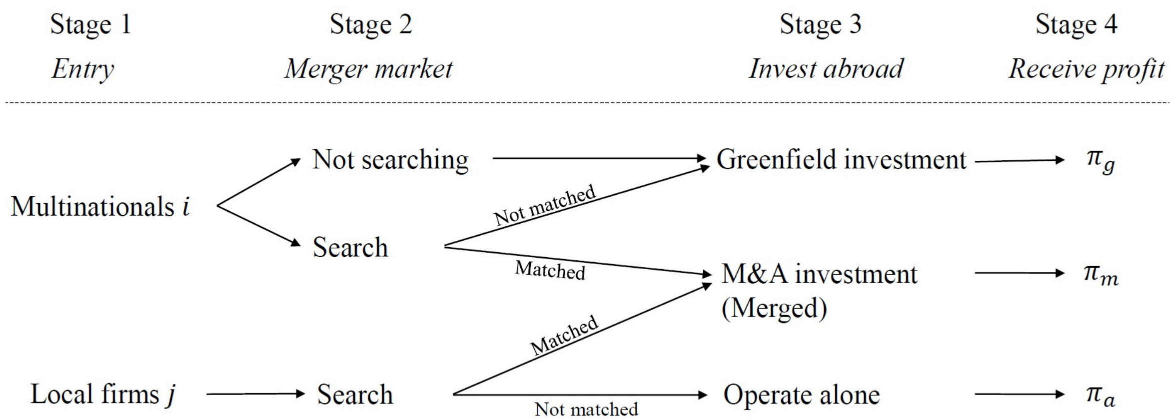
where $\sigma > 1$ is the elasticity of substitution and (with a slight abuse of notation) ω now indexes the type of firm after investment, $\omega = \{m, g, a\}$.[19] Ω is the set of the firms.

4.1.5 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.

[19] 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).

Figure 3: Timing of the Model



4.1.6 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.

4.2 Model Solution

I solve the model backwards according to the timing given in section 4.1.6.

4.2.1 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 4.1.3.

First, the final-good producer minimizes its expenditure:

$$\min_{y_\omega} \int_\Omega p_\omega y_\omega d\omega \qquad \text{subject to equation (3).} \tag{4}$$

$\Xi = [\int_\Omega p_\omega^{1-\sigma} d\omega]^{1/(1-\sigma)}$ is the unit price of the final output. 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.[20] The inverse demand function for good ω is

$$p_\omega = \left(\frac{Y}{y_\omega}\right)^{1/\sigma}. \tag{5}$$

Given the CES demand function, each type of firm $\omega = \{m, g, a\}$ solves the maximization problem for its profit:

$$\max_{\ell_\omega, p_\omega, y_\omega} p_\omega y_\omega - w\ell_\omega \qquad \text{subject to equations (3) and (5).}$$

w is the wage in the host country. I assume that $\alpha = \sigma/(\sigma-1) - \beta$ (with $\beta \leq 1$). 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.[21]

Solutions for the labor demand, ℓ_ω, are:

$$\begin{cases} \ell_m(K_i; w, Y) = \tilde{\Theta}(w, Y) Z(\kappa + \eta K_i) & \text{for merged multinationals,} \\ \ell_g(K_i; w, Y) = \tilde{\Theta}(w, Y) Z K_i & \text{for GF multinationals, and} \\ \ell_a(w, Y) = \tilde{\Theta}(w, Y) z\kappa & \text{for non-merged local firms.} \end{cases} \tag{6}$$

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 $z \equiv \tilde{z}^{1/\alpha}$.

[20] 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.

[21] Note, however, that the distribution $G(K)$ is for the post-transformed value of K. 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.

The profits of each type of entities are:

$$\begin{cases} \pi_m(K_i; w, Y) = \Theta(w, Y)Z(\kappa + \eta K_i) & \text{for merged multinationals,} \\ \pi_g(K_i; w, Y) \ = \Theta(w, Y)ZK_i & \text{for GF multinationals, and} \\ \pi_a(w, Y) \ = \Theta(w, Y)z\kappa & \text{for non-merged local firms.} \end{cases} \tag{7}$$

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.[22]

4.2.2 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:

$$\begin{aligned} \Sigma(K_i) &= \pi_m(K_i) - \pi_g(K_i) - \pi_a \\ &= \Theta Z(\kappa + \eta K_i) - \Theta Z K_i - \Theta z\kappa \\ &= \Theta\left[(Z - z)\kappa - Z(1 - \eta)K_i\right]. \end{aligned} \tag{8}$$

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 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

[22] 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 complimentary between two production technologies (i.e., $\frac{\partial^2\pi}{\partial Z\partial K} > 0$), similarly to Nocke and Yeaple (2008).

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 (8) and (7),

$$P(K_i) = \Theta z\kappa + \chi\Theta\left[(Z - z)\kappa - Z(1 - \eta)K_i\right]. \tag{9}$$

4.2.3 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,

$$\mu(n)\left[\pi_m(K_i) - P(K_i)\right] + (1 - \mu(n))\pi_g(K_i) - \psi \geq \pi_g(K_i), \tag{10}$$

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 (9) and (7), inequality (10) can be rewritten as

$$(1 - \chi)\mu(n)\underbrace{\Theta\left[(Z - z)\kappa - Z(1 - \eta)K_i\right]}_{\text{gain from merger, }\Sigma} \geq \psi. \tag{11}$$

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 *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:

$$(1-\chi)\hat{\mu}(K^*)\Theta\left[(Z-z)\kappa - Z(1-\eta)K^*\right] = \psi. \tag{12}$$

Proof. See Appendix C.1.

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 $n = MG(K^*)$. $\hat{\mu}(K^*)$ is a decreasing function of K^*.

One of the main objectives of this paper 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 3.

4.2.4 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:

$$E_m = \hat{\mu}(K^*)MG(K^*). \tag{13}$$

The measure of multinational firms which make GF investments is:

$$E_g = [1-\hat{\mu}(K^*)]MG(K^*) + M(1-G(K^*)), \tag{14}$$

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:

$$\lambda(K^*) = \frac{E_m}{N} = \frac{\hat{\mu}(K^*)MG(K^*)}{N}. \tag{15}$$

4.3 Intermediate Good Firm Outcomes

The cutoff level of intangible capital for M&A, K^*, is pinned down in the analyses conducted above for a given (w, Y). To compute the aggregate output and the aggregate labor demand, I first organize the output, y_ω, and labor demand, ℓ_ω, for each type of firm, $\omega = \{m, g, a\}$, using the cutoff K^* 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, and the equilibrium.

4.3.1 Intermediate Goods Market

There are three unknowns in the equilibrium, (w, K^*, Y). First, using the production function (3), I show that Y can be represented as a function of (w, K^*). From equation (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) and thus one can solve this equation for Y and represent Y as a function of (w, K^*). Appendix C.2 provides the detailed derivation. Below, I use the notation $\tilde{\Theta}(w, K^*)$ and $\Theta(w, K^*)$ in place of $\tilde{\Theta}(w, Y)$ and $\Theta(w, Y)$.

4.3.2 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 4.3, and equating it to the labor supply, L:

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

Inserting equation (1), (6) and (15) to the right-hand side of this equation, the expression for the aggregate labor demand below:

$$\begin{aligned} L = {} & \mu(K^*)M\tilde{\Theta}(w,K^*)Z\left[\kappa(\underline{K}^{-\theta} - K^{*-\theta}) + \frac{\eta\theta}{\theta-1}(\underline{K}^{1-\theta} - K^{*1-\theta})\right] \\ & + [1-\mu(K^*)]M\tilde{\Theta}(w,K^*)Z\frac{\theta}{\theta-1}\left[\underline{K}^{1-\theta} - K^{*1-\theta}\right] \\ & + M\tilde{\Theta}(w,K^*)Z\frac{\theta}{\theta-1}K^{*1-\theta} \\ & + \tilde{\Theta}(w,K^*)z\kappa\left[N - \mu(K^*)M(1-K^{*1-\theta})\right]. \end{aligned} \tag{16}$$

4.3.3 Equilibrium

In sections 4.2.2 and 4.2.3, I showed that K^* can be solved for a given (w, Y). Restating the cutoff condition, equation (12), using the notation $\Theta(w, K^*)$ instead of Θ,

$$(1-\chi)\hat{\mu}(K^*)\Theta(w,K^*)\left[(Z-z)\kappa - Z(1-\eta)K^*\right] = \psi. \tag{17}$$

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 (16).

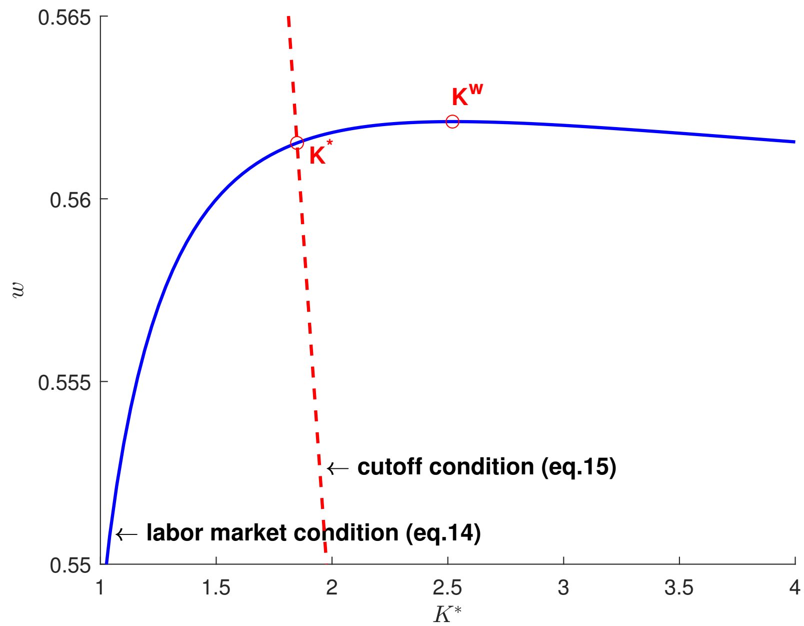
(ii) The cutoff condition in equation (17).

There are three markets in host country h: the final-good market, the intermediate-goods market, and the labor market. The intermediate-goods market clears because the intermediate-good producer selects the combination of p_i and y_i on the intermediate-good demand curve, and the labor market clears when equation (16) is satisfied. From Walras' Law, the final-good market automatically clears.[23]

The system of two equations—the labor market condition (equation 16), and the cutoff condition (equation 17)—has a unique solution. In Figure 4, I plot the equilibrium wage level, w, and the threshold level of intangible capital, K^*, which satisfy each of the conditions.

[23] A part of final good becomes wage payment, and a part of final good becomes profit (net of search cost). In my model, multinationals are owned by foreigners and the local firms are owned by locals, the locals consume the profit from local firms (which operates alone without being acquired) plus the acquisition transfer in addition to the labor earnings.

Figure 4: Equilibrium Conditions



[a] The lines in this figure show the K^* and w which satisfy the labor market condition (equation 16 is shown as the blue straight line) and the cutoff condition (equation 17 is shown as the red dashed line). The parameter values are in Table 6.

The cutoff condition is strictly decreasing, while the labor market condition is a concave function.

There is a level of cutoff, K^w, which maximizes the real wage, w. Both my empirical evidence and the model prediction indicate that multinationals with more intangible capital choose GF rather than M&A. Therefore, GF investment can bring higher-productivity firms to the local economy. In this model, the threshold level of intangible capital, K^*, determines the types of investment that host country receives. If the threshold level of intangible capital, K^*, is low, more multinationals choose GF rather than M&A. M&A multinationals upgrade local firms' intangible capital using their higher level of technology. Thus, increasing K^* may increase local wages, w, by receiving more M&A investment. If K^* is high, more multinationals choose M&A rather than GF. Multinationals lose some part of intangible capital when they make an M&A investment. Therefore, inducing higher-productivity multinationals make M&As can be inefficient for the host country, and may decrease wages. The maximum wage level will occur at K^w where the benefit from receiving M&A (i.e., upgrading a local firm's intangibles) equals its loss (i.e., losing the multinational's intangibles).

If policymakers seek to maximize the total wage payment, wL, they would like to pursue a policy that leads to the cutoff, K^w. For example, suppose there is a country that receives more M&As than GF investments, and its threshold level of intangibles is higher than K^w. In this case, policymakers may prefer to maximize the real wages, w, by restricting M&As to lower the value of K^*. The above reasoning also shows that there is another cutoff which maximizes the local welfare (i.e., sum of total wage payment, local profits, and acquisition transfer). This model prediction motivates me to conduct experiments regarding FDI policies by an investment-receiving country.

5 Quantitative Analyses

I match the model to the data in order to see 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.

5.1 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 the Pareto distribution, and it's cumulative distribution function is $G(K)$ as defined in equation (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.[24] 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 5).[25]

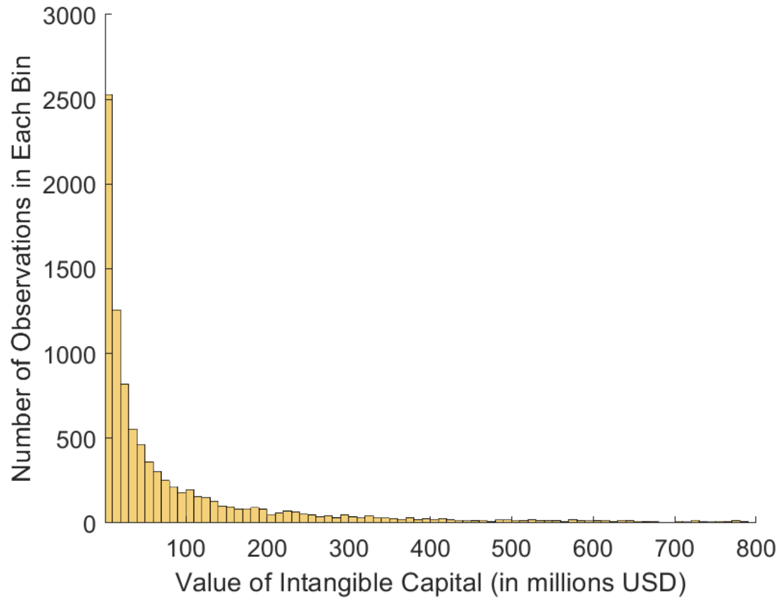
I estimate the value of the shape parameter, θ, following Axtell (2001) and Helpman et al. (2004). First, I rank firms in descending order, according to their amount of intangible capital (i.e., the firm with the largest intangible capital is ranked first). I then plot the logarithms of the ranking and 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.[26] This log-log plot (Figure 6) is known

[24]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 (at least in the right tail).

[25]Figure A.1 in Appendix C.3 shows the quantile plots of intangible capital and sales. The figures shows that the shapes of both distribution are the same.

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

Figure 5: 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 4: 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.

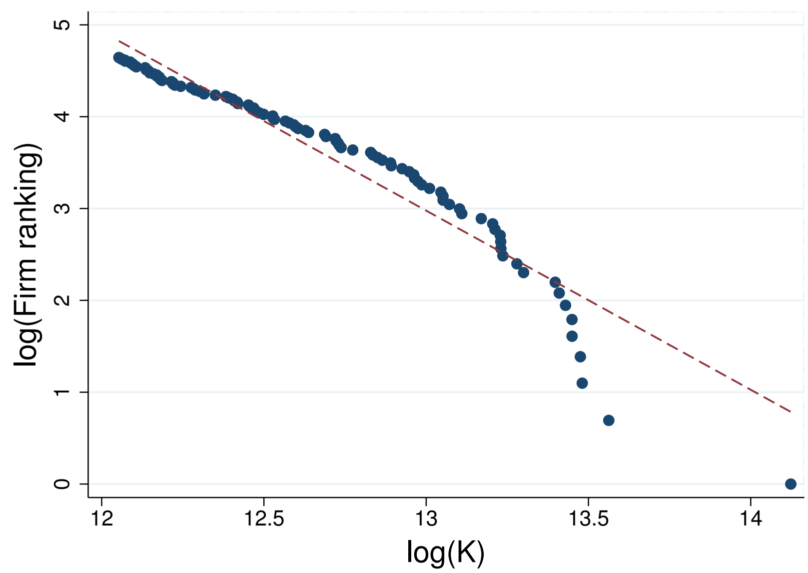
as a Zipf plot. We expect to observe a negative linear relationship in the Zipt plot if the data follow a Pareto distribution. Finally, I estimate the slope of the line using OLS. The absolute value of the coefficient is equivalent to the shape parameter, θ.[27] I set $\theta = 2$ from the regression result (Table 4).[28]

data, I obtain a similar degree of coefficient ($\theta \approx 2$) using the other cutoffs at around the 99th percentile of the data.

[27]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 $-\theta$. I normalize the data by setting the lowest value of intangibles equal to one since I set the scale parameter $\underline{K} = 1$.

[28]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 6: 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 4.

5.2 Baseline Parameters

I set the cutoff level of intangible capital, K^*, and the matching function parameter, ρ, using moments obtained from my data. The values from both the data and also the calibrated model are shown in Table 5. In this subsection, I do not distinguish the US investing firms by destination countries and instead use the whole sample. I call these parameters the baseline parameters. These numbers are reported in Table 6.

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. In order to pin down K^*, I first calculate the mean of M&A firms' intangibles, and divide the value by the overall mean of intangibles. This moment describes how much the mean of intangibles among M&A firms deviates from that of all firms. As the moment gets larger, firms with larger intangible capital make more M&A investments. The moment is represented in the model as:

$$\frac{\overline{K}_{MA}}{\overline{K}} = \frac{[\int_1^{K^*} KdG(K)]/G(K^*)}{\int_1^{\infty} KdG(K)} = \frac{1-K^{*1-\theta}}{1-K^{*-\theta}},$$

where $\overline{K}_{MA}$ is the mean of M&A firms' intangibles, and $\overline{K}$ is the mean of all firms' intangi-

Table 5: 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.

bles. I then match this moment with the one in the data. The value in the data is 0.65, so I set $K^* = 1.85$.[29]

Matching probability: Using equation (13) and (14), the share of multinational firms which make M&A investments is:

$$\frac{E_m}{E_m + E_g} = \hat{\mu}(K^*)G(K^*). \tag{18}$$

The number is 0.42 in the dataset (Table 1). Since $G(K^*)$ is 0.71, I find $\hat{\mu}(K^*) = 0.59$. Using the matching function (equation 2), I set the elasticity parameter, ρ, to 0.547. In order to pin down ρ, I need to choose the number of multinationals, M, and the number of local firms, N. In my dataset, the total number of FDI projects is 15,500 (Table 1). For the number of local firms, I predict the numbers of firms in destination countries, using their GDPs and the number of US firms. I set $M = 15,500$ and $N = 90,900$.[30]

Firm's technology: I set the exogenous technology parameter Z and z using productivity per hour worked.[31] In the data, the labor productivity in US (61.056) is double the average

[29] 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 targets, it makes 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 result of matching 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 $K_i \leq K^*$

[30] The number of total firms are not available in each destination, 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 GDPs (correlation is 0.97), I project the number of local firms in each destination country. I use the number of US firms with more than 250 employees (the number is 26,225 and comes from the Census data). Around 90% of US multinationals in my dataset have more than 250 employees. Since acquirers usually buy targets with similar size, I focus on firms with more than 250 employees.

[31] The data come from Our World in Data, a project by the University of Oxford. The data are based on Feenstra et al. (2015) and Penn World Table. I take the average values during my data pe-

Table 6: Baseline Parameters

Parameters	Definition	Value
θ	Shape parameter of $G(K)$	2
ρ	Elasticity of the matching function	0.55
M	Number of multinationals	$15,500$
N	Number of local firms	$90,900$
Z	Technology level in the US	2
z	Technology level in host countries	1
κ	Intangible capital of local firms	1.08
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	58×10^7
η	M&A friction	0.9
ψ	Search cost	695

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

of the values across destination countries (30.174). I normalize the technology level in the target firm, z, to one, and set the level of US firms, Z, to 2. Additionally, I use the fact that the average productivity of US acquirers, ZK in my model, is 7.5 times larger than that of US target firms, $z\kappa$ in my model (David, forthcoming). Following this relationship, I set the level of local firm's intangibles κ to 1.080. While this fact is observed in the US domestic M&A market, existing studies also report the fact that foreign acquirers are more productive than domestic target firms (e.g., Guadalupe et al., 2012).

I take the remaining parameters from existing literature and other data sources. I take elasticity of substitution, σ, from Broda and Weinstein (2006), and the bargaining power of target firms from David (forthcoming): $\sigma = 6$ and $\chi = 0.5$. I also set the labor share in the Cobb-Douglas production function, β, to 0.7. I use the number of labor forces in each destination country, provided by the world bank database, and set L to 580 million.[32] Lastly, I use M&A friction parameter, $\eta = 0.9$. This number mainly affects the level of search cost, ψ.

riod (https://ourworldindata.org/grapher/labor-productivity-per-hour-pennworldtable, last access on Sep 17, 2020).

[32] I focus on the number of US firms with more than 250 employees when I project the number of local firms (see footnote [30]). People who work at firms with more than 250 employees account for 20% of the total US labor force. Thus, I multiply labor force size in the host countries (2894×10^6) by 0.2.

Table 7: 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)	$14,951$
$\overline{K}_{MA}$	$P(\overline{K}_{MA})$	Acquisition price	$4,954$
	$\pi_g(\overline{K}_{MA})$	GF profits (firms which have searched)	$8,634$
$\overline{K}_{GF}$	$\pi_g(\overline{K}_{GF})$	GF profits (firms which have not search)	$24,599$
κ	π_a	Profit of a local firm	$3,590$

[a] Numbers are replicated with the parameters shown in Table 6. $\overline{K}_{MA}$ 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). $\overline{K}_{MA} = 1.30$, $\overline{K}_{GF} = 3.70$, and $\kappa = 1.08$.

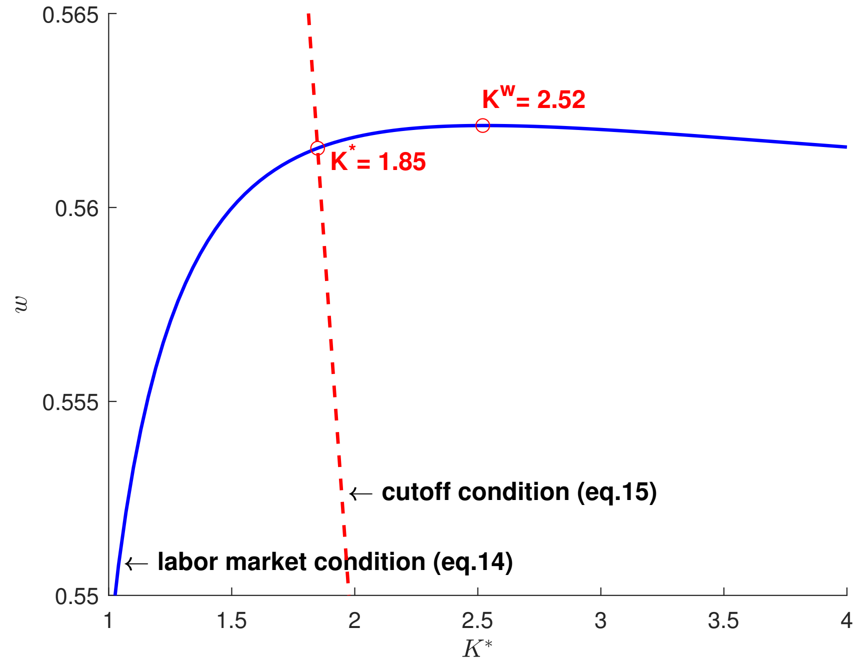
As I showed in section 4.3.3, the equilibrium can be characterized by two parameters, w and K^*. I pin down the wage level, w, using the labor market clearing condition (equation 16), and obtain $w = 0.56$. I also set the search cost, $\psi = 695.0$, using the cutoff condition (equation 12).

With the baseline parameters, the cutoff leading to the highest wage, K^w, is equal to 2.52, and is larger than the cutoff in equilibrium ($K^w > K^*$ in Figure 7). This means that the local economy, representing all countries which have received FDIs from US listed firms over the sample period, can maximize their wage until 42% of the total FDIs from these US firms are made by M&A. The calibrated model also replicates the profits of each type of firm and the acquisition price. Table 7 shows the average of each type of profits. Using these numbers, I define the average merger premium as $\frac{\Sigma(\overline{K}_{MA})}{\pi_g(\overline{K}_{MA})+\pi_a}$. Σ is the gain from merging, defined in equation (8). The average merger premium is 0.22. According to a report by Thomson Reuters (2018), the average world M&A premium ranges between 20% and 25%. Although this number includes domestic M&A deals, this result shows that the baseline calibration replicates produces reasonable values. In addition, as Table 5 shows, the calibrated model produce moments similar to the data.

5.3 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 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

Figure 7: K^* and K^w (Baseline)



[a] The lines in this figure show the K^* and w which satisfy the labor market condition (equation 16 is shown as the blue straight line) and the cutoff condition (equation 17 is shown as the red dashed line). I use the parameters in Table 6. K^w is the cutoff maximizing the real wages in the local economy.

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 8. 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 5). Reflecting this difference, I find that firms investing in the North face a higher level of cutoff K^*. I set $K^* = 3.41$ 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

Table 8: Parameters (by Destination)

Parameter	Definition	Value	
		North	South
ρ	Elasticity of the matching function	0.62	0.39
M	Number of multinationals	$9,348$	$6,127$
N	Number of local firms	$44,000$	$46,000$
Z	Technology level in the US	1.5	4
κ	Intangible capital of local firms	1.11	1.08
L	Labor force size	7×10^6	5×10^8
ψ	Search cost	2.88	2459

[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.

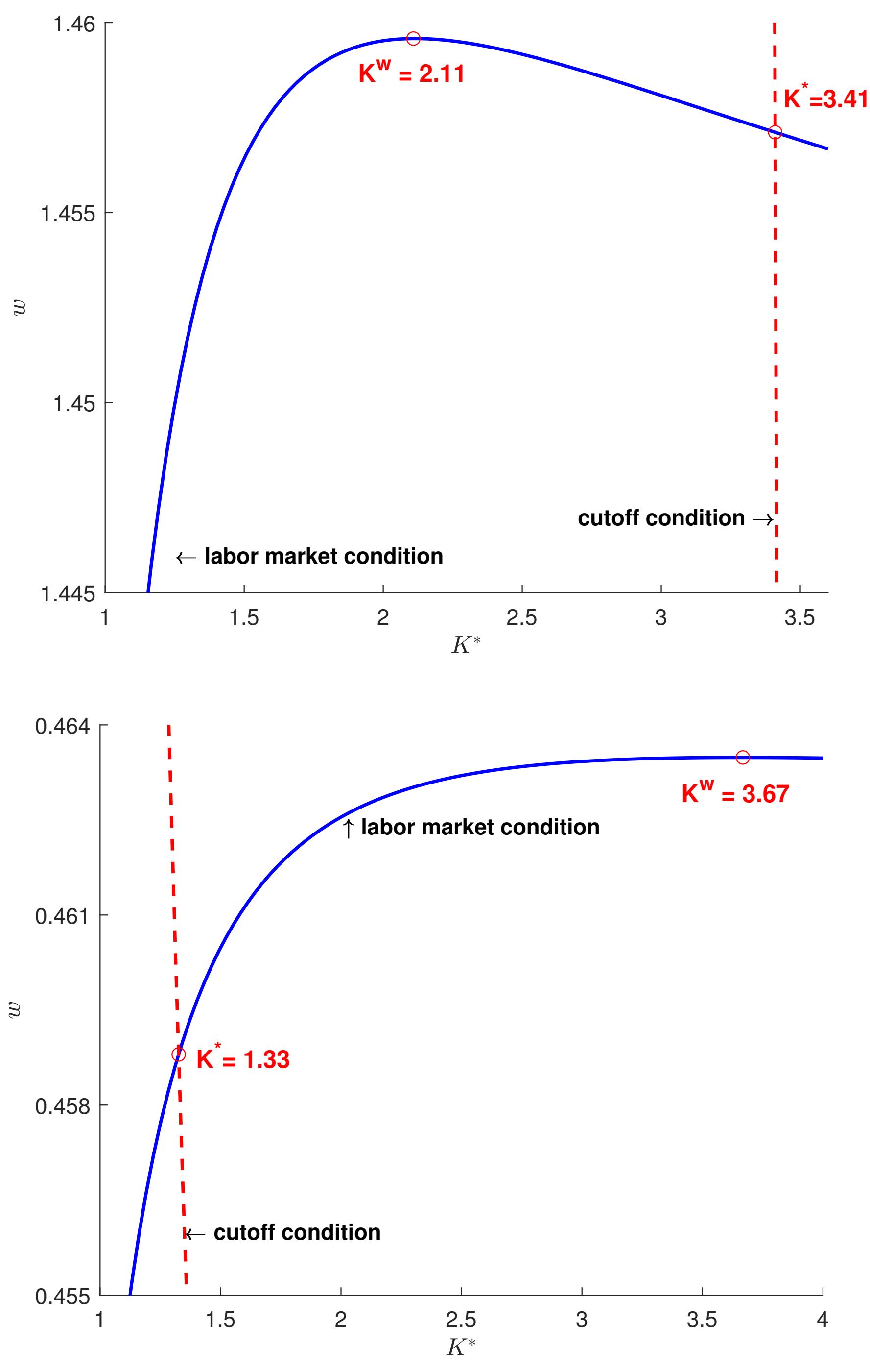
the North is 2.5 times larger than that in the South. Therefore, firms making GF in the North have a larger amount of intangible capital than those in the South.

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. I set the exogenous technology parameter of US firms, Z, to 1.5 for firms investing in the North, and 4 for firms investing in the South (again, $z = 1$ for local firms).[33] 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., $Z - z = 0.5$ in the North, while $Z - z = 3$ 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.

The equilibrium wage in the North is 1.46 and 0.46 in the South. The lower wage in the South is mostly driven by the larger labor force size. The labor force in the South is 71 times larger than that in the North. 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 8). 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.

[33] The average labor productivity in the North is 45.84, while that in the South is 14.51. Compared to the labor productivity in the US (which is 61.06), I set $Z = 1.5$ and $z = 1$ in the North, and $Z = 4$ and $z = 1$ in the South.

Figure 8: 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 16 is shown as the blue straight line) and the cutoff condition (equation 17 is shown as the red dashed line). I use the parameters in Table 8. K^w is the cutoff maximizing the real wages in the local economy.

6 Counterfactual Experiments

In this section, I evaluate the impact of FDI policies on welfare in host countries. In particular, I consider the effects of merger regulations in the North, and liberalization of foreign ownership restriction in the South.

6.1 Regulations of Merger Deals in the North

According to UNCTAD (2019b), the share of restrictive and regulatory policy measures in total FDI policies introduced has increased from 21% in 2017 to 34% in 2018. The aggregate value of cross-border M&As, blocked or withdrawn for national security reasons, is equivalent to 11.6% of total global FDI flows in 2018. Most of these regulations were introduced by developed economies and specify the ownership thresholds for particular industries. If the threshold is met, foreign acquirers need to submit notifications to the government in order to complete M&As. For example, Japan introduced a new policy in June, 2020, and lowered the foreign ownership threshold from 10% to 1%. These new regulations apply for mergers with publicly-listed firms in selected industries. Such restrictions mainly have two effects. First, new merger controls often impose additional costs and risks to foreign acquirers. Lawyers need to prepare for the required documents and, even after they complete this paperwork, their merger deals might be blocked. Second, such new regulations also increase competition in the merger market. In the Japanese case, the government released a list of publicly-traded Japanese companies affected by this regulation, and the number of firms accounts for around 17% of the total listed firms. Acquirers may need to exert more search effort, and the competition in the merger market will increase as firms try to find partners which are unaffected by this new regulation. In my model, these effects can be interpreted as increased search costs and increased severity of the matching friction in the merger market. I look at these two effects in the following subsections.

6.1.1 Increase in Search Costs

Using my calibrated model, I look at the effect of an increase in search costs, ψ, in the North. A change in search costs affects the cutoff condition (equation 17) which determines the level of intangible capital whether multinational firms search for M&A targets or not. Figure 9 shows that if search costs increase, the cutoff condition shifts to the right. The equilibrium level of intangible capital, K^{**}, is smaller than the previous cutoff level, K^{*}. Since higher search costs discourage multinationals from finding an M&A partner, fewer M&As (and more

Table 9: Welfare Change: Increase in Search Costs, ψ, in the North

Welfare	ψ: baseline	1.1ψ		1.2ψ	
	value ($\times 10^6$)	value ($\times 10^6$)	change (%)	value ($\times 10^6$)	change (%)
Wage payment	10.200	10.200	0.005	10.201	0.009
Profits of local firms	9.427	9.428	0.011	9.429	0.023
Acquisition transfer	1.448	1.445	−0.107	1.444	−0.215
Total	21.073	21.073	2.813×10^{-5}	21.073	4.120×10^{-5}

[a] This table shows how welfare changes when search costs, ψ, increase.

GF investments) occur.

Table 9 shows how welfare in the host country changes when it increases search costs by 10% and 20%. The local welfare consists of three parts: total wage payments, wL, total local profits, $E_a\pi_a$, and total acquisition transfer, $E_m \int_1^\infty P(K_i)dG(K)$. When the host country receives more GF investments, both wage payments and total profits of local firms increase. However, since the country receives lower total acquisition receipts, these positive effects on welfare are almost canceled out. In fact, if there is no total acquisition receipts in total welfare, the total welfare increase is 0.02%. Therefore, the net effect of increasing search costs depends on the counterfactual share of total welfare that would have been given by total acquisition receipts. There are two key findings to note. First, the recent restrictions on M&As by the North have not affected local welfare by much. This result supports the recent implementations of restrictive policies in the North on the basis of national security concerns. Second, my counterfactual analysis shows that if policymakers would like to increase wage payments, they can restrict M&As even though the total welfare may not appreciably change. 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.

6.1.2 Higher Matching Frictions

I analyze how the welfare in the host country changes when the matching friction is higher. In my model, the matching function parameter ρ governs the degree of the matching friction. A lower ρ decreases the number of matches. Figure 9 shows that higher matching frictions decrease wages, and also decrease the cutoff level of intangible capital. Because both the matching probability and the number of searching firms gets lower, the number of M&A firms

Table 10: Welfare Change: Higher Matching Frictions in the North

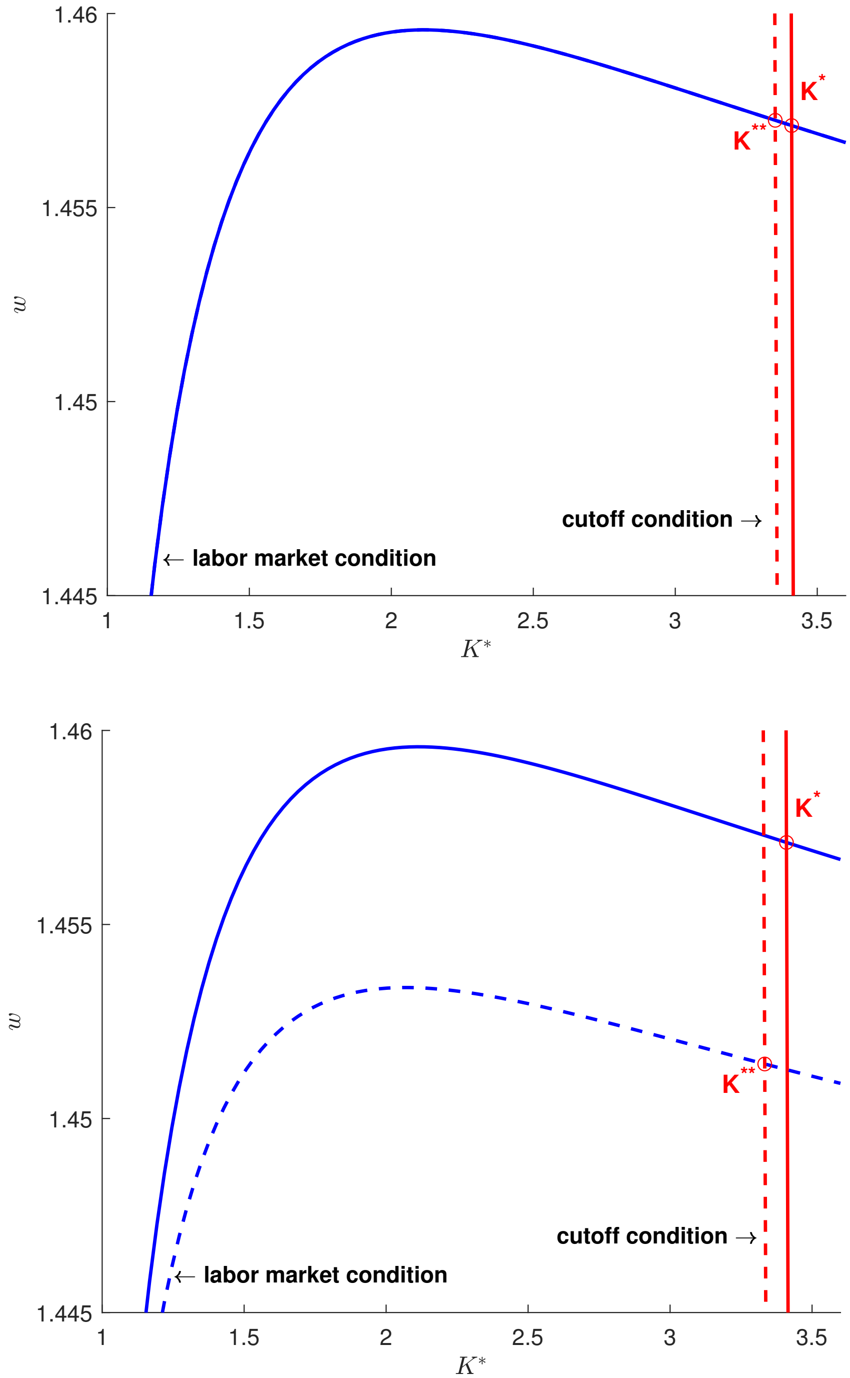
Welfare	ρ: baseline	0.9ρ		0.8ρ	
	value ($\times 10^6$)	value ($\times 10^6$)	change (%)	value ($\times 10^6$)	change (%)
Wage payment	10.200	10.181	-0.183	9.738	-0.392
Profits of local firms	9.427	9.572	1.541	9.739	3.310
Acquisition transfer	1.447	1.303	-9.932	1.138	-21.337
Total	21.073	21.056	-0.081	21.037	-0.174

[a] This table shows how welfare changes when the matching function parameter, ρ, decreases.

decrease by 22% in the new equilibrium, K^{**}, compared to the previous equilibrium, K^*. the case with an increase in the search cost, the probability of matching, $\hat{\mu}(K^*)$, affects both the labor market condition and the cutoff condition. For the labor market condition, the lower probability of a match leads to a lower wage for given K^*. If searching multinationals cannot find partners due to a lower matching probability, and invest through GF as opposed to M&A, then labor demand decreases. This is because searching multinationals are inefficient if they cannot acquire existing intangibles. For the cutoff condition, a lower probability of match, $\hat{\mu}(K^*)$, leads to smaller expected merger gains for given w. This effect shifts the cutoff condition to the left, and hence the number of searching firms decreases (i.e., smaller K^*).

Table 10 shows that higher matching friction decreases local welfare. Lower wages decrease the amount of total acquisition transfers since both the value of local firms and also the value of merger gains get smaller with a lower wage level.

Figure 9: the North: [top] Increase in Search Costs, [bottom] Higher Matching Frictions



[a] The lines in this figure show the K^* and w which satisfy the labor market condition (equation 16 is shown as the blue straight line) and the cutoff condition (equation 17 is shown as the a red straight line). I use the parameters in Table 8.

[b] [top] The dashed line is the cutoff condition when search costs increase by 20%.

[b] [bottom] The dashed lines are the conditions when the matching function parameter, ρ, decreases by 20%.

6.2 Liberalization of Foreign Ownership Policies in the South

In this section, I investigate the effect of liberalization of foreign ownership policies in the South. Implementing cross-border transactions in emerging countries poses challenges that multinationals do not generally encounter in developed countries, such as excessive local government regulations, restrictions on cash remittances, and weak legal systems (DePamphilis, 2019). Most of the investment liberalization policies enacted in 2018 took effect in developing countries, and 60% of those policies were adopted by developing countries in Asia (UNCTAD, 2019a). For example, Myanmar allows foreign acquirers to hold up to 35% of local companies. India eliminated the approval procedure for foreign investors in selected industries such as telecommunication, private security, and defense. Unlike restrictions on M&As in the North, these liberalizations could lower the barriers (i.e., search costs in my model) that foreign acquires face when conducting M&As in the South. Also, increasing foreign ownership ratios increase the matching probability in the M&A market since there are more potential target firms in the host countries. In the following subsections, I analyze the effect of a decrease in search costs and an increase in the matching probability in the South.

6.2.1 Decrease in Search Costs

If governments ease the restrictions on foreign ownership, search costs, ψ decrease. As Figure 10 shows, lower search costs shift the cutoff condition to the right. When search costs decrease, more multinationals participate in the M&A market, which brings more M&A investments (i.e., a higher cutoff level of intangibles). Wages are higher at the new equilibrium, K^{**}.

Moreover, total welfare increases as the reduction in the search costs gets larger (Table 11). Since more local firms will be acquired, the household will receive less amount of local firms' profits. However, the increase in wage payment and acquisition transfer outweighs the loss, and the effect on total welfare will be positive. The model predicts that if there are more M&A multinationals, more of local firms' intangible assets will be upgraded via mergers, which increases real wages.

Table 11: Welfare Change: Decrease in Search Costs, ψ, in the South

Welfare	ψ: baseline	0.9ψ		0.8ψ	
	value ($\times 10^7$)	value ($\times 10^7$)	change (%)	value ($\times 10^7$)	change (%)
Wage payment	22.940	23.032	0.402	23.109	0.738
Profits of local firms	18.255	18.255	−1.036	18.084	−1.962
Acquisition transfer	1.187	1.442	21.494	1.674	41.083
Total	42.573	42.729	0.367	42.868	0.693

[a] This table shows how welfare changes when search costs, ψ, decrease in the South.

Table 12: Welfare Change: Lower Matching Frictions in the South

Welfare	ρ: baseline	1.1ρ		1.2ρ	
	value ($\times 10^7$)	value ($\times 10^7$)	change (%)	value ($\times 10^7$)	change (%)
Wage payment	22.940	23.135	0.852	23.300	1.570
Profits of local firms	18.446	18.050	−2.151	17.703	−4.027
Acquisition transfer	1.187	1.715	44.538	21.830	83.959
Total	42.573	42.900	0.769	43.187	1.441

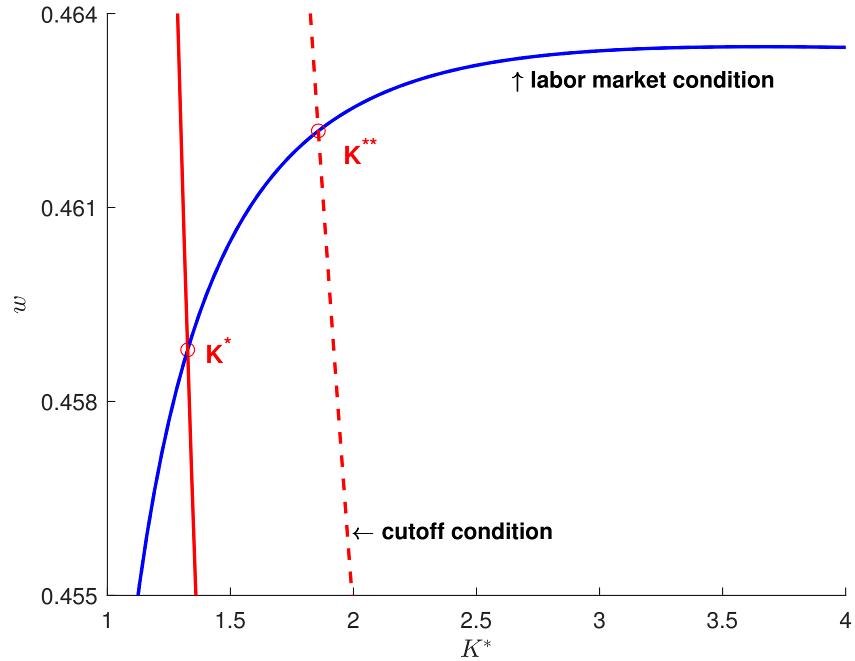
[a] This table shows how welfare changes when the matching function parameter, ρ, increase in the South.

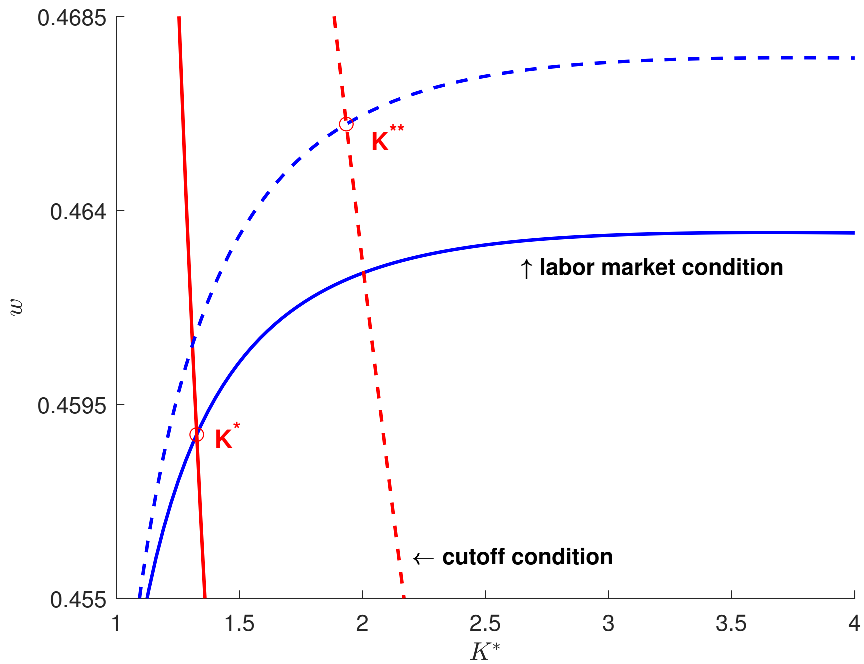
6.2.2 Lower Matching Frictions

In order to analyze the effect of lower matching frictions, I increase the matching function parameter, ρ, in the South. Higher elasticity, ρ, leads to a higher matching probability, $\hat{\mu}(K^*)$. Unlike changes in the search costs, changes in the matching probability affect both the cutoff and the labor market conditions (Figure 10). A higher matching probability encourages multinationals to search their targets in the merger market, and thus the cutoff condition shifts to the right. In addition, local firms become more productive through mergers, and this positive effect on the labor demand shifts up the labor market condition. The new equilibrium, K^{**}, leads to higher wages and more M&A investments.

Since changes in the matching probability affect both conditions, the net effects on welfare is larger relative to the effect of lower search costs (Table 12). Higher wages increase the value of local firms and merger gains, which amplifies the effect on the total welfare.

Figure 10: the South: [top] Decrease in Search Costs, [bottom] Lower Matching Frictions





[a] The lines in this figure show the K^* and w which satisfy the labor market condition (equation 16 is shown as the blue straight line) and the cutoff condition (equation 17 is shown as the a red straight line). I use the parameters in Table 8.

[b] [top] The dashed line is the cutoff condition when search costs decrease by 20%.

[b] [bottom] The dashed lines are the conditions when the matching function parameter, ρ, increase by 20%.

7 Conclusion

In this paper, I investigate the determinants of firm FDI entry mode choice, and also how that choice affects welfare in investment-receiving countries. I use a unique dataset and empirically show that a firm with less intangible capital is more likely to make M&A investments, while one with more intangible capital is more likely to choose GF. This result motivates me to develop a model of firm FDI choice. In the model, firms' intangible capital levels determine which mode of FDI they pursue. Under a reasonable set of assumptions, I show that the firms with lower intangible capital tend to choose GF, consistent with the data. Moreover, I show that there is a level of intangible capital which maximizes the real wage. Therefore, policymakers can attain the maximum wage level using FDI policies. The resulting equilibrium of the model allows me to assess welfare effects of various policies in investment-receiving countries through changes in FDI. In particular, I find that the effects of FDI policies are different between a developed economy (i.e., the North) and a developing economy (i.e., the South). In the North, I find that the policies restricting M&As increase local wages. By contrast, in the South, the policies liberalizing M&As raise local wages. This outcome may explain the recent divergence in FDI policies between the North and the South.

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

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Appendix A Data Appendix

A.1 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.

- I replace the following NAICS codes in accordance with 2007 NAICS to merge the data with Compustat:

  - BBBBBA: Internet Service Providers (such as Comcast) → NAICS code: 517911
  - BBBBBB: Web Search Portals (such as Google) → NAICS code: 518210

A.2 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. I aggregated these investments.

- I assign unique NAICS 2007 code to each sub-sector by referring to the cross-work the vendor provided.

A.3 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 datasets 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 and manually filled out the industry codes.

- Compustat assigns industry codes 9999 (unclassified establishment), which 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.

A.4 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. Most of the firms choose the same entry mode in the subsequent FDIs.

Table A.1: Entry Modes in Additional Investments

	Subsequent FDIs			
First FDI	GF	M&A	Both	Total
GF	**1923**	189	166	2278
M&A	225	**814**	99	1138

[a] There are 9,163 first GF deals, and 6,595 first M&A deals in firm-affiliate industry-country.

Appendix B 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.

Appendix C Detailed Calculations and Parameters

C.1 Proof for Equation (12)

Let H is the left-hand side of equation (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 (12) is decreasing in K^* (i.e., $\frac{\partial H}{\partial K^*} < 0$). The right-hand side of equation (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 (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.

C.2 Solution for Y

From equation (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

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

Thus,

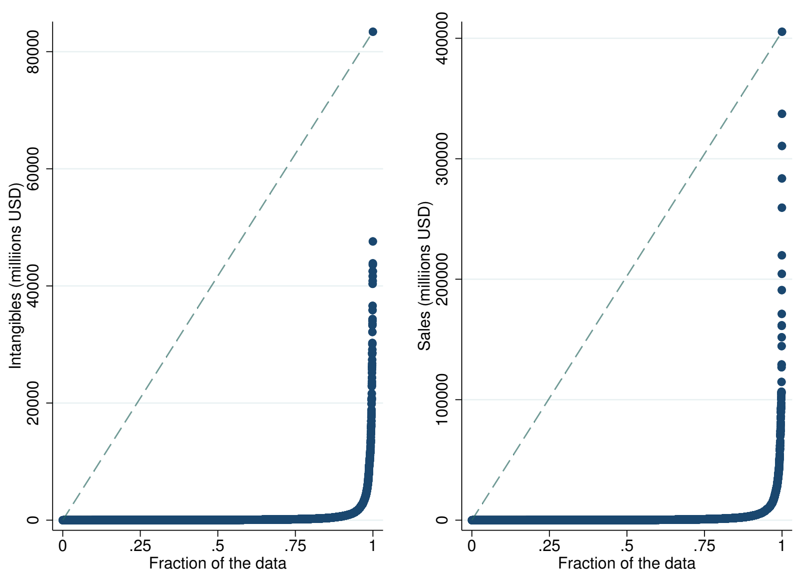
$$Y = \left[\frac{1}{w}\left(1-\frac{\sigma-1}{\sigma}\alpha\right)\right]^{\frac{\beta}{1-\beta}} \left\{\hat{\mu}(K^*)MZ\int_{\underline{K}}^{K^*} k_m \, dG(K) + (1-\hat{\mu}(K^*))MZ\int_{\underline{K}}^{K^*} k_g \, dG(K) + MZ\int_{K^*}^{\infty} k_g \, dG(K) + (1-\lambda(K^*))NZk_a\right\}^{\frac{\sigma\alpha}{\alpha(\sigma-1)-\beta}}.$$

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

C.3 Additional Figures in Section 5

This figure 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.

Figure A.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.