Greenfield or Brownfield?
FDI Entry Mode and Intangible Capital*

Haruka Takayama

University at Albany, SUNY

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Abstract

When a multinational firm invests abroad, it can either establish a new facility (greenfield investment, GF) or purchase a local firm (cross-border merger and acquisition, M&A). Using a novel US firm-level dataset, I provide the first evidence that multinationals with higher levels of intangible capital systematically invest through GF rather than M&A. Motivated by this empirical result, I develop a general equilibrium search model of a multinational firm's choice between M&A and GF. The model implies that equilibrium FDI patterns can be suboptimal. In particular, policymakers in less developed economies can increase welfare by incentivizing M&A. By allowing highly productive multinationals to use local intangible capital, this policy raises aggregate productivity relative to the laissez-faire outcome.

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

JEL Classification: F14, F21, F23

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1 Introduction

Multinationals and their foreign affiliates generated one-third of global GDP and accounted for two-thirds of international trade.[1] In light of their economic importance, governments have offered subsidies and tax incentives to attract multinationals' foreign direct investment (FDI). Host countries can receive two types of FDI—one is *greenfield investment* (the development of new facilities by foreign multinationals), and the other is *brownfield investment*, also called *cross-border mergers and acquisitions* (the purchase of local firms by foreign multinationals). In recent years, there have been over twice as many greenfield investments (GF) as cross-border mergers and acquisitions (M&A), whereas the total values of these transactions are virtually the same (UNCTAD, 2019). Although both modes of investment are economically important, policymakers assume that new facilities create more jobs than acquisitions of existing facilities, and therefore almost all investment promotion agencies encourage GF rather than M&A (Caves, 2007).[2] Given that FDI policies focus on promoting GF investment, it is of first-order policy importance to understand how multinational firms decide whether to pursue a GF or M&A investment. However, the literature does not provide a rigorous framework to analyze this choice and its welfare consequences for host countries. To fill this gap, 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 start with the premise that the key difference between GF and M&A is the role of intangible capital, such as a firm's brand name, intellectual property, and supplier network. One of the defining characteristics of intangible capital is its non-rivalry in use (Crouzet et al., 2022). That is, unlike physical capital, intangible capital can be used in multiple locations simultaneously. Because of this characteristic, intangible capital plays an important role in FDI (Markusen, 1995; Burstein and Monge-Naranjo, 2009; McGrattan and Prescott, 2009, 2010). If investing firms intensively use their own intangible capital, they are also likely to use those intangibles in foreign markets, thus relying less on M&A and more on GF. For example, multinational firms such as Walmart with established global brands—a type of intangible capital—will likely pursue GF investments (DePamphilis, 2019). Firms that do not have well-known brands or reputations will seek instead to acquire local brands.

[1] This information comes from the OECD analytical AMNE database in 2016. I refer to the VOX EU CEPR column, "Multinational enterprises in the global economy: Heavily discussed, hardly measured," published on September 25, 2019.

[2] For example, in the survey for the OECD and Latin America and the Caribbean countries, around 80% of agencies target GF, while around 5% of them target M&A (Martincus and Sztajerowska, 2019). In the survey for the OECD countries, none of the countries target M&A (OECD, 2018)

To test this hypothesis, I empirically analyze how the amount of intangible capital affects a firm's choice of FDI mode. I construct a novel US firm-level dataset using financial information on US publicly listed firms (Compustat), data on GF projects (fDi Market), and the universe of M&A deals (SDC Platinum). I measure the amount of firm's intangible capital following Peters and Taylor (2017) and Ewens et al. (2020). Although my data focus only on publicly listed firms, this new dataset covers approximately 60% of US multinational firms.

Using the data, I show that firms with less intangible capital are more likely to choose M&A rather than GF. This result is consistent with the above hypothesis: Firms with low pre-FDI stocks of intangible capital benefit more from the extra intangible capital gained through M&A. My data also reveal the fact that firm heterogeneity matters most in firms' FDI mode decisions, compared to country and industry variation. Further, I find that firms are less likely to make M&A investments if geographic, linguistic, or institutional barriers are larger (i.e., if a host country is more distant, has a different language, or is has tighter FDI restrictions). This can reflect the fact that barriers to searching for local partners matter when multinationals make M&A.

Motivated by these empirical facts, I develop a general equilibrium search model of a firm's FDI mode choice, building on Nocke and Yeaple (2007, 2008). Expanding on prior studies of domestic M&A markets (Rhodes-Kropf and Robinson, 2008; David, 2021), I develop a model in which a multinational's intangible assets play a key role in determining whether the firm pursues M&A or GF, while search frictions can deter multinationals from searching for their M&A partners.

In my model, a multinational firm searches for a partner and chooses M&A if it matches with a local target firm; otherwise, it invests via GF. A multinational's production technology in the host country has two components: its productivity (TFP) and its intangible capital. I assume that multinationals are heterogeneous in intangible capital but have a uniform productivity, which exceeds the productivity of local firms. Both components of the production technology are transferable across countries, and the complementarity between these two technologies generates a trade-off in the multinational's M&A decision. In particular, if a multinational firm invests via M&A, it cannot use all of its own intangible capital at its new foreign affiliate, but obtains additional intangible capital from the acquired local firm and upgrades the acquired firm's intangibles by leveraging its higher productivity.

The investing firm's optimal search effort depends on the attractiveness of M&A. The attractiveness of M&A, in turn, depends on the expected return from acquiring intangible capital, which is decreasing in the firm's own intangible capital stock. Because of the

Melitz-type (2003) firm heterogeneity, there is a cutoff level of intangible capital below which multinationals prefer to invest via M&A. The model implies that multinationals with higher levels of intangible capital are more likely to invest through GF, consistent with my empirical results. The model also implies that multinationals are more likely to choose M&A if there are more firms (i.e., potential M&A partners) in the host country and if local firms have more intangible capital on average. I find empirical support for these model predictions in my FDI data.

I also examine the efficiency of the market equilibrium by solving the social planner's constrained problem. I find that the equilibrium FDI pattern (i.e., the amount of M&A or GF investment that a local economy receives in the market equilibrium) can be suboptimal because of search externalities. To explore this model implication, I calibrate the model parameters and conduct simulations. The results show that there exists a sizable difference in FDI patterns between the market equilibrium and the social optimum in the South; there is no such difference in the North. Specifically, the South receives too much GF investment compared to the socially optimal level, which means that restricting FDI through GF would increase local social welfare. In counterfactual analyses, I introduce a tax on the profits of GF multinationals in the South and find that this policy increases real wages and local welfare. M&A can allow highly productive multinationals to utilize local intangible capital, and thus taxing GF increases aggregate productivity more than the laissez-faire outcome.

This paper develops a new model to explain how multinationals choose between M&A and GF investment, focusing on the role of intangible capital. My work builds on a robust literature that models foreign market entry, including Helpman et al. (2004), Ramondo and Rodríguez-Clare (2013), and Tintelnot (2017). Unlike these prior studies, which consider the extensive-margin decision over whether to pursue FDI at all, my research focuses on the intensive margin, describing why firms choose one mode of FDI over the other. This approach extends Nocke and Yeaple (2007, 2008) by fully incorporating intangible capital into a search and matching model of M&A.[3] Using a current and comprehensive dataset of multinational firm investments, I provide the first empirical evidence that intangible assets are strongly correlated with multinational FDI choices. This finding underlines the critical role that FDI plays in transferring firms' technology and knowledge (i.e., their intangible

[3] Other studies on firm's FDI mode choice focus on geographical and cultural barriers (Davies et al., 2018); matching of core competencies between acquirer and target firms (Díez and Spearot, 2014); vertical and horizontal FDI (Ramondo, 2016); total factor productivity in developed and developing countries (Ashraf et al., 2016); and two GF ownership choices, whole ownership or a joint venture (Raff et al., 2012). Similarly, my research builds on a theoretical literature that aims to predict how FDI mode choice affects welfare (Norbäck and Persson, 2007; Kim, 2009; Bertrand et al., 2012).

capital) across countries, a fact well-documented in the literature (Teece, 1977; Dunning, 1980; Burstein and Monge-Naranjo, 2009; McGrattan and Prescott, 2010; Bloom et al., 2012; Keller and Yeaple, 2013; Arkolakis et al., 2018; Bilir and Morales, 2020), but which I tie explicitly to firms' FDI mode choices specifically for the first time.[4] Altogether, my unique data and novel model allow me to assess the accuracy of my theoretical predictions while analyzing the welfare effects of changes in FDI policy. This analysis provides new insight into potential inefficiencies in developing economies' FDI policies.

The outline of this paper is as follows. I describe the novel FDI data I use in Section 2, report my empirical evidence on the relationship between intangible assets and FDI mode choice in Section 3, and present my search and matching model in Section 4. I test the model's empirical implications in Section 5 and present counterfactual analyses of different FDI policies using calibrated parameters in Section 6. I conclude in Section 7.

2 Data

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

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 to be 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. In this paper, I focus exclusively on new investment projects made by US parent companies

[4] Atalay et al. (2014) demonstrate that firms engage in intangible capital transfer rather than intra-firm trade using data on US multi-plant firms. Ramondo et al. (2016) also show that few foreign affiliates engaged in trade with their parent firms using data on US multinationals.

(that is, companies with headquarters in the US).[5]

(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. I extract all cross-border projects involving US acquiring (parent) firms.[6] I restrict my attention to deals involving acquisitions of more than 10% ownership. The 10% cutoff is common in most FDI studies to determine whether an acquiring firm has control over its target firm.[7]

(iii) US Firms' Financial Information: 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.[8] Intangible capital is defined as the sum of a firm's *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.[9] Following Peter and Taylor (2017), I assume that organizational capital has a 20% depreciation rate. The multiplier of SG&A spending and the depreciation rate for R&D spending are from Ewens, et al. (2020), and both vary across industries. On average, 27% of SG&A spending is used to form organizational capital, and the knowledge capital depreciation rate is 33%.[10]

[5]Unlike the SDC Platinum (the database of cross-border M&As), I can sort only by headquarter location of parent firms (not the locations of investing firms) in the fDi Market database. I do not use the data for the expansion of existing projects and joint ventures. The expansion and joint ventures account for around 10% and less than 1% of the investment made by US firms, respectively.

[6]I exclude deals involving investment funds such as hedge funds and sovereign wealth funds because these acquisitions are conducted based on speculative activities, not on seeking a new business in foreign markets.

[7]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. Most acquirers obtain more than 10% ownership. Acquisitions with less than 10% ownership consist of only 3% of the total deals in my dataset.

[8]There are two types of intangible capital, internally generated intangible capital and externally generated intangible capital. Recall that internally generated intangible capital refers to assets that the firm creates itself through R&D and SG&A spending. Externally generated intangible capital refers to assets the firm acquires by purchasing another firm. The Compustat data record intangible assets, but these only include externally generated intangible capital (Corrado et al., 2022). In this paper, I focus on internally generated intangible capital, which reflects actual investment in intangible assets without the markups that accompany firm acquisitions (i.e., goodwill).

[9]I use firms' R&D and SG&A spending between 1980 and 2018.

[10]My empirical results are robust to using alternative calculations of intangible capital with different depreciation rates and multipliers for SG&A spending. Alternate parameters are 20% or 40% for the SG&A

These depreciation rates of intangible capital are higher than the depreciation rate of physical capital. Intangible capital adjusts slowly compared with physical capital, which makes purchasing already-accumulated capital stock attractive. In addition to intangible capital, I obtain sales and value-added per worker to consider a firm's size and productivity.[11]

(iv) Information of Host Countries: I include variables describing host country characteristics in my regression analyses. I measure the level of development using GDP per capita and the market size using population. These two variables are from the Penn World Table. I also measure the level of openness to trade using the ratio of the sum of exports and imports to GDP. These data come from the World Bank Database. The CEPII database gives the following information: distance from the US to each host country and whether English is the official language in that country (i.e., if a host country shares a common language with the US). I also obtain the FDI Regulatory Restrictiveness Index from the OECD database.[12]

I obtain the number of local firms and intangible capital stocks in host countries from the OECD database and the EUKLEMS & INTANProd database. These datasets are only available for a subset of countries and industries but are still useful for considering how the characteristics of local firms in host countries affect multinationals' FDI mode choices.[13]

2.2 Merging the Firm Datasets

I merge both (i) greenfield investment projects (fDi Market) and (ii) cross-border M&A deals (SDC Platinum) 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

multiplier, 15% or 25% for the depreciation rate of organizational capital, and 20% or 40% for the depreciation rate of knowledge capital.

[11]I refer to İmrohoroğlu and Şelale (2014) to construct value-added per worker.

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

[13]In the SDBS Structural Business Statistics database, the OECD reports the number of firms in 45 countries by ISIC Rev.4 industry classification. In the EUKLEMS & INTANProd database, I observe the total intangible capital stocks of 30 countries by NACE Rev.2 industry classification.

Table 1: Summary Statistics

	My data				Nocke & Yeaple	
	All industries		Manufacturing only			
Variable	mean	s.d.	mean	s.d.	mean	s.d.
M&A	0.414	0.493	0.415	0.493	0.435	0.496
Intangibles	20.541	2.127	20.760	2.068	-	-
Sales	21.826	2.287	22.038	2.223	15.37	1.61
Value-added per worker	4.562	0.6981	4.572	0.605	4.45	0.523
Distance	8.769	0.814	8.809	0.776	8.72	0.69
Common language	0.377	0.485	0.344	0.475	-	-
GDP per capita	10.053	0.838	10.018	0.849	9.81	0.723
Population	17.613	1.645	17.705	1.680	16.7	1.38
Openness	4.263	0.558	4.260	0.554	3.94	0.648
FDI restrictiveness	0.123	0.118	0.135	0.123	-	-
Number of observations	16,062		8,976		856	

Notes: 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). M&A is equal to one if the firm made an M&A investment. All continuous variables, except the FDI index, are in logs. The unit of distance is a kilometer, and other monetary values, such as intangible capital and sales, are in USD. The summary statistics for the number of local firms and local intangible capital stock is in Table B.1.

changed their names manually using the internet.[14]

There are 2,645 Compustat firms in my final data. During the sample period (from 2003 to 2018), 693 firms made only GF investments, while 784 firms made only cross-border M&A deals. 1,168 firms made investments using both FDI modes. According to the BEA data, there are around 4,500 US multinational parents in 2014, and thus my dataset covers roughly 60% of US multinational parents.[15]

I aggregate firms' investments by firm-industry-destination to run regressions. For firms that made more than one investment in the same industry and destination country, I extract the first FDI from the merged data.[16] I focus on a firm's first investment in a given industry-by-destination because my research question concerns market entry, not additional

[14]In SDC Platinum, I match around 92% of deals made by publicly-listed ultimate acquirers with Compustat firms. I do not identify which firms are publicly-listed in the fDi Market database, and therefore I cannot measure the matching rate for GF investing firms.

[15]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.

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

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 B.2 shows that 84% of firms that made a GF investment in their first entry in a particular industry and country, also made GF investments in their subsequent FDIs in the same industry and country.

In Table 1, I compare my data to the BEA data (i.e., confidential data of all US multinationals) in Nocke and Yeaple (2008).[17] Unlike my data spanning 2003-2018, Nocke and Yeaple (2008) use data from 1994-1998. Notably, although my data contains only publicly listed firms, 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 the service industry, and interestingly the share of M&A investment is similar both in the manufacturing and service industries.

In total, the data show that 2,645 US-listed firms invested in 153 countries. The five major FDI destinations are the UK, Canada, China, Germany, and India (Table B.3). China and India attract more GF investments, while the other three destinations are major locations of cross-border M&A.

I also observe a range of industries that received investment. One of the most useful features of my FDI data is that the industry classification represents the specific operations of the new establishment.[18] 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.[19] For around half of FDI, the main industry of a US multinational is different from the industry of its new foreign affiliate (i.e., inter-industry FDI). This share is almost the same both in GF and M&A FDI, but relatively more M&A firms (63% of total M&A firms) invest in an industry other than their own industry compared to GF firms (51% of total GF firms).

Moreover, I observe the costs associated with FDI (the amount of capital invested for GF firms and the acquisition prices for M&A firms) in my datasets.[20] The average GF investment

[17] 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.

[18] The classification in the fDi market database does not describe the investing firm's primary business. For example, if a firm establishes its new research center in the IT software industry, the industry sector of this project is classified as Software & IT Services, regardless of what kind of primary business the firm operates. By contrast, in SDC Platinum, a target's listed industry can be different from that of its parent multinational.

[19] US multinationals invest in multiple industrial sectors; the main investing industries are information and software, computer and electronic product, chemical products, professional and technical services, and machinery. The corresponding three-digit NAICS codes are 511, 334, 325, 541, 333.

[20] Acquisition prices are available for 43% of M&A deals in my data. I observe the value of capital invested in almost all GF investments, however 84% of the GF capital investment data reflect estimates provided by the Financial Times. Even though the data are estimated, they still represent the most comprehensive and

is worth $60 million, while that of M&A is $252 million. The average M&A investment is actually worth more than the average GF investment, for any sized firm (Appendix B.4). This pattern reflects the fact that firms need to spend more to acquire existing firms than to establish their own firms via GF because the existing entities have intangible capital in addition to physical assets.

3 Empirical Evidence of FDI Entry Modes

My unique and extensive dataset reveals the three facts on firms' FDI mode choice. These three empirical findings guide the model to be introduced in the subsequent section.

3.1 Fact 1: FDI mode decisions are mainly driven by firm heterogeneity.

My data provide information on GF investments and cross-border M&A deals undertaken by US-listed firms, including descriptions of the industries and countries involved in the transactions. These unique data allow me to analyze the extent to which three different sources of variation—firm-level heterogeneity, cross-industry variation, and cross-country variation—drive GF and M&A investment decisions. I investigate which of these factors matters most when a firm decides which FDI mode it chooses.

Several studies conduct empirical analyses on firms' investment mode decisions and arrive at different conclusions about the relative importance of firm, industry, and country variation in driving decisions over FDI mode. For example, Nocke and Yeaple (2008) focus on firm efficiency and show that more efficient firms choose GF investments, while Davies et al. (2018) focus on the characteristics of host countries and conclude that firms are less likely to choose M&A investments when they invest in distant countries with larger cultural differences. Industry characteristics likely matter as well, and in fact, more M&A investment occurs in intangible-intensive industries such as beverages and medical devices (World Bank, 2018). All factors seem important, and we do not know so much about which factor plays the biggest role when firms decide which investment mode to pursue.

To empirically investigate this question, I follow Coşar and Demir (2018) and run fixed effect regressions to analyze the source of variation in firm FDI mode choices. Let $MA_{i,h,j,t}$ be an indicator representing firm i's FDI mode choice. This variable equals one if firm i uses

accurate data on GF investments.

Table 2: Sources of Variation in Firm FDI Mode Decisions

	Single fixed effects			Pairwise fixed effects		
	Firm_i	Country_h	Industry_j	Firm-country_{ih}	Firm-ind_{ij}	Country-ind_{hj}
Direct effect						
	0.273	0.210	0.144	0.357	0.467	0.327
Partial determination						
	0.212	0.135	0.147	0.359	0.417	0.270

Notes: The unit of observation is a firm-FDI deal. The first panel (direct effect) shows adjusted R^2 values from regressions of whether the deal involves M&A on the fixed effects given in each column. For example, I regress MA_{ihjt} on firm fixed effects, α_i and record the adjusted R_i^2 for the first column. The second panel (partial determination) shows the share of variation each of the fixed effects explains compared to the variation explained by the other fixed effects specification. For example, in the first column, I regress MA_{ihjt} on firm fixed effects, α_i, and country-industry fixed effects, α_{hj}, and keep the adjusted R^2, $R^2_{i,hj}$. I then regress MA_{ihjt} only using country-industry fixed effects, α_{hj}, and keep the adjusted R^2, R^2_{hj}. I then get the partial contribution of firm variation by calculating $(R^2_{i,hj} - R^2_{hj})/(1 - R^2_{hj})$.

M&A for its first FDI in host country h and industry j in year t, and equals zero if firm i chooses GF investment. To gauge the relative importance of different sources of variation in FDI mode decisions, I regress $MA_{i,h,j,t}$ separately on firm, industry, and country fixed effects, and compare the resulting adjusted R-squared values.

In the first panel of Table 2, titled *direct effect*, I present adjusted R-squared values from my three fixed effects specifications.[21] Firm heterogeneity explains around 30% of the variation in FDI mode choices; the explanatory power of industry variation is noticeably lower, as is the explanatory power of country-level variation. This comparison suggests that firm-level heterogeneity matters most in FDI mode decisions.

To probe these results further, I consider interacted fixed effects models in which I consider the respective roles of firm-country, firm-industry, and country-by-industry variation. The results with pair fixed effects again show the firm-industry level factors matter the most. In particular, firm-industry fixed effects explain almost half (46.7%) of the total variation in FDI mode choices.

In the second panel of Table 2, titled *partial determination*, I explore the robustness of the findings from the first panel. Specifically, I evaluate the relative explanatory power of the fixed effects involving firm-level variation to the best-performing specification that does

[21] I exclude year fixed effects because they explain very little variation. For example, the direct effect of year variation is 0.010.

not include firm-level effects—namely, the model with country-industry fixed effects. These "partial determination" results confirm my findings from the first panel.[22]

3.2 Fact 2: Firms with more intangible capital are more likely to make GF investments rather than M&A.

I showed that firm heterogeneity matters most in terms of multinationals' FDI mode decisions. I next analyze which firm-level variable affects the firms' FDI decisions. Firms will obtain physical capital either through GF or M&A investment, but they can acquire existing intangible capital only through M&A. Therefore, I hypothesize that M&A is the preferred market entry option for firms that seek to obtain existing intangible capital.

Giving a glimpse of the detailed empirical analysis to be presented below, Figure 1 plots the relationship between firm intangible capital intensity (intangible assets divided by sales) and the share of FDI investments done through GF. The positive and statistically significant correlation supports the hypothesis that firms with higher levels of intangible capital tend to pursue GF rather than M&A.

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

$$\begin{aligned} MA_{i,h,j,t} = \beta_1 \times intangibles_{i,t-1} + \beta_2 \times sales_{i,t-1} + \beta_3 \times value\text{-}added\text{-}per\text{-}worker_{i,t-1} \\ + \alpha_{h,t} + \alpha_{j_p,j} + \epsilon_{i,h,j,t}, \end{aligned} \tag{1}$$

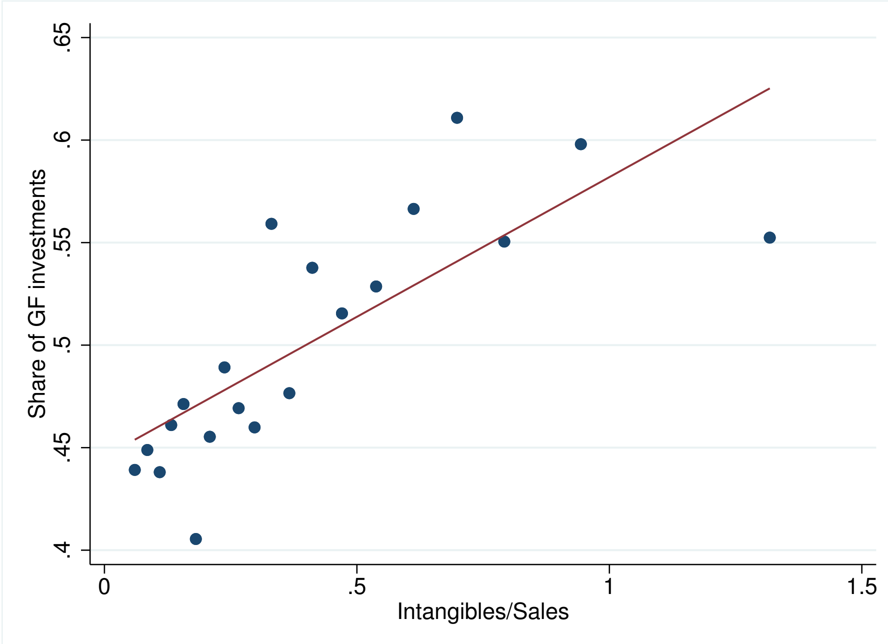
where $MA_{i,h,j,t}$ is an indicator for whether US parent firm i uses M&A for its first FDI in market h and industry j in year t. There are two types of industry: parent industry, j_p, and foreign affiliate industry, j. All explanatory variables in regressions are in logs. Firm i's intangible capital in year $t-1$ is denoted by $Intangibles_{i,t-1}$. Using lagged explanatory variables prevents a potential simultaneity issue between firms' investment decisions and their financial status in the same data period.[23] In addition, I control for firm size and productivity using $sales_{i,t-1}$ and $value\text{-}added\text{-}per\text{-}worker_{i,t-1}$.[24] I also add country-year fixed effects, $\alpha_{h,t}$,

[22] I obtain coefficients of partial determination using the same logic as Coşar and Demir (2018). For firm i, I first regress $MA_{i,h,j,t}$ on firm fixed effects and country-industry pair fixed effects (i.e., individual fixed effects and pair fixed effects of the remaining factors) and obtain the adjusted $R^2_{i,hj}$. I next regress $MA_{i,h,j,t}$ only on country-industry pair fixed effects (without firm fixed effects) and keep the adjusted R^2_{hj}. I then obtain the share of variation that firm fixed effects can explain by computing $(R^2_{i,hj} - R^2_{hj})/(1 - R^2_{hj})$.

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

[24] 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

Figure 1: Share of GF Investments and Intangible Capital



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

and industry-pair fixed effects, $\alpha_{j_p,j}$. The former controls for any shocks affecting a firm's entry decision in country and year (such as a policy change regarding M&A), and the latter controls for industry characteristics between an investing firm and an affiliate firm.

Table 3 presents the results. In the first specification, I estimate the correlation between a firm's intangible capital and the probability of making cross-border M&A without controlling for sales and value-added per worker. The coefficient on intangible capital is negative and statistically significant in the first specification, and it stays the same when I control for sales and value-added per worker (in column 2). This result shows that the probability of making a GF investment increases with the amount of intangible capital that a parent firm holds. In the third specification, I use industry-pair-year fixed effects instead of industry-pair fixed effects to control for any shocks specific to an industry pair between an investing firm and an affiliate firm in year t (such as demand or supply shocks affecting an industry pair, j_p and j). Using industry-pair-year fixed effects will drop many observations that are unique parent industry-affiliate industry-year triplets. The sign and statistical significance of the

intangibles and *sales* must be the same values.

Table 3: Firms' FDI Decisions and Intangibles

	Dependent variable: $MA_{i,h,j,t}$		
	(1)	(2)	(3)
Intangible capital	-0.020^{***}	-0.043^{***}	-0.052^{***}
	(0.003)	(0.008)	(0.010)
Sales		0.014	0.024^{**}
		(0.009)	(0.010)
Value-added per worker		0.014	0.012
		(0.011)	(0.012)
Country × Year FE	Yes	Yes	Yes
Industry Pair FE	Yes	Yes	
Industry Pair × Year FE			Yes
Observations	15,161	14,373	12,258
Adjusted R^2	0.393	0.402	0.385

Notes: Standard errors are clustered by parent firm. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. All explanatory variables are in logs.

coefficient on intangible capital remain the same.

Overall, the results in Table 3 show that firms with more intangible capital are likely to choose GF investment rather than M&A. This suggests that if firms have enough intangible capital, they invest via GF; otherwise, they invest via M&A to benefit more from acquiring local intangibles. Note that these results provide a new perspective on the literature studying the determinant of firms' FDI decisions. For example, Nocke and Yeaple (2008) show that more productive firms (i.e., firms with greater sales and value-added per worker) are more likely to choose GF investment rather than M&A. My results show that there is an additional determinant of firms' FDI decisions—the amount of intangible capital.

I also run linear probability regressions, disaggregating intangible capital into its components, to see whether a specific type of intangible capital matters more for a firm's choice of FDI mode. A firm's intangible capital is the sum of its knowledge capital and organizational capital. Instead of using the total amount of intangible capital as the explanatory variable, I include knowledge capital and organizational capital separately in columns 1 and 2 of Table 4.[25] Both types of intangible capital yield qualitatively similar results (negative and sta-

[25] Note that R&D spending (the variable with which I measure knowledge capital) is missing for some Compustat firms.

Table 4: Firms' FDI Decisions and Other Types of Capital

	Dependent variable: $MA_{i,h,j,t}$		
	(1)	(2)	(3)
	Intangible		Non-intangible
	Knowledge	Organizational	Physical
Capital	-0.023^{***}	-0.031^{***}	-0.009
	(0.009)	(0.009)	(0.009)
Sales	0.003	0.003	-0.016^{*}
	(0.010)	(0.009)	(0.010)
Value-added per worker	0.020	0.013	0.013
	(0.013)	(0.011)	(0.011)
Country × Year FE	Yes	Yes	Yes
Industry Pair FE	Yes	Yes	Yes
Observations	8,620	14,373	14,171
Adjusted R^2	0.384	0.400	0.398

Notes: Standard errors are clustered by parent firm. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. All explanatory variables are in logs.

tistically significant coefficients) as the total intangible capital (i.e., the result in column 2 of Table 3). This means that the effects of total intangible capital are driven both by the amount of knowledge capital and organizational capital. Finally, I include physical capital as an explanatory variable. As expected, column 3 shows that the coefficient on physical capital is insignificant. This result supports my prediction that only intangible capital, not physical capital, is a significant determinant of an investment mode because firms establish their physical facilities abroad either through M&A or GF. This finding underlines the importance of intangible capital in FDI mode choice.

3.3 Fact 3: Frictions to search for local partners affect a firm's FDI mode choice.

Unlike GF investment, a multinational needs to search and finds a local partner in its host country to conduct M&A. Existing studies highlight the importance of the friction between an acquirer and a target firm. For example, Head and Ries (2008) show that geographical and cultural frictions hinder cross-border M&A as investing firms have imperfect information on foreign firms. Given this background, I consider how geographical and cultural frictions

Table 5: Firms' FDI Decisions and Country Characteristics

	Dependent variable: $MA_{i,h,j,t}$			
	(1)	(2)	(3)	(4)
DIST	-0.071^{***}	-0.072^{***}	-0.045^{***}	-0.053^{***}
	(0.017)	(0.022)	(0.010)	(0.011)
LANG	0.065^{**}	0.078^{***}	0.112^{***}	0.111^{***}
	(0.026)	(0.030)	(0.025)	(0.027)
GDPPC	0.111^{***}	0.128^{***}	0.150^{***}	0.148^{***}
	(0.019)	(0.022)	(0.019)	(0.018)
POP	-0.003	-0.006	0.006	0.014
	(0.009)	(0.010)	(0.011)	(0.013)
OPEN	-0.098^{***}	-0.120^{***}	-0.056^{*}	-0.028
	(0.022)	(0.029)	(0.032)	(0.037)
FDI restrictiveness			-0.032^{**}	-0.325^{**}
			(0.013)	(0.129)
Intangibles		-0.040^{***}	-0.043^{***}	-0.049^{***}
		(0.009)	(0.010)	(0.012)
Firm FE	Yes			
Industry Pair FE	Yes	Yes	Yes	
Year FE	Yes	Yes	Yes	
Industry Pair × Year FE				Yes
Observations	11,891	14,027	12,410	10,471
Adjusted R^2	0.470	0.363	0.367	0.349

Notes: Standard errors are clustered by firm and country. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. All continuous variables are in logs. I control for firm size and efficiency using sales and value-added per worker.

affect firms' FDI mode choices.

Instead of country-year fixed effects, I include the following covariates describing the host country in equation (1): distance (DIST), common language (LANG), GDP per capita (GDPPC), population (POP), openness to trade (OPEN), and FDI regulatory restrictiveness index.[26] I take logs for all continuous variables. DIST, LANG, and FDI restrictiveness are variables that relate to frictions for multinationals to conduct M&A.

The results are in the first and second columns of Table 5. In the first specification, I control for firm heterogeneity using fixed effects instead of using firms' financial information,

[26] Nocke and Yeaple (2008) use the four country variables in their regressions: GDP per capita, population, openness to trade, and distance. I use language and the FDI regulatory restrictiveness index additionally.

such as intangibles, sales, and value-added per worker. The second and third column shows the results with the main specification, including country characteristics instead of country-year fixed effects. In the fourth specification, I use industry-pair-year fixed effects that absorb the average probability that a firm chooses M&A investment in each industry pair and year. I include the FDI regulatory restrictiveness index only in the third and fourth specifications because the OECD reports the FDI regulatory restrictiveness index only for 66 countries.

The signs and statistical significance of the coefficients are similar across four specifications. The coefficients on DIST and LANG are both statistically significant, and the signs of the coefficients on DIST are negative, while those on LANG are positive. These estimates indicate that American investing firms are less likely to make M&A investments in countries far from the US and in counties where English is not the most common language. This result corresponds to Davies et al. (2018), who analyze a firm's investment mode choice using global transaction data from 2003-2010. They conclude that there are fewer M&A investments as barriers between countries get larger because M&A relies on intra-firm integration. The positive coefficients on GDPPC show that there are more M&A investments in developed countries. Firms in countries with high GDPPC likely have more intangible capital on average, and thus investing firms can easily find target firms in these countries. I also study the effect of institutional restrictions on firms' FDI mode choices using the FDI regulatory restrictiveness index. The statistically significant and negative coefficients on the regulatory index show that tighter restrictions in a destination country deter firms from making M&A investments.[27]

Overall, this analysis suggests that geographic, linguistic, and institutional barriers matter for multinationals in their search for partners with whom to conduct M&A. This could reflect the fact that there is a smaller matching probability between target and acquiring firms, as well as higher search costs, if the barriers between the US and a destination country get larger.

4 A Model of FDI Entry Mode by Multinational Firms

I develop a model to further investigate how intangible capital stock—the main source of firm heterogeneity—affects a firm's FDI mode choice. My static model builds upon Nocke

[27]Trade restrictions affect a country's openness to trade, and both trade and FDI restrictions are closely related (i.e., countries with fewer trade restrictions have fewer FDI restrictions). Once I control for FDI restrictiveness, the FDI regulatory restrictiveness index captures most of the variation that explains institutional barriers, and the coefficients on openness (OPEN) become insignificant.

and Yeaple (2007, 2008), who model a firm's production efficiency as a function of two exogenous parameters.[28] I adapt this framework to consider the effects of firm productivity and intangible capital.[29] Along the lines of Nocke and Yeaple's study, firms can trade one of the parameters—intangible capital—in the merger market, which incentivizes firms to conduct M&A rather than greenfield (GF).

A multinational's search decision is characterized based on the Diamond-Mortensen-Pissarides (DMP) model (Diamond, 1993; Mortensen and Pissarides, 1994). I follow Rhodes-Kropf and Robinson (2008) and David (2021), who analyze domestic M&A activity, to incorporate search frictions into my model of the international merger market. A multinational and its local partner bargain over their surplus from merging. A firm's outside option of conducting M&A is making a GF investment, and the merger gains and acquisition price are endogenously determined depending on the stock of total intangible capital that the acquiring and target firms hold.

One of this paper's main goals is to study how foreign investment affects welfare in an investment-receiving country. I construct a general equilibrium model of host country economies to study these effects. The model endogenously determines wages and the volumes of M&A and GF investment made by multinationals in the host country. Finally, I analyze the social efficiency of the market equilibrium.

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 for their M&A partners, while some of them conduct GF without searching. If multinationals search and find their partners, they can merge with local firms. Multinationals that do not search, as

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

[29] I omit physical capital in my model because it does not affect firms' FDI mode decisions (see Section 3.2).

well as those that fail to search, make GF investments and establish their own affiliates to produce.[30]

I assume host country h is a small open economy, and labor is not mobile across countries.[31] Here, the final good, Y, is traded between s and h, but each intermediate good, y, is not traded. Part of the final good becomes the firm's wage bill and profit. Multinational firms are owned by foreign entities, and the profits are shipped out to source country s, whereas local firms are owned by local entities. Households supply labor and consume the 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 multinationals follows a Pareto distribution. The cumulative distribution function is:

$$G(K) = 1 - K^{-\theta} \quad \text{with support} \quad [\underline{K}, \infty) \quad \text{for} \quad \underline{K} = 1 \quad \text{and} \quad \theta > 1, \tag{2}$$

where θ is a shape parameter. For simplicity, assume that productivity for multinational firm i is constant at the value $\tilde{Z}$.[32]

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.[33]

[30] In other words, I implicitly assume that all firms either pursue greenfield or M&A, and no firm chooses not to invest. This assumption follows from anecdotal evidence that, in the due-diligence phase of a deal, firms that are weighing an M&A investment consider the potential cost of an alternative GF investment as the primary outside option.

[31] 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 recent papers on the small open economy framework in the monopolistic competition setting.

[32] 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 $Tz^{-\theta}$, where T is an exogenous technology parameter.

[33] I choose this assumption because I don't observe the local firm's intangible capital in the data. See Section 7 for potential extensions.

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 matching function:[34]

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

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

$$\begin{aligned} \tilde{\mu}(n) &= \frac{v(N, n)}{n} \\ &= \left(\frac{1}{1 + (n/N)^\rho} \right)^{\frac{1}{\rho}}. \end{aligned} \tag{3}$$

Because $\tilde{\mu}'(n) < 0$, 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 host country h.
(i) Greenfield (GF) Firms: Multinational firm i which either did not search or failed to find a target conducts a GF investment. Unlike physical capital, both productivity, $\tilde{Z}$, and intangible capital, K_i, can easily be replicated and transferred into the new market. Thus, a GF multinational can operate with the same level of production technology as it had before FDI in a host country, h.[35] The production function for GF firm g is

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

[34] 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.

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

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

(ii) Merged Firms: When multinational firm i merges with a local firm, it can take advantage of the acquired firm's intangibles, κ, in production. I assume that a merged firm inherits its acquirer's productivity, $\tilde{Z}$, and both the target's and acquirer's intangible capital, κ and K_i. This assumption is in line with the fact that M&As improve the acquirer's productivity (e.g., Schoar 2002; Li 2013; Dimopoulos and Sacchetto 2017), and the performance of merged firms depends on productivities both of target and acquired firms (Guadalupe et al. 2012; David 2021).[36] The production function for merged firm m is

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

where $\eta \in (0, 1)$. In the post-merger integration process, a multinational will not be able to transfer all of its intangible capital to the new foreign affiliate. For example, some business segments are duplicated between acquiring and target firms, and a multinational uses some part of target firm's intangibles (instead of its intangible capital) in the local market.[37] This imperfect "scalability" in M&A investments is represented by η. Note that the formulation here highlights the difference between technology and intangible capital: technology does not have an additive property (for example, a better management practice prevails within a firm) whereas intangible capital can accumulate within a firm (patents can have independent values; local network and brand name can have separate effects). Let the amount of intangible capital of the merged firm m be $k_m \equiv (\kappa + \eta K_i)$, and its productivity be $\tilde{Z}_m \equiv \tilde{Z}$.

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

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

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

[36] Guadalupe et al. (2012) emphasize two sources of complimentarity (i) between the market size of an acquiring multinational (A in their model) and post-merger innovation, and (ii) between productivity of a target firm (φ in their model) and post-merger innovation. Although this paper is not looking at post-merger innovation, my production function is similar to their variable profit function if I set A as Z (a multinational's TFP) and φ as κ (a local firm's intangibles). Building on Guadalupe et al. (2012), I have an additional source of profitability (ηK_i) transferred from an acquiring multinational to a local target.

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

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. I index firms in the host country after investment by ω. Each firm, ω, is assigned to one of the firm types: M&A firms, m, GF firms, g, or local firms, a. Ω is the set of all of the firms, $\omega \in \Omega$.

The final-good production function is:

$$Y = \left[\int_{\Omega} y_{\omega}^{\frac{\sigma-1}{\sigma}} d\omega \right]^{\frac{\sigma}{\sigma-1}}, \tag{4}$$

where $\sigma > 1$ is the elasticity of substitution.[38]

4.1.5 Households

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

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

4.1.6 Timing

There are four stages in the model:

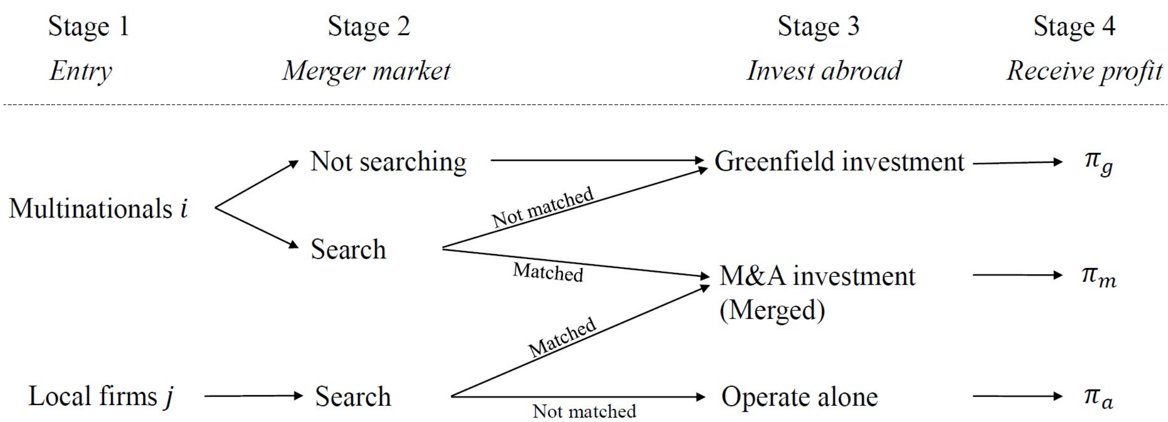
Stage 1: Multinationals in s and local firms in h enter.

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

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

[38] 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" because one firm is negligible with a continuum of firms.

Figure 2: Timing of the Model



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

4.2 Model Solution

To solve the model, I start with the final stage (described in Section 4.1.6) and work backwards.

4.2.1 Profit Maximization (Stage 4)

After multinationals invest in Stage 3, three types of intermediate goods firms exist in country h: merged multinationals, m, greenfield multinationals, g, and local firms which operate 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:

$$\min_{y_\omega} \int_\Omega p_\omega y_\omega d\omega \qquad \text{subject to equation (4).} \tag{5}$$

The unit price of the final output is $\Xi = [\int_\Omega p_\omega^{1-\sigma} d\omega]^{1/(1-\sigma)}$. The final good market is perfectly competitive, and a final good producer can sell any amount of good Y at the market price, Ξ. I use the final good as a numéraire, and normalize Ξ to one.[39] The inverse demand function

[39] 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

for good ω is

$$p_\omega = \left(\frac{Y}{y_\omega}\right)^{1/\sigma}. \tag{6}$$

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

$$\max_{\ell_\omega, p_\omega, y_\omega} p_\omega y_\omega - w\ell_\omega \qquad \text{subject to equations (4) and (6).}$$

w is the wage in the host country. I assume that $\alpha = \sigma/(\sigma-1) - \beta$ (with $0 < \beta \leq 1$). Note that the amount of intangibles, K, is determined exogenously. This assumption is without a loss of generality in the setting here, as one can always change the unit of measurement for K by a monotonic transformation, so that α satisfies this relationship.[40]

Solutions for the labor demand, ℓ_ω, are:

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

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

The profits of each type of entity are:

$$\begin{cases} \pi_m(K_i; w, Y) = \Theta(w,Y)Z(\kappa + \eta K_i) & \text{for merged multinationals,} \\ \pi_g(K_i; w, Y) \ = \Theta(w,Y)ZK_i & \text{for GF multinationals, and} \\ \pi_a(w, Y) \ = \Theta(w,Y)z\kappa & \text{for non-merged local firms,} \end{cases} \tag{8}$$

where $\Theta(w,Y) \equiv \frac{\sigma-(\sigma-1)\beta}{\sigma} Y^{\frac{1}{\sigma}} \tilde{\Theta}(w,Y)^{\frac{\sigma-1}{\sigma}\beta}$. Here, $\tilde{\Theta}(w,Y)$ and $\Theta(w,Y)$ are decreasing in w and increasing in Y, and so do the labor demand and the profits. 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.[41]

traded—I am explicit that intermediate goods are non-tradables and the final good is used for international transactions.

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

[41]Although I set the levels of productivity, Z and z, are constant in this study, if I make the productivity heterogeneous across firms, I can also state that the profit functions show the complementary between two

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). 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 that match with local firms is given by:

$$\begin{aligned}\Sigma(K_i) &= \pi_m(K_i) - \pi_g(K_i) - \pi_a \\ &= \Theta Z(\kappa + \eta K_i) - \Theta Z K_i - \Theta z \kappa \\ &= \Theta\left[(Z - z)\kappa - Z(1-\eta)K_i\right].\end{aligned} \tag{9}$$

Multinationals consummate mergers so long as they have positive merger gains. 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 stocks observe larger marginal benefits from obtaining additional intangibles through M&As, and have a greater incentive to merge. One can also see that the gains from merging are higher if a 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 the sum of the profit of the local firm, π_a, and the target's share of the combined gain, $\chi\Sigma$:

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

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

Using equation (8) and (9),

$$P(K_i) = \Theta z\kappa + \chi\Theta\left[(Z-z)\kappa - Z(1-\eta)K_i\right]. \tag{10}$$

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:

$$\tilde{\mu}(n)\left[\pi_m(K_i) - P(K_i)\right] + (1-\tilde{\mu}(n))\pi_g(K_i) - \psi \geq \pi_g(K_i), \tag{11}$$

that is, its expected net profit from searching (left-hand side) must be higher than its profit from making a GF investment, the outside option from searching (right-hand side).[42]

Using (8) and (10), inequality (11) becomes to

$$\underbrace{\tilde{\mu}(n)(1-\chi)\Theta\left[(Z-z)\kappa - Z(1-\eta)K_i\right]}_{\text{a multinational's expected gain from merging, } (1-\chi)\Sigma} \geq \psi. \tag{12}$$

The left-hand side equation is a multinational's expected gain from merging. A multinational searches for a local partner as far as its expected gain from merging is larger than search costs and that expected gain 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. Further, the above inequality implies that a searching multinational will always obtain a positive gain from merging, which means $(1-\chi)\Sigma \geq 0$ because $\psi > 0$ and $\tilde{\mu}(n) > 0$. Thus, if a multinational firm searches for and finds a target firm, it always conducts M&A.

These findings lead to the following proposition:

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

$$\mu(K^*)(1-\chi)\Theta\left[(Z-z)\kappa - Z(1-\eta)K^*\right] = \psi. \tag{13}$$

[42] For simplicity, I assume that there are no fixed costs associated with making GF. The cost of doing an M&A deal is higher than the cost of doing GF no matter the size (intangible intensity) of the investing firm (Figure B.1). That is, the cost of investing through M&A always exceeds the cost of investing through GF. Multinationals need to pay higher costs in order to obtain additional intangibles from local firms, which in turn generates higher expected gains from M&A than the firm would realize through GF investment.

This condition gives the upper bound of K^* such that $\bar{K}^* = \frac{(Z-z)\kappa}{Z(1-\eta)}$ because $\psi > 0$.

Proof. See Appendix C.1.

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 3.2. 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 $\tilde{\mu}(n)$ as $\mu(K^*)$ because the mass of searching multinationals is now $n = MG(K^*)$. The matching probability, $\mu(K^*)$, is a decreasing function of K^*.

4.2.4 Measures of Firms

I summarize the four types of firms that exist after multinationals invest in terms of the threshold level of intangible capital, K^*:

(i) Multinationals with $K_i \in [\underline{K}, K^*]$ search for local target firms and successfully merge with probability, $\mu(K^*)$. The measure of such M&A firms is $\mu(K^*)MG(K^*)$.

(ii) Multinationals with $K_i \in [\underline{K}, K^*]$ search for local target firms but fail to merge with probability, $1 - \mu(K^*)$. The measure of such GF firms is $[1 - \mu(K^*)]MG(K^*)$.

(iii) Multinationals with $K_i \in [K^*, \infty]$ make GF investment without searching. The measure of such GF firms is $M(1 - G(K^*))$.

(iv) Local firms that have not merged with multinationals operate independently. The measure of such firms is $N - \mu(K^*)MG(K^*)$. The probability that local firms operate alone is $1 - (\mu(K^*)MG(K^*)/N)$.

Using these measures of firms, the share of M&A and GF that a host country receives can be represented as

$$\begin{cases} \text{Share of M\&A} & = \mu(K^*)G(K^*) \\ \text{Share of GF} & = 1 - \mu(K^*)G(K^*). \end{cases}$$

4.3 Characterization of the Equilibrium

I consider the domestic equilibrium in the host country—a country that receives FDI—in this section. I first show that total output, Y, is a function of the wage level, w, and the threshold level of multinational's intangibles, K^*. I then state two conditions, the cutoff condition and the labor market clearing condition, that are satisfied in equilibrium. These two equilibrium conditions uniquely determine w and K^*.

4.3.1 Total Output in the Host Country

Both multinationals and local firms produce in the host country after multinationals invest. From the production function (4), total output is defined as

$$Y = \Bigg\{\mu(K^*)M\int_{\underline{K}=1}^{K^*}[Z^\alpha(\kappa+\eta K)^\alpha \ell_m^\beta]^{\frac{\sigma-1}{\sigma}}dG(K) + (1-\mu(K^*))M\int_{\underline{K}=1}^{K^*}[Z^\alpha K^\alpha \ell_g^\beta]^{\frac{\sigma-1}{\sigma}}dG(K)$$
$$+M\int_{K^*}^{\infty}[Z^\alpha K^\alpha \ell_g^\beta]^{\frac{\sigma-1}{\sigma}}dG(K) + (N-\mu(K^*)MG(K^*))[z^\alpha \kappa^\alpha \ell_a^\beta]^{\frac{\sigma-1}{\sigma}}\Bigg\}^{\frac{\sigma}{\sigma-1}}.$$

Each term on the left-hand side corresponds to the output produced by each type of firm, as defined in Section 4.2.4. Using the labor demand (equation 7), one can solve for Y:

$$Y = \left(\frac{1}{w}\frac{\beta(\sigma-1)}{\sigma}\right)^{\frac{\beta}{1-\beta}} \mathbb{Y}(K^*)^{\frac{\alpha}{1-\beta}}, \tag{14}$$

where

$$\mathbb{Y}(K^*) = \underbrace{Nz\kappa + MZ\int_{\underline{K}=1}^{\infty} K\ dG(K)}_{\text{Baseline productivity}} + \underbrace{\mu(K^*)M\int_{\underline{K}=1}^{K^*}\left[(Z-z)\kappa - Z(1-\eta)\right]KdG(K)}_{\text{Productivity trade-off through M\&A}}.$$

Appendix C.2 provides the detailed derivation.

Equation (14) shows that the aggregate output, Y, is decreasing in the local wage, w, and increasing in the total productivity of the local economy, $\mathbb{Y}(K^*)$. The total productivity consists of two parts. The first two terms of $\mathbb{Y}(K^*)$ represent the baseline level of productivity in the local economy (i.e., the initial productivity of all local firms plus that of all multinationals). If there is no M&A (i.e., when $K^* \to \underline{K}$), all local firms operate independently and all multinationals invest via GF.

The last term of $\mathbb{Y}(K^*)$ is aggregate productivity trade-off through M&A that comes from the measure of M&A multinationals, $\mu(K^*)MG(K^*)$, multiplied by the average change in productivity through M&A, $\int_{\underline{K}=1}^{K^*}[(Z-z)\kappa - Z(1-\eta)K]dG(K)/G(K^*)$. When multinationals conduct M&A, they upgrade locals' intangibles, κ, by exploiting the gap in productivities between multinationals and locals, $(Z-z)$. However, M&A multinationals cannot transfer all of their intangibles to their merged entities, which decreases the combined productivity of acquiring multinationals by $Z(1-\eta)K$.

This productivity trade-off can be positive or negative. When few multinationals conduct M&A (i.e., if K^* is small and the share of GF is large), the positive effect dominates the negative effect, and M&A multinationals continue to upgrade the productivity of the host country until some level of M&A investment, $\hat{K}^*$, where the positive effect is offset by the negative effect. As more multinationals choose M&A (i.e., if K^* is large and the share of GF is small), the negative effect dominates the positive effect, and the total productivity becomes lower than the maximum. This trade-off in the aggregate merger gains provides intuition for the following proposition:

Proposition 2 *The aggregate productivity function in the local economy, $\mathbb{Y}(K^*)$, is concave, and there exists K^* that maximizes the total productivity of the local economy such that $\hat{K}^* = \arg\max_{K^*} \mathbb{Y}(K^*)^{\frac{\alpha}{1-\beta}}$.*

Proof. See Appendix C.3.

When the local economy receives too much M&A (if $\hat{K}^* < K^*$) or too little M&A (if $\hat{K}^* > K^*$), aggregate productivity is less than the maximum possible level. Thus, there exists a certain level of M&A investment that maximizes the total productivity of the host country.

4.3.2 Cutoff Condition

In Section 4.2.3, I showed that there exists a threshold level of intangible capital, K^*, below which a multinational searches for a local target and above which it invests via GF. Because Y is a function of w and K^* (shown in the previous Section 4.3.1), I restate the equation that determines the cutoff level of intangibles (equation 13) with the notation $\Theta(w, K^*)$ instead of $\Theta(w, Y)$. I call the following equation the cutoff condition:

$$\mu(K^*)(1-\chi)\Theta(w, K^*)\left[(Z-z)\kappa - Z(1-\eta)K^*\right] = \psi. \tag{15}$$

4.3.3 Labor Market Clearing

The labor market in the host country is cleared by equating the labor supply (L on the left-hand side) to the aggregate labor demand (shown on the right-hand side). Using the labor demand by each type of firm (equation 7),

$$L = \mu(K^*)M\int_{\underline{K}=1}^{K^*}\tilde{\Theta}(w,Y)Z(\kappa+\eta K)dG(K) + [1-\mu(K^*)]M\int_{\underline{K}=1}^{K^*}\tilde{\Theta}(w,Y)ZKdG(K)$$
$$+ M\int_{K^*}^{\infty}\tilde{\Theta}(w,Y)ZKdG(K) + (N-\mu(K^*)MG(K^*))\tilde{\Theta}(w,Y)z\kappa. \quad (16)$$

The expression for the aggregate labor demand can be defined as $L = \tilde{\Theta}(w,Y)\mathbb{Y}(K^*)$.

Using this expression, total output Y (equation 14) can be represented as:

$$Y = w\frac{\sigma}{\beta(\sigma-1)}L. \quad (17)$$

The function above shows that there exists a one-to-one linear transformation between total output, Y, and real wages, w. To simplify the notation, I will use $\tilde{\Theta}(w)$ in place of $\tilde{\Theta}(w,Y)$ and rewrite the labor market clearing condition as:[43]

$$L = \tilde{\Theta}(w)\mathbb{Y}(K^*), \quad (18)$$

where $\tilde{\Theta}(w)$ is decreasing in w. Based on equations (17) and (18), I present the following lemma:

Lemma 1 *Under the labor market condition, the maximum real wage, w, is achieved if and only if total output, Y, is maximized. Moreover, the maximum total output, Y, is associated with the threshold value, $\hat{K}^*$, which maximizes aggregate productivity, $\mathbb{Y}(K^*)$.*

Proof. See Appendix C.4.

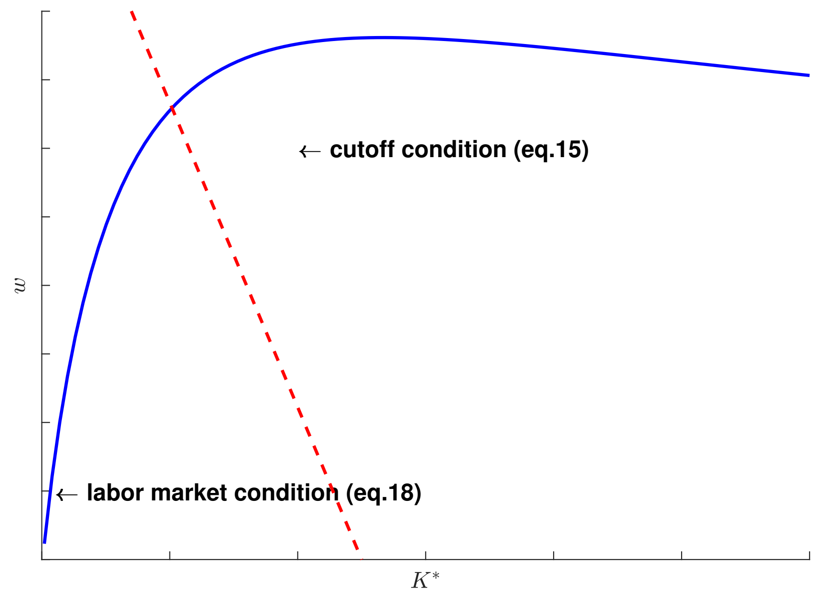
This lemma implies that local policymakers can choose a level of M&A (determined by $\hat{K}^*$) to maximize total output, which improves consumer welfare by maximizing the real wage.

4.3.4 Equilibrium

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

[43] Under the labor market condition, I can use the notation $\tilde{\Theta}(w)$ and $\Theta(w)$ instead of $\tilde{\Theta}(w,Y)$ and $\Theta(w,Y)$. Both terms are decreasing in w. The calculation is in Appendix C.5.

Figure 3: Cutoff and Labor Market Clearing Conditions



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 cutoff condition in equation (15).

(ii) The labor market clearing condition in equation (18).

There are three markets in the host country, h: the final-good market, the intermediate-goods market, and the labor market. The intermediate good market clears such that p_ω and y_ω satisfy the firm's profit maximization problem and the intermediate good demand curve in equation (6). The labor market clears when equation (18) is satisfied. From Walras' Law, the final-good market automatically clears.[44]

Proposition 3 *There exists a unique equilibrium combination of (w, K^*).*

Proof. See Appendix C.5.

Proposition 3 states that the system of two equations, the cutoff condition (equation 18) and the labor market condition (equation 15), has a unique solution. If I plot the two conditions by setting the equilibrium wage level, w, on the y-axis and the threshold level of

[44]The final-good market clearing condition is in Appendix C.6.

intangible capital, K^*, on the x-axis, then the cutoff condition is strictly decreasing and the labor market condition is concave (see Figure 3).

4.4 Efficiency

Recall that wages and the patterns of FDI (i.e., the threshold level of multinationals' intangibles, K^*) are uniquely determined in equilibrium. A multinational is willing to invest via M&A while its net expected gain from merging is positive. However, there is friction in searching for a local partner, and a multinational needs to bargain over the merger gains with a local partner after matching. In this section, I examine whether the equilibrium solution is socially efficient and how the search externalities affect the efficiency of equilibrium. The detailed derivation is in Appendix C.7.

4.4.1 Market Equilibrium Condition

I first state the equation that characterizes the value of K^* in the market equilibrium. The two equilibrium conditions, the cutoff condition (equation 15) and the labor market condition (equation 18), lead to the following equation:

$$\frac{\sigma-(\sigma-1)\beta}{\sigma}\,\mathbb{Y}(K^*)^{\frac{1}{\sigma-1}-\beta}L^{\beta}\mu(K^*)(1-\chi)[(Z-z)\kappa-Z(1-\eta)K^*]=\psi. \tag{19}$$

The threshold level of intangibles, K^*, satisfies the equation above in the market equilibrium.

4.4.2 Socially Optimal Condition

I now consider the social planner's constrained problem. The social planner decides how many multinationals search for their target firms in a host country and the allocation of workers to three types of firms (M&A multinationals, GF multinationals, and local firms) to maximize total output in the host country. The social planner makes these decisions given the labor endowment and the search-matching friction.

The social planner's problem is

$$\max_{K^{**},\ell_\omega}\; Y-MG(K^{**})\psi,$$

subject to the resource constraint, $L=\int \ell_\omega d\omega$. K^{**} is the threshold value of intangibles in the social planner's constrained problem, and total output, Y, is defined in equation (4).

The optimal solution is

$$\frac{\sigma-(\sigma-1)\beta}{\sigma-1}\ \mathbb{Y}(K^{**})^{\frac{1}{\sigma-1}-\beta}L^{\beta}\mu(K^{**})$$
$$\times\left((1-\xi(K^{**}))[(Z-z)\kappa-Z(1-\eta)K^{**}]-\frac{\xi(K^{**})}{G(K^{**})}\int_{\underline{K}}^{K^{**}}[Z(1-\eta)(K^{**}-K)]dG(K)\right)=\psi, \tag{20}$$

where $\xi(K^{**})$ is the elasticity of the matching function:

$$\xi(K^{**})=-\frac{\mu'(MG(K^{**}))MG(K^{**})}{\mu(MG(K^{**}))}.$$

4.4.3 Externalities

I compare the two equations that characterize the volumes of M&A and GF investment in the market equilibrium (K^* in equation 19) and the social optimum (K^{**} in equation 20). The differences between the two equations reveal the four types of externalities.

The first two externalities are the ones defined under the efficiency condition studied by Hosios (1990).[45] The first externality is known as the *congestion externality*. Multinationals decide to search for local firms by looking only at the probability of matching, $\mu(K^*)$ in equation (19), while the social planner cares about the marginal change in the probability of matching, $\mu(K^{**})(1-\xi(K^{**}))$ in equation (20). If the elasticity of the matching function, $\xi(K^{**})$, is high, marginal searching multinationals cause more congestion for other searching firms. This congestion externality makes more multinationals search in the market equilibrium than in the socially optimal situation (i.e., $K^* > K^{**}$).

The second externality is called the *appropriability problem*. This externality occurs as multinationals consider only the fraction $1-\chi$ (the bargaining power of multinationals) of their merger surplus, whereas the social planner evaluates the whole gains from mergers. This externality leads to fewer searching multinationals (i.e., $K^* < K^{**}$).

The other two externalities do not exist in the standard DMP model. The third externality is the additional congestion externality and corresponds to the last term in parentheses in equation (20), $-\frac{\xi(K^{**})}{G(K^{**})}\int_{\underline{K}}^{K^{**}}[Z(1-\eta)(K^{**}-K)]dG(K)$. This term exists because searching multinationals are heterogeneous, and therefore the congestion externality is heterogeneous as well. In particular, a firm with less intangible capital, K, realizes larger gains from merg-

[45] David (2021) develops a search and matching model that describes the US domestic M&A market and highlights the presence of a congestion externality and an appropriability problem by solving a social planner's problem.

ing, $Z(1-\eta)(K^{**}-K)$, and thus suffers from extra losses due to congestion. Multinationals overestimate the benefit of searching compared to the social benefit because of this negative congestion externality, and there will be too many searching multinationals in the market equilibrium (i.e., $K^* > K^{**}$).

The fourth externality comes from the difference between the objective functions of firms and the social planner. In the market equilibrium, each firm maximizes its profit under monopolistic competition, whereas the social planner decides which multinational makes GF or M&A and allocates workers to multinationals and local firms to maximize social welfare. The social planner's allocation decisions are not subject to competition. Specifically, the market equilibrium solution is discounted by $(\sigma-1)/\sigma$ relative to the socially optimal solution (i.e., $K^* < K^{**}$).[46]

Given the above conflicting effects, in equilibrium, the volumes of M&A and GF investment a host country receives may be too high or too low, relative to the social optimum. Additionally, the Hosios condition, $\xi(K^{**}) = \chi$, does not guarantee the efficiency of the market equilibrium because additional externalities exist in my model. This model prediction motivates me to quantitatively analyze the level of social welfare in Section 6.

5 Testing Model Implications

In this section, I aim to empirically test the implications of my stylized general equilibrium model for a host country. Specifically, I examine the relationship between host-country and affiliate-industry characteristics and the probability that multinationals choose M&A. These characteristics include the number of local firms and the level of intangibles of local firms, which might influence a multinational's FDI mode decision.

5.1 Regression Specifications

I rewrite the multinational's net expected gain from merging (equation 12), including the exogenous parameters and the multinational's intangible capital, K_i.[47] For multinational firm i, host country h, and affiliate industry j, the multinational's net expected gain from

[46]The first term of the socially optimal solution (equation 20), $\frac{\sigma-(\sigma-1)\beta}{\sigma-1}$, is from the derivative of total output, Y, with respect to K^{**}. On the other hand, the first term of the market equilibrium condition, $\frac{\sigma-(\sigma-1)\beta}{\sigma}$, comes from $\Theta(w, Y)$, the part of the profit function.

[47]In this equation, I do not consider the number of multinationals, M_{hj}, as an exogenous parameter because the number of multinationals, together with the endogenous K^*, affects the net expected gain from merging by driving the measure of searching multinationals, $M_{hj}G(K^*)$.

merging is

$$\tilde{\Sigma}_{ihj} = \mu(N_{hj})(1-\chi)\Theta\left[(Z^{US} - z_h)\kappa_{hj} - Z^{US}(1-\eta)K_i\right] - \psi_h.$$

If multinationals observe that their net expected gain from merging, $\tilde{\Sigma}$, is positive, they search for local partners; otherwise, they invest via GF without searching. The parameters that vary across country and industry are the number of local firms, N_{hj}, and the average level of local firm intangibles, κ_{hj}. I still assume that the level of productivity (or TFP) of US and local firms, Z^{US} and z_h, and search costs, ψ_h, vary only across countries, not within industries.

Using the data varying across host-country and affiliate-industry, I run linear probability regressions to test the model implication for the multinational's M&A decisions.[48] Specifically, I include the host-country and affiliate-industry variables in equation (1). The sign on the coefficient of multinationals' intangibles, K_i, should be negative, same as the empirical fact in Section 3.2.

I expect the signs of the coefficients both on the number of local firms, N_{hj}, and the level of a local firm's intangibles, κ_{hj}, to be positive. If there are more local firms in a host country, that increases a matching probability, and thus multinationals observe higher expected gains from mergers. Similarly, a higher average level of intangible capital among local firms, κ_{hj}, increases the expected merger gains, making more multinationals search for a local partner.

5.2 Results

As expected, I observe a negative coefficient on multinationals' intangibles, K_i, and positive coefficients on the number of local firms, N_{hj}, and average local firm intangibles, κ_{hj} (columns 1 and 2 of Table 6). All coefficients are significant at least at the 5% level. Moreover, when I instead consider the effect of a host country's total intangible capital stock ($N_{hj} \times \kappa_{hj}$), I again find a positive and significant coefficient.[49]

Additionally, I consider the search costs, ψ_h, that multinationals face when trying to find a local partner with which to pursue an M&A deal. The model implies that the net expected

[48] Although some searching multinationals that do not match with local firms make GF investment instead of M&A, the decision to search is positively correlated with the probability that multinationals choose M&A.

[49] Recall that I only observe the number of local firms and the total amount of intangible stock for a subset of industries and countries. Therefore, the number of observations is significantly smaller than that in the analyses in Section 3. I obtain the number of local firms for 45 OECD countries and the total amount of intangible stock for 23 countries (the UK, Japan, and EU countries). The summary statistics of three industry-country variables are in Appendix B.1.

Table 6: Testing Model Implications: Multinationals' Searching Decisions

Dependent variable: $MA_{i,h,j,t}$	Country-industry variation			Country variation		
	(1)	(2)	(3)	(4)	(5)	(6)
Number of local firms (N_{hj})	0.047***			0.069***		
	(0.016)			(0.013)		
Average local intangibles (κ_{hj})		0.017**			0.041**	
		(0.007)			(0.017)	
Local intangible stock ($N_{hj}\kappa_{hj}$)			0.028**			0.066**
			(0.006)			(0.015)
Distance (ψ_h)				−0.143**	−0.538**	−0.478***
				(0.063)	(0.227)	(0.062)
Intangible capital (K_i)	−0.033**	−0.028***	−0.044***	−0.033**	−0.028*	−0.044***
	(0.013)	(0.011)	(0.013)	(0.014)	(0.016)	(0.014)
Country × Year FE	Yes	Yes	Yes			
Industry Pair FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE				Yes	Yes	Yes
Observations	5,911	3,642	4,878	5,653	3,457	4,676
Adjusted R^2	0.287	0.254	0.267	0.245	0.226	0.243

I control for firm size and efficiency using sales and value-added per worker in all specifications. Other country variables, such as the FDI regulatory restrictiveness index, population, and openness, are included in columns 4-6. I do not include common language (because the UK is only the English-speaking country in my data sample) and GDP per capita (because it is highly correlated with the total intangible stocks). Standard errors are clustered by country and firm. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. All explanatory variables are in logs.

gain from merging decreases in search costs. However, I cannot observe search costs directly. Rather, I use the distance between the US and each host country as a proxy for search costs, similar to my analysis in Section 3.3.[50] Columns 4-6 of Table 6 show that all of the signs on distance are negative and significant, which suggests that, as expected, higher search costs reduce the rate at which multinational firms choose M&A.

Overall, the data support the predictions from my model—namely, (1) multinationals with more intangibles assets are more likely to choose GF; (2) countries with more local firms and higher intangible capital stock are more likely to attract M&A; and (3) higher search costs (i.e., more distant host countries) decrease the rate of M&A investment.[51]

[50] I do not use common language as the indicator of search costs because the UK is only the English-speaking country in the data sample.

[51] I aggregate the data to the country and affiliate-industry level and conduct a similar analysis using the

6 Quantitative Analyses

I match the model to the data to assess how a multinational firm's intangible capital relates to its FDI decision and local welfare in host countries receiving investment. Based on IMF classifications, I divide host countries into two groups: "advanced economies" and "emerging and developing economies." I refer to the former as the North and the latter as the South. The North has historically received more M&A investment than the South, and therefore, the two endogenous parameters, the cutoff level of intangibles and wages, likely differ across these economies. Using calibrated parameters, I analyze the differences between the market equilibrium and the socially optimal FDI patterns in the North and South.

6.1 Fit the Data to the Model

I first analyze the distribution of intangible capital among US investing firms. A large number of studies suggest that the distribution of firm sizes can be characterized by a Pareto distribution.[52] In my US firm-level data, the distribution of firms' intangibles is also skewed right (Figure B.2). I estimate the shape parameter value, θ, following Helpman et al. (2004). Specifically, 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 run an OLS regression of the log of the ranking on the log of the firm's intangible capital.[53] The absolute value of the coefficient is equivalent to the shape parameter. I obtain $\theta = 1.990$ from the whole data, and $\theta^{\mathcal{N}} = 2.197$ and $\theta^{\mathcal{S}} = 2.060$ from firms investing in the North and the South, respectively. A larger parameter indicates that firms' intangible capital is more dispersed for FDI to the North than to the South.

Second, I use the moments I introduced below and set four parameters, ρ, κ, η, and ψ, where the elasticity of the matching function, ρ, the intangible capital of local firms, κ, the friction parameter (i.e., the degree of incomplete transfer of intangibles), η, and the search cost, ψ.

Share of M&A multinationals The first moment is the share of multinational firms

share of M&A. The data also support the model predictions. The results are in Appendix B.5.

[52] For example, Arrighetti et al. (2014) use the data on Italian manufacturing firms and show that the probability of investing in intangibles depends on a firm's size.

[53] Following Helpman et al. (2004) and Eaton et al. (2011), I focus on the upper tail of the distribution when estimating the shape parameter. Specifically, I consider firms within the top 1 percentile, according to Eaton et al. (2011). I also normalize the data by setting the lowest value of intangibles equal to one because I set the scale parameter $\underline{K} = 1$ in the cumulative distribution function, $G(K)$, in equation (2). Each firm's intangibles is weighted by its number of projects.

Table 7: Moments

Moment	Definition	All	North	South
$\mu(K^*)G(K^*)$	Share of M&A multinationals	0.414	0.552	0.198
$\frac{\overline{K}_{MA}}{\overline{K}}$	Mean of M&A firms' intangibles	0.647	0.763	0.554

Notes: The values in the third, fourth, and fifth columns are the moments that I obtained using the whole FDI sample, FDI to the North, and FDI to the South, respectively.

that make M&A investments, which is defined as $\mu(K^*)G(K^*)$ in Section 4.2.4. In my data, more than half of FDI to the North is conducted through M&A, while 20% of FDI to the South has been made by M&A (Table 7). The matching function μ (equation 3) is a function of K^* and other parameters: the elasticity of the matching function ρ, the number of multinationals M, the number of local firms N, and the shape parameter, θ.

Mean of M&A firms' intangibles The second moment describes how much the mean of intangibles among M&A firms deviates from that of all firms.[54] The equation is

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

where the mean of M&A firms' intangibles, $\overline{K}_{MA}$, is divided by the mean of all firms' intangibles, $\overline{K}$. A larger value indicates that firms with larger intangible capital make more M&A investments. M&A firms investing in the North have a higher level of intangibles than those investing in the South (Table 7).

Productivity difference between acquiring and target firms The average profitability of US acquirers is 7.5 times that of US target firms (David, 2021). I assume this same ratio applies to international acquisitions as well. This assumption is consistent with research showing that foreign acquirers are more productive than their domestic targets

[54] I use the mean of intangibles among M&A firms rather than that among GF firms. In the model, the moments relating to GF firms include not only the firms that decide not to search (i.e., firms with $K_i > K^*$) but also the firms that make search efforts and fail to find their M&A partners (i.e., firms with $K_i \leq K^*$). Matching outcomes do not depend on the level of intangible capital that firms exogenously received before investing (i.e., random search), and therefore the moments relating to M&A firms represent the firms only with $K_i \leq K^*$.

(Guadalupe et al., 2012). This relationship is represented in the model as:

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

Average merger premium According to Thomson Reuters (2018), the average world M&A premium in 2017-2018 is 24.6%. The average merger premium is

$$\frac{P(\overline{K}_{MA}) - \pi_a}{\pi_a} = 0.246,$$

where $P(\overline{K}_{MA})$ is the average acquisition price and π_a is the profit of the local firm.

Lastly, I set other parameters, $\{Z, z, L/M, N/M, \sigma, \beta, \chi, L\}$, by normalizing or using values in the literature. First, I set two technology parameters—the technology level in the US, Z, and the technology in host countries, z—using productivity per hour worked from the Penn World Table.[55] I normalize Z to one, and set the average technology level of all host countries, z, to 0.487. Similarly, I set $z^{\mathcal{N}} = 0.717$ for host countries in the North and $z^{\mathcal{S}} = 0.228$ in the South.

I divide both sides of the labor market clearing condition (equation 16) by the number of multinationals, M. Then the left-hand side of the equation, L/M, is the number of employees per multinational, while the right-hand side is the ratio of local firms to multinationals, N/M. I take the number of employees per multinational from my GF dataset and treat the number of FDI projects as a proxy for the number of multinationals, M.[56] To obtain a measure of local firms, N—which is unobservable—I use the US as a baseline.[57] I set $L/M = 161.572$ and $N/M = 5.772$ for the whole sample; $(L/M)^{\mathcal{N}} = 91.347$ and $(N/M)^{\mathcal{N}} = 4.668$ for the North; and $(L/M)^{\mathcal{S}} = 183.944$ and $(N/M)^{\mathcal{S}} = 7.541$ for the South.[58]

[55] The data can be found at the following URL: https://ourworldindata.org/grapher/labor-productivity-per-hour-pennworldtable (last accessed on Sep 17, 2020).

[56] I cannot observe the number of employees across all multinationals — I only observe employment in GF multinationals. I assume that the average multinational employment equals the average employment in GF firms. This follows from my model's assumption that M&A firms would have pursued GF if they had randomly failed to match with a local firm. Thus, GF firms are a suitable counterfactual for M&A firms.

[57] I assume that local firms are similarly sized compared to US multinationals because an acquirer usually buys targets of a similar size. Although the total number of firms is not available for every destination country, I observe the number of listed firms in the World Bank data. Since there is a strong relationship between the number of listed firms and GDP (correlation is 0.97), I project the number of local firms in each destination country using GDP. I use the number of US firms with more than 250 employees (of which there are 26,225 in 2014, according to the Census) as 90% of US multinationals in my dataset have more than 250 employees.

[58] For the whole sample, $N/M = 606.022/104.980$, where the numerator is the average number of FDI

Table 8: Parameter Values

Parameter	Definition	All	North	South
estimated/ calibrated				
θ	Shape parameter of $G(K)$	1.990	2.197	2.060
ρ	Elasticity of the matching function, $\hat{\mu}(K^*)$	0.389	0.651	0.519
κ	Intangible capital of local firms	1.076	1.075	1.045
η	M&A friction	0.769	0.886	0.732
ψ	Search cost	0.014	0.034	1.443
exogenously determined				
z	Technology level in host countries	0.487	0.717	0.228
L/M	Number of employees per multinational	161.572	91.437	183.944
N/M	Number of locals per multinational	5.772	4.668	7.541

Notes: Other exogenously determined parameters are the elasticity of substitution, $\sigma = 6$, the labor share of the production function, $\beta = 0.7$, the bargaining power of local firms, $\chi = 0.51$, and the technology level of US multinationals, $Z = 1$.

For the remaining parameters, I take the elasticity of substitution, σ, from Broda and Weinstein (2006), and the bargaining power of target firms from David (2021): $\sigma = 6$ and $\chi = 0.51$. I also set the labor share in the Cobb-Douglas production function, β, to 0.7.

Using the moments and the exogenously determined parameters, $\{Z, z, L/M, N/M, \sigma, \beta, \chi\}$, I set $\rho = 0.389$, $\kappa = 1.076$, $\eta = 0.769$, and $\psi = 0.020$ for the whole FDI sample. Unfortunately, the average merger premium, a moment that mainly affects the M&A friction, η, is only observable globally, across all worldwide M&A deals. To approximate the M&A friction parameters for the North and the South specifically, $\eta^{\mathcal{N}}$ and $\eta^{\mathcal{S}}$, I decompose the global average using weights given by countries' GDP per capita. This approach builds on the idea that the level of GDP per capita is associated with institutional quality, and the difference in institutional quality between host and source countries affects the profitability of mergers (Chari et al. 2010). For example, countries with higher GDP per capita often have stronger legal institutions that are better able to protect firms' intangible assets in merger contracts.

Using the average difference in GDP per capita between the US and host countries, I set $\eta^{\mathcal{N}} = 0.886$ and $\eta^{\mathcal{S}} = 0.732$.[59] I obtain $\rho^{\mathcal{N}} = 0.651$, $\kappa^{\mathcal{N}} = 1.075$, and $\psi^{\mathcal{N}} = 0.034$ for FDI to

projects, and the denominator is the average number of local firms. Similarly, for the North, $(N/M)^{\mathcal{N}} = 1270.067/272.083$, and for the South, $(N/M)^{\mathcal{S}} = 403.921/53.564$.

[59] The friction parameter, $1 - \eta$, indicates the degree of friction in the merger process, which means that, on average, across my entire sample, 23% of a multinational's intangibles cannot be transferred to its target firm. I project the merger frictions for the North and the South using the difference in GDP per capita between the US and host countries. The differences in GDP per capita are \$34,356 for the whole sample, \$16,994 for the North, and \$39,839 for the South.

Table 9: Market Equilibrium K^* and Social Optimum K^{**}

	North		South	
	K^*	K^{**}	K^*	K^{**}
Share of M&A	0.552	0.558	0.198	0.454
Threshold level of intangibles	2.430	2.528	1.166	1.983

Notes: Market equilibrium K^* and social optimum K^{**} are computed using equations (19) and (20) and calibrated parameters.

the North, and $\rho^{\mathcal{S}} = 0.519$, $\kappa^{\mathcal{S}} = 1.045$, and $\psi^{\mathcal{S}} = 1.443$ for FDI to the South.

The two equilibrium conditions, represented by (15) and (18), along with their associated parameters, determine the two endogenous variables: the threshold value of intangible capital, K^*, and the wage level, w. For all FDI, $K^* = 1.858$ and $w = 0.288$, for FDI to the North, $K^{*\mathcal{N}} = 2.430$ and $w^{\mathcal{N}} = 0.353$, and for FDI to the South, $K^{*\mathcal{S}} = 1.166$ and $w^{\mathcal{S}} = 0.239$. There are fewer searching multinationals in the South than the North (i.e., $K^{*\mathcal{N}} > K^{*\mathcal{S}}$). The matching function parameter in the South is lower than the North, $\rho^{\mathcal{N}} > \rho^{\mathcal{S}}$, because less occurrence of M&As in the South means lower matching probability in the M&A market there. In the South, US acquirers have more opportunities to leverage the difference in productivity between acquirers and targets when they are making M&As (i.e., $Z - z^{\mathcal{S}} = 0.772$ in the South, while $Z - z^{\mathcal{N}} = 0.283$ in the North). The larger expected gain from merging, and the lower probability of matching, create a much higher search cost, which discourages firms from searching for M&A partners in the South.

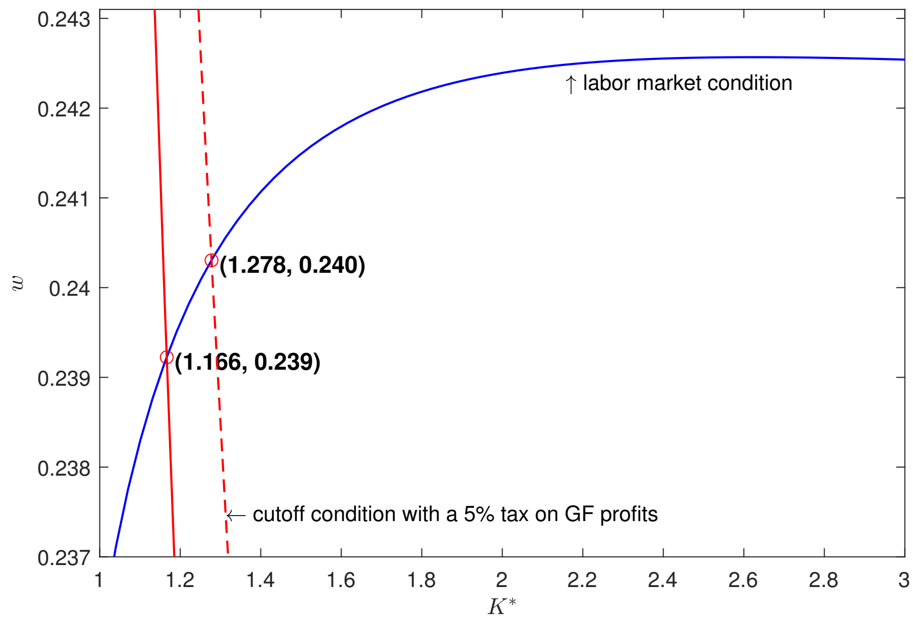
6.2 Policy Implications

In Section 4.4, I showed that the market equilibrium can be socially inefficient, which means that the threshold level of intangibles in market equilibrium, K^*, is different from that in social optimum, K^{**}. Using the calibrated parameters, I compute the socially optimal K^{**} that maximizes social welfare. Table 9 shows the share of M&A received by a host country at the market equilibrium and the socially optimal levels. In the North, the shares of M&A are nearly the same in the market equilibrium and social optimum.[60]

However, in the South, the market equilibrium share of M&A is much lower than the socially optimal value. The gap between the market equilibrium and the social optimum

[60] While in the North there is a small difference between K^* and K^{**}, the market equilibrium and social optimum threshold values of K, the respective M&A shares are almost the identical. This follows from the Pareto distribution of K, and the thin density in the right tail, where K* and K** lie.

Figure 4: Counterfactual Experiment: A 5% Tax on GF Profits in the South



Notes: This figure shows the cutoff conditions without a tax (the red straight line) and with a 5% tax on GF profits (the red dotted line). The labor market and cutoff conditions are plotted using calibrated parameters.

in the South reflects the role of the externalities introduced in Section 4.4.3. In particular, the South has more local firms compared to the North, which generates fewer congestion externalities.

This observation provides insight into how a policymaker can achieve a more efficient allocation of resources. In the South, the market equilibrium leads to fewer M&A deals (or more GF) compared to the social optimum, which suggests that a policymaker in the South can attract more M&A (or restrict GF) to enhance social welfare (i.e., total output minus search costs).[61]

6.2.1 Counterfactual Experiments

I consider the effect of a tax on the profits of GF multinationals in the South. When a multinational decides whether to search for an M&A target, it compares its expected profits from M&A and GF investment. Lower expected profits from choosing GF investment encourage a multinational to instead try to find an M&A partner, resulting in more M&A

[61] One might think that developing economies do not have much potential to receive M&A and a policy to incentivize M&A is unrealistic. However, market entry through M&A is in fact prevalent in the South: in my data, 20% of total FDI in the South is made via M&A. In particular, industries that rely more heavily on intangible capital, such as food manufacturing and wholesale trade, attract more M&A (34% of total FDI in each sector) compared to other industries.

deals and fewer GF investments.[62]

Consider a $\tau\%$ tax on GF profits. The profits of a GF multinational with intangible capital, K_i, are given by:

$$(1-\tau)\pi_g(w, Y, K_i) \; = (1-\tau)\Theta(w, K^*)ZK_i,$$

where $\tau > 0$. A change in GF firms' profits affects the cutoff condition which determines the minimum level of intangible capital whether a multinational firm needs to make an M&A search worthwhile. The cutoff condition (equation 15) becomes

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

This equation reflects the reduction in the expected gain from merging due to the tax of GF profits, τ.

In the experiment, I analyze the effect of a 5% tax on multinationals' GF profits. Figure 4 illustrates that the cutoff condition shifts to the right due to the lower expected gain from merging caused by the tax. As a result, the threshold value of intangibles, K^*, moves closer to its socially optimal level, K^{**}. This shift leads to an increase in total output, Y, which in turn raises real wages, w (as stated in Lemma 1). With the 5% tax on GF profits, real wages increase by 0.45%.

As discussed in Section 4.3.1, the increase in total output, Y, is driven by an increase in aggregate productivity, $\mathbb{Y}(K^*)$. Multinationals that choose M&A over GF as a result of the tax upgrade additional local intangibles, κ by leveraging the productivity gap between multinationals and locals, $(Z-z)$. This mechanism helps increase aggregate productivity, leading to higher real wages, w.

Given this change in wages, I assess the effect of a tax on GF profits on the representative household income (e.g., local welfare). In Section 4.1.5, I define the household income, I, is the sum of wage payments, profits of local firms, and acquisition transfers:

$$I(w, K^*) = wL + [N - \mu(K^*)MG(K^*)]\Theta(w)z\kappa + \mu(K^*)M\int_{\underline{K}=1}^{K^*} P(K)dG(K). \tag{21}$$

[62] It is important to note that in this analysis, I assume that all multinationals invest either through GF or M&A, leaving no possibility for a "free-entry" option. Less productive firms (i.e., firms with fewer intangibles) try to search for their M&A partners and conduct GF investments only if their search is unsuccessful. However, if there is a tax imposed on GF profits, these less-productive firms may not be able to afford pursuing GF due to the increased cost. The results in these policy exercises may represent an upper bound, and the actual welfare effects may be smaller if a "free-entry" option were available to multinationals.

Table 10: Change in Local Welfare: Tax on Profits of GF Multinationals in the South

Welfare	Baseline	1%tax		5%tax	
	Value	Value	Change (%)	Value	Change (%)
Wage payment	44.004	44.044	0.091	44.203	0.452
Profits of local firms	14.309	14.268	−0.287	14.102	−1.446
Acquisition transfer	0.229	0.243	6.402	1.097	34.836
Tax transfer	0	0.096	–	0.667	–
Total	58.542	58.651	0.187	60.069	1.594

Notes: This table shows how welfare changes when there is a 1% and 5% tax on the profits of GF multinationals in the South. I divide both sides of the equation (21) by the number of multinationals, M. The left-hand side, representing local welfare, is then scaled by the number of investing multinationals.

Table 10 shows that the amount of wage payment accounts for the largest share of total local welfare. If the government taxes GF multinationals, both wages and acquisition transfers increase (by 0.452% and 34.836%, respectively, for a 5% tax). By contrast, local firms' profits decline (by 1.446%). The net welfare effect of the tax is positive: the increases in wages and acquisition transfers more than offset the decrease in local profits. Since more local firms will be acquired, households will receive lower profit dividends from local firms. However, the increase in wages and the additional acquisition transfers more than offset this loss, and thus the net effect on welfare will be positive. The government transfers all tax revenue to households.

These policy analyses suggest that a policymaker in the South could increase real wages and local welfare by attracting more M&A. This optimal policy differs from the actual FDI policies pursued by many developing economies, which often prioritize GF over M&A. Governments often assume that GF brings more physical capital and increases labor demand. However, my model emphasizes how M&A expands aggregate productivity. By promoting M&A, policymakers incentivize highly-productive multinationals to utilize local intangible capital, thereby raising aggregate productivity relative to the laissez-faire outcome. Thus, this paper highlights the importance of receiving M&A for a host country, particularly by focusing on the role of intangible capital in driving productivity growth.

7 Conclusion

This paper investigates the determinants of firm FDI entry mode choice and how that choice affects welfare in investment-receiving countries. To do so, I first construct a novel dataset and empirically show that firms with less intangible capital are more likely to make M&A investments, whereas those with more intangible capital are more likely to choose GF. Motivated by this new empirical fact, I build a general equilibrium search 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 firms with lower intangible capital tend to choose M&A, which is consistent with the empirical results.

Furthermore, I show that equilibrium FDI patterns can be suboptimal because of search externalities. This motivates me to calibrate model parameters and assess the welfare effects of changes in FDI patterns in investment-receiving countries. Notably, this study demonstrates that policies restricting GF investments raise real wages and total welfare in developing economies (i.e., the South), primarily by enhancing aggregate productivity.

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

References

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

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

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

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

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

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

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

[8] Broda, Christian, and David E. Weinstein. "Globalization and the Gains from Variety." *Quarterly Journal of Economics* 121, no. 2 (2006): 541-585.

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

[10] Caves, Richard E. *Multinational Enterprise and Economic Analysis.* Cambridge university press, 1996.

[11] Chari, Anusha, Paige P. Ouimet, and Linda L. Tesar. "The value of control in emerging markets." *Review of Financial Studies* 23, no. 4 (2010): 1741-1770.

[12] Coşar, A. Kerem, and Banu Demir. "Shipping inside the box: Containerization and trade." *Journal of International Economics* 114 (2018): 331-345.

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

[14] Crouzet, Nicolas, Janice C. Eberly, Andrea L. Eisfeldt, and Dimitris Papanikolaou. "The Economics of Intangible Capital." *Journal of Economic Perspectives* 36, no. 3 (2022): 29-52.

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

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

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

[18] Den Haan, Wouter J., Garey Ramey, and Joel Watson. "Job destruction and propagation of shocks." *American Economic Review* 90, no. 3 (2000): 482-498.

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

[20] Diamond, Peter A. "Search, sticky prices, and inflation." *Review of Economic Studies* 60, no. 1 (1993): 53-68.

[21] Díez, Federico J., and Alan C. Spearot. "Core competencies, matching and the structure of foreign direct investment." *Canadian Journal of Economics* 47, no. 3 (2014): 813-855.

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

[23] Dunning, John H. "Toward an eclectic theory of international production: Some empirical tests." *Journal of International Business Studies* 11 (1980): 9-31.

[24] Eaton, Jonathan, Samuel Kortum, and Francis Kramarz. "An anatomy of international trade: Evidence from French firms" *Econometrica* 79, no. 5 (2011): 1453-1498.

[25] Ewens, Michael and Peters, Ryan H and Wang, Sean. "Acquisition Prices and the Measurement of Intangible Capital." *NEBR working paper* 25960 (2020).

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

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

[28] Head, Keith, and John Ries. "FDI as an outcome of the market for corporate control: Theory and evidence." *Journal of International Economics* 74, no. 1 (2008): 2-20.

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

[30] Hosios, Arthur J. "On the efficiency of matching and related models of search and unemployment." *Review of Economic Studies* 57, no. 2 (1990): 279-298.

[31] İmrohoroğlu, Ayşe, and Şelale Tüzel. "Firm-level productivity, risk, and return." *Management Science* 60, no. 8 (2014): 2073-2090.

[32] Keller, Wolfgang, and Stephen Yeaple. "The gravity of knowledge." *American Economic Review* 103, no. 4 (2013): 1414-1444.

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

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

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

[36] Martincus, Christian Volpe, and Monika Sztajerowska. "How to Solve the Investment Promotion Puzzle: A mapping of investment promotion agencies in Latin America and the Caribbean and OECD countries." Vol. 735. Inter-American Development Bank, 2019.

[37] McGrattan, Ellen R., and Edward C. Prescott. "Openness, technology capital, and development." *Journal of Economic Theory* 144, no. 6 (2009): 2454-2476.

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

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

[40] Mortensen, Dale T., and Christopher A. Pissarides. "Job creation and job destruction in the theory of unemployment." *Review of Economic Studies* 61, no. 3 (1994): 397-415.

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

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

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

[44] OECD. *Mapping of investment promotion agencies in OECD countries.* OECD, 2018.

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

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

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

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

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

[50] Rhodes-Kropf, Matthew, and David T. Robinson. "The market for mergers and the boundaries of the firm." *Journal of Finance* 63, no. 3 (2008): 1169-1211.

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

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

[53] Thomson Reuters. *Mergers & Acquisitions Review.* 2018.

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

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

[56] UNCTAD. *World Investment Report 2019.* 2019.

[57] World Bank. *Global Investment Competitiveness Report 2017/2018: Foreign Investor Perspectives and Policy Implications.* (2017).

Appendix A Data Appendix

I provide a detailed explanation of how to treat the three main datasets that I described in Section 2.1.

A.1 Greenfield Projects (fDi Market)

- The database provides source and destination locations at the city level. If a company made more than one investment in several cities (in the same country) on the same project date, these investments are recorded as different investments in the fDi Market database. I aggregated these investments.

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

A.2 Cross-border M&A Deals (SDC Platinum)

- There are mainly two dates concerning completed M&A deals: one is "date announced" and the other is "date effective" (i.e., completion date). fDi Market provides "project date" which indicates the month when the GF project started and does not provide information about 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 was started.

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

- The information of the acquisition share 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 businesses takes place, or 100% of the stock of a public or private company is acquired.
  - ACQUISITION: A deal in which 100% of a company is spun off or split off is classified as an acquisition by shareholders.

- ACQ OF MAJORITY INTEREST: An 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: A deal in which the acquirer holds over 50% and is seeking to acquire 100% of the target company's stock.

- I delete the deals with targets or acquirers in the following three-digit SDC Platinum NAICS codes (i.e., deals that involve investing funds and also government related agencies):
  - 523: Securities, Commodity Contracts, and Other Financial Investments and Related Activities
  - 525: Funds, Trusts, and Other Financial Vehicles
  - BCC: Blank Check Company, Sovereign Wealth Fund, Infrastructure Fund, Hedge Fund, and Financial Sponsor.
  - AAA: EU organizations and Bodies, Public Enterprise and Authority, Non-government Agency, City Agency, City Government, Regional/State Agency, Regional/State Government, National Government Agency, and National Government
  - 999: Non-government Agencies, City Agency, City Government, Regional Agency, Regional Government, National Government Agency, and National Government

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

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 the 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 a six-year period.

- Since the industry classification both in SDC Platinum and fDi Market databases are NAICS 2007, I changed NAICS codes in Compustat from 2017 NAICS to 2007 NAICS using historical NAICS codes (Compustat item *naicsh*). If the historical codes are missing, I checked their NAICS 2007 codes manually.

- Compustat assigns industry code 9999 (unclassified establishment) to some firms, and the code 9999 does not exist in the 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.

Appendix B Additional Figures and Tables

B.1 Summary Statistics of Host Country Variables

Table B.1 shows the summary statistics of variables in host countries. The mean of average local intangible capital stock is smaller than multinationals' intangible capital stock (shown in Table 1). Local intangible capital stock includes non-multinational firms (small and medium-sized firms).

Table B.1: Summary Statistics (Local Firms' Variables)

Variable	mean	s.d.	min	max	Number of observations
Number of local firms	10.451	2.081	2.079	14.824	6,581
Average local intangibles	11.817	1.588	6.053	19.043	4,127
Local intangible stock	22.500	1.649	14.164	25.168	5,440

Notes: The number of local firms is from the SDBS Structural Business Statistics, and the total intangible stock is from the EUKLEMS & INTANProd database. Both variables are at the host country-affiliate industry level. The unit of intangible stock is a million USD. All variables are in logs.

B.2 Subsequent Investments

Table B.2 shows the relationship between the entry mode in the first FDI and that in the subsequent FDIs made in the same country and industry. There are 9,163 first GF deals, and 6,595 first M&A deals in firm-affiliate industry-country. 96% of GF investments were never followed up by M&A, and 95% of M&A investments were never followed up by GF.

Table B.2: Entry Modes in Additional Investments

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

Notes: This table shows the types of investment in the subsequent FDI for firms that made GF and M&A in their first investment.

B.3 FDI destinations of US multinationals

This table shows the five major FDI destinations in terms of the number of FDI investments they received between 2003 and 2018. China and India attract more GF investments, while the UK, Canada, and Germany attract cross-border M&A.

Table B.3: Top Five FDI destinations

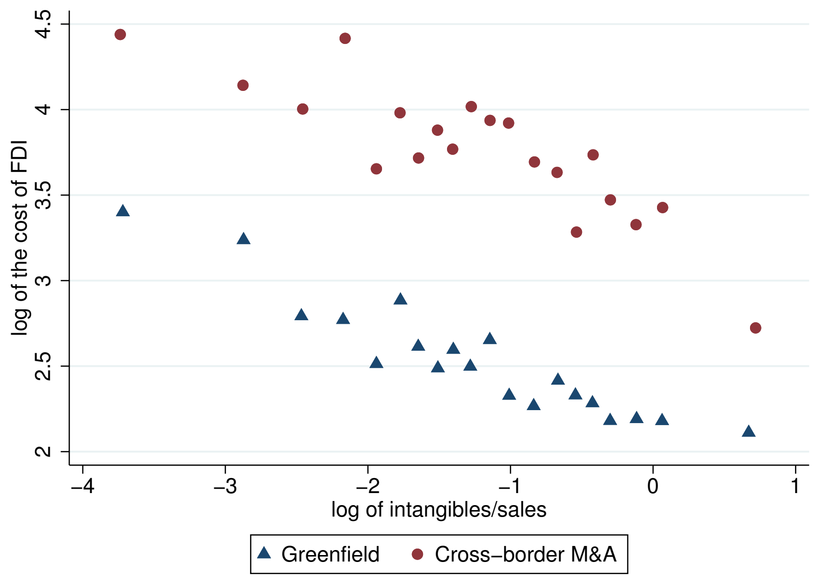
	All		GF		M&A	
Rank	Country	Share (%)	Country	Share (%)	Country	Share (%)
1	UK	10.2	China	9.0	UK	16.7
2	Canada	7.8	India	6.6	Canada	14.3
3	China	6.3	UK	5.6	Germany	8.0
4	Germany	5.5	Germany	3.8	Australia	4.6
5	India	4.9	Singapore	3.7	France	4.4

Notes: This table shows the five most common FDI destinations of US multinational firms. I rank the countries in terms of the number of FDI investments they received between 2003 and 2018. The first two columns show the names of host countries and the share of all FDI investments by US-listed firms that went to that location. The following columns show the same information by spiting FDI into GF investment and cross-border M&A.

B.4 Costs for GF and M&A

Figure B.1 is the bin-scatter plot on the log of the cost of FDI (in the y-axis) and the log of intangible capital intensity (the ratio of intangible capital to sales in the x-axis). I observe that M&A firms spend more than GF firms for any size of intangible intensity.

Figure B.1: Costs for FDI and Intangible Capital Intensity



Notes: The vertical axis shows the costs of investment, and the horizontal axis shows the ratio of intangible capital to sales. The cost of GF is the amount of capital investment (that comes from the fDi market database), and the cost for M&A is the acquisition price (that comes from the SDC Platinum database). This figure is a binned scatter plot. The data space is partitioned into rectangular bins and compute the mean of the variables in the horizontal and vertical axes within each bin. I then create a scatter plot of these data points.

B.5 Testing Model Implications: Share of M&A

I test model implications using the share of M&A. The share of M&A can be represented using the measure of firms defined in Section 4.2.4:

$$MA\text{-}share = \mu(K^*)G(K^*),$$

where K^* is the threshold level of multinationals' intangibles. Here, I aggregate the data to the host-country-affiliate-industry level. The exogenous parameters that I considered in Section 5, $\{N_{hj}, \kappa_{hj}, \psi_h\}$, affect the share of M&A investment, $MA\text{-}share_{hj}$, through K^*. Taking derivatives of $MA\text{-}share_{hj}$ with respect the exogenous parameters, I expect signs on each coefficient: $\frac{\partial MA\text{-}share_{hj}}{\partial N_{hj}} > 0$, $\frac{\partial MA\text{-}share_{hj}}{\partial \kappa_{hj}} > 0$, $\frac{\partial MA\text{-}share_{hj}}{\partial N_{hj}\kappa_{hj}} > 0$, and $\frac{\partial MA\text{-}share_{hj}}{\partial \phi_h} < 0$.

Table B.4: Testing Model Implications: Share of M&A

Dependent variable: $MA\text{-}share_{hj}$	Country-industry variation			Country variation		
	(1)	(2)	(3)	(4)	(5)	(6)
Number of local firms (N_{hj})	0.028**			0.048***		
	(0.014)			(0.015)		
Average local intangibles (κ_{hj})		0.017***			0.089***	
		(0.007)			(0.023)	
Local intangible stock ($N_{hj}\kappa_{hj}$)			0.045**			0.122***
			(0.011)			(0.020)
Distance (ψ_h)				−0.118**	−0.611**	−0.570***
				(0.059)	(0.244)	(0.102)
Country FE	Yes	Yes	Yes			
Affiliate-industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	789	378	436	750	352	408
Adjusted R^2	0.498	0.542	0.508	0.360	0.469	0.457

Notes: Other country variables, such as the FDI regulatory restrictiveness index, population, and openness, are included in columns 4-6. I do not include common language (because the UK is only the English-speaking country in my data sample) and GDP per capita (because it is highly correlated with the total intangible stocks). Standard errors are clustered by country and affiliate-industry. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. All explanatory variables are in logs.

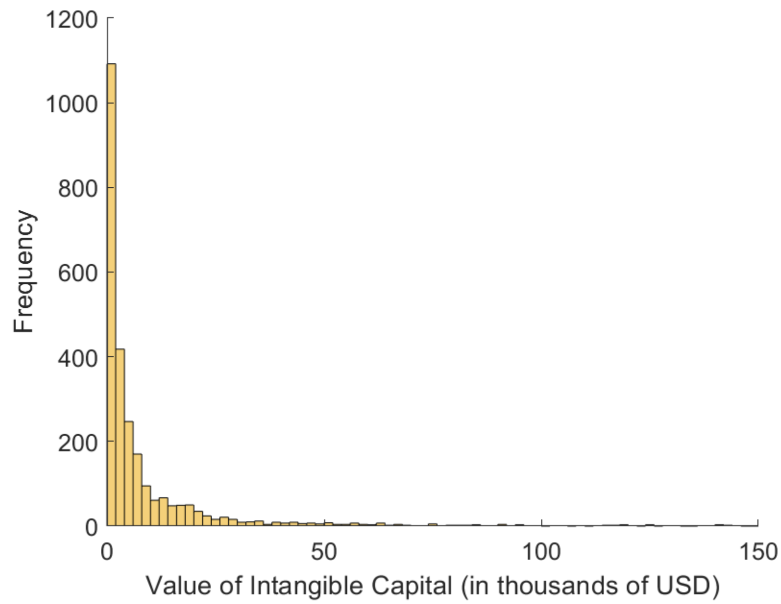
I regress the share of M&A, $MA\text{-}share_{hj}$, on each of the exogenous parameters, N_{hj}, κ_{hj} and $N_{hj}\kappa_{hj}$, together with country and affiliate industry fixed effects. Columns 1-3 of Table B.4 show that each of the coefficients has the same sign indicated by the partial derivative.

I include distance and other country variables instead of using country fixed effects in the specifications of columns 4-6. I observe the negative signs on distance, which corresponds to the sign of the partial derivative.

B.6 Distribution of Intangible Capital in Section 6

Figure B.2 shows the histogram of US investing firm's intangible capital. The distribution of intangible capital is skewed to the right.

Figure B.2: Distribution of Firms' Intangible Capital



Notes: Each bin has a width of 10 thousand dollars. The vertical axis shows the number of observations that fall in each bin. Each firm's intangible capital is weighted by the number of projects and I plot firms less than the 98 percentile.

Appendix C Detailed Calculations

C.1 Proof for Equation (13)

The derivative of the left-hand side of equation (13) with respect to K^* is:

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

Because $\frac{\partial \mu(K^*)}{\partial K^*} < 0$ and the second term is negative, the left-hand side of equation (13) is decreasing in K^*. The right-hand side of equation (13) is constant as $\psi > 0$, and therefore there exists the threshold level of intangible capital, K^*. If multinational's intangible capital, K_i, is lower than the cutoff, K^*, the search condition, equation (12), holds. Such multinational obtains the positive merger gain. Thus, a multinational firm with $K_i < K^*$ will search and consummate the M&A.

Since $\psi > 0$, the right-hand side of equation (13) should be positive. This provides an upper bound of K^* such that $\bar{K}^* = \frac{(Z-z)\kappa}{Z(1-\eta)}$.

C.2 Solution for Y

From equation (4): $Y = \left[\int_\Omega y_\omega^{\frac{\sigma-1}{\sigma}} d\omega\right]^{\frac{\sigma}{\sigma-1}}$,

$$\begin{aligned}
Y^{\frac{\sigma-1}{\sigma}} &= \int_\Omega y_\omega^{\frac{\sigma-1}{\sigma}} d\omega \\
&= \mu(K^*)M\int_{\underline{K}=1}^{K^*}[Z^\alpha(\kappa+\eta K)^\alpha \ell_m^\beta]^{\frac{\sigma-1}{\sigma}} dG(K) + (1-\mu(K^*))M\int_{\underline{K}=1}^{K^*}[Z^\alpha K^\alpha \ell_g^\beta]^{\frac{\sigma-1}{\sigma}} dG(K) \\
&\quad + M\int_{K^*}^{\infty}[Z^\alpha K^\alpha \ell_g^\beta]^{\frac{\sigma-1}{\sigma}} dG(K) + (N-\mu(K^*)MG(K^*))[z^\alpha \kappa^\alpha \ell_a^\beta]^{\frac{\sigma-1}{\sigma}}. \\
&= \left(\frac{1}{w}\frac{\beta(\sigma-1)}{\sigma}\right)^{\beta/\alpha} Y^{\beta/\sigma\alpha}\left\{\mu(K^*)MZ\int_{\underline{K}=1}^{K^*}(\kappa+\eta K)\ dG(K) + (1-\mu(K^*))MZ\int_{\underline{K}=1}^{K^*} K\ dG(K)\right. \\
&\quad \left. + MZ\int_{K^*}^{\infty} K\ dG(K) + (N-\mu(K^*)MG(K^*))z\kappa\right\},
\end{aligned}$$

where I use the labor demand (equation 7) in the third equality. This becomes

$$Y^{\frac{\sigma-1}{\sigma}-\frac{\beta}{\sigma\alpha}} = \left(\frac{1}{w}\frac{\beta(\sigma-1)}{\sigma}\right)^{\beta/\alpha}\mathbb{Y}(K^*),$$

where

$$
\begin{aligned}
\mathbb{Y}(K^*) = {} & \mu(K^*)MZ\int_{\underline{K}=1}^{K^*}(\kappa+\eta K)\ dG(K)+(1-\mu(K^*))MZ\int_{\underline{K}=1}^{K^*}K\ dG(K) \\
& + MZ\int_{K^*}^{\infty}K\ dG(K)+(N-\mu(K^*)MG(K^*))z\kappa \\
= {} & Nz\kappa+MZ\int_{\underline{K}=1}^{\infty}k\ dG(K)+\mu(K^*)MG(K^*)\left[(Z-z)\kappa-Z(1-\eta)\int_{\underline{K}=1}^{K^*}K\ \frac{1}{G(K^*)}\ dG(K)\right].
\end{aligned}
$$

Thus, $Y=\left(\frac{1}{w}\frac{\beta(\sigma-1)}{\sigma}\right)^{\frac{\beta}{1-\beta}}\mathbb{Y}(K^*)^{\frac{\alpha}{1-\beta}}$. This shows that the aggregate output, Y, is a function of w and K^*.

C.3 Proof for Lemma 1

$$
\begin{aligned}
\frac{\partial\mathbb{Y}(K^*)}{\partial K^*} = {} & \frac{\partial\mu(K^*)}{\partial K^*}MG(K^*)\left[(Z-z)\kappa-Z(1-\eta)\int_{\underline{K}=1}^{K^*}K\ \frac{1}{G(K^*)}\ dG(K)\right] \\
& + \mu(K^*)Mg(K^*)[(Z-z)\kappa-Z(1-\eta)K^*]. \\
= {} & \mu(K^*)Mg(K^*)\left\{-\frac{(MG(K^*)/N)^\rho}{1+(MG(K^*)/N)^\rho}\left[(Z-z)\kappa-Z(1-\eta)\int_{\underline{K}=1}^{K^*}K\ \frac{1}{G(K^*)}\ dG(K)\right]\right. \\
& \left. +[(Z-z)\kappa-Z(1-\eta)K^*]\right\}.
\end{aligned}
$$

$\frac{(MG(K^*)/N)^\rho}{1+(MG(K^*)/N)^\rho}\in(0,1)$ and $K^*>E[K^*]=\int_{\underline{K}=1}^{K^*}K\ \frac{1}{G(K^*)}\ dG(K)$. This gives $\frac{\partial\mathbb{Y}(K^*)}{\partial K^*}>0$ if $K^*\to 1$, and $\frac{\partial\mathbb{Y}(K^*)}{\partial K^*}<0$ if $K^*\to\bar{K}^*=\frac{(Z-z)\kappa}{Z(1-\eta)}$. Thus, $\mathbb{Y}(K^*)$ is a concave function. Since $\mathbb{Y}(K^*)$ is continuous, there exists $\hat{K}^*$ that maximizes $\mathbb{Y}(K^*)$ and also the aggregate output Y.

C.4 Proof for Lemma 1

According to equations (17) and (18), there exist one-to-one positive linear relationships between total output, Y, and real wages, w, and between real wages, w and aggregate productivity, $\mathbb{Y}(K^*)$, respectively. Therefore, if total output, Y, is maximized, it implies that real wages, w, are also maximized. Furthermore, the threshold value, $\hat{K}^*$, that maximizes aggregate productivity, $\mathbb{Y}(K^*)$, corresponds to the maximum total output, Y. This completes the proof.

C.5 Proof for Proposition 3

Before showing the existence and uniqueness, I show $\tilde{\Theta}(w)$ and $\Theta(w)$ are decreasing in w. In Section 4.3.3, I show that under the labor market condition, total output, Y, is a function only of w. Inserting $Y = w\frac{\sigma}{\beta(\sigma-1)}L$ into $\tilde{\Theta}(w, Y) \equiv \left[\frac{Y^{1/\sigma}}{w}(\beta(\sigma-1)/\sigma)\right]^{\frac{\sigma}{(1-\beta)\sigma+\beta}}$ (from equation 7) and $\Theta(w, Y) \equiv \left(w\frac{(1-\beta)\sigma+\beta}{\beta(\sigma-1)}\right)\tilde{\Theta}(w, Y)$ (from equation 8) gives $\tilde{\Theta}(w) = \Phi w^{-u}$ and $\Theta(w) = \frac{\Phi}{\beta u}w^{1-u}$ where $u = \frac{\sigma-1}{(1-\beta)\sigma+\beta}$ and $\Phi = L^{\frac{u}{\sigma-1}}(\beta(\sigma-1)/\sigma)^u$. Since $\Phi > 0$ and $u > 0$, $\tilde{\Theta}(w)$ is decreasing in w. $\Theta(w)$ is decreasing in w if $u > 1 \leftrightarrow \sigma > (1+\beta)/\beta$. I assume $u > 1$ in the following proof.

Existence: I restate the cutoff condition (equation 15) using $\Theta(w) = \frac{\Phi}{\beta u}w^{1-u}$

$$w^{u-1} = \frac{(1-\chi)\Phi\mu(K^*)\left[(Z-z)\kappa - Z(1-\eta)K^*\right]}{\psi\beta u}. \tag{C.1}$$

$\mu(K^*)$ has a property that it is decreasing in K^*, and it takes $\mu(K^*) = 1$ when $K^* = \underline{K} = 1$ and $\lim_{K^*\to\infty} = \underline{\mu}$ where μ is the minimum value of $\underline{\mu}$. Thus, the right-hand side of equation C.1 is decreasing in K^*, and there exists $\bar{w} > 0$ and $\bar{K}^* > 0$ such that $w = \bar{w}$ when $K^* = \underline{K}$ and $w = 0$ when $K^* = \bar{K}^*$.

Using $\tilde{\Theta}(w) = w^{-u}\Phi$, the labor market condition (equation 18) is

$$w^u = \frac{\Phi}{L}\mathbb{Y}(K^*), \tag{C.2}$$

where $\mathbb{Y}(K^*)$ is defined by equation (14). $\mathbb{Y}(K^*)$ is a concave function (as I showed in proposition 2) and finite for any $K^* \geq 1$, and thus there exists $w > 0$ that solves this equation. To show the existence, it is sufficient to show that the solution to this equation when $K^* = \underline{K}$ is lower than $\bar{w}$. Whether this is the case depends on parameter values. In particular, it is straightforward to see that it is the case when ψ is sufficiently small (i.e., when $\bar{w}$ is large) or L is sufficiently large (i.e., the solution to this equation when $K^* = \underline{K}$ is small).

Uniqueness: To show the uniqueness, it is sufficient to show that the slope of the cutoff condition (equation C.1) is smaller (more negative) than the slope of the labor market condition (equation C.2) at the point where these two equations cross. The slope of equation

C.1, $\frac{\partial w}{\partial K^*}$, is

$$\frac{1}{u-1}\left\{\left(\frac{(1-\chi)\hat{\mu}(K^*)[(Z-z)\kappa-Z(1-\eta)K^*]}{\psi}\right)^{\frac{1}{u-1}-1}\left(\frac{(1-\chi)\hat{\mu}'(K^*)[(Z-z)\kappa-Z(1-\eta)K^*]}{\psi}\right)\right.$$
$$\left.-\left(\frac{(1-\chi)\hat{\mu}(K^*)[(Z-z)\kappa-Z(1-\eta)K^*]}{\psi}\right)^{\frac{1}{u-1}-1}\left(\frac{(1-\chi)\hat{\mu}(K^*)Z(1-\eta)}{\psi}\right)\right\}.$$

The second term is negative, so it is sufficient to show that the first term is sufficiently small. Using equation C.1, the first term can be written as

$$\frac{w}{u-1}\frac{\hat{\mu}'(K^*)}{\hat{\mu}(K^*)}.$$

Next, the slope of equation C.2 is

$$\frac{w}{u}\frac{\hat{\mu}'(K^*)MG(K^*)[(Z-z)\kappa-Z(1-\eta)\int_{\underline{K}=1}^{K^*}K\ \frac{1}{G(K^*)}\ dG(K)]+\hat{\mu}(K^*)Mg(K^*)[(Z-z)\kappa-Z(1-\eta)K^*]}{Nz\kappa+MZ\int_{\underline{K}=1}^{\infty}k\ dG(K)+\mu(K^*)MG(K^*)\left[(Z-z)\kappa-Z(1-\eta)\int_{\underline{K}=1}^{K^*}K\ \frac{1}{G(K^*)}\ dG(K)\right]}$$

Since the second term of the numerator is positive, it is sufficient to show that the above value is sufficiently large even without it. Now our task is to show that

$$\frac{w}{u}\frac{\hat{\mu}'(K^*)MG(K^*)[(Z-z)\kappa-Z(1-\eta)\int_{\underline{K}=1}^{K^*}K\ \frac{1}{G(K^*)}\ dG(K)]}{Nz\kappa+MZ\int_{\underline{K}=1}^{\infty}k\ dG(K)+\mu(K^*)MG(K^*)\left[(Z-z)\kappa-Z(1-\eta)\int_{\underline{K}=1}^{K^*}K\ \frac{1}{G(K^*)}\ dG(K)\right]}$$

is larger than

$$\frac{w}{u-1}\frac{\hat{\mu}'(K^*)}{\hat{\mu}(K^*)}.$$

We can rewrite the former equation as

$$\frac{w}{u}\frac{\hat{\mu}'(K^*)}{\hat{\mu}(K^*)}\frac{Q}{Q+S},$$

where Q is the numerator value and $S=Nz\kappa+MZ\int_{\underline{K}=1}^{\infty}k\ dG(K)$. Because $Q>0$ and $S>0$, $\frac{Q}{Q+S}\in(0,1)$. Thus,

$$\frac{w}{u}\frac{\hat{\mu}'(K^*)}{\hat{\mu}(K^*)}\frac{Q}{Q+S}>\frac{w}{u-1}\frac{\hat{\mu}'(K^*)}{\hat{\mu}(K^*)}.$$

Note that both sides in the inequality are negative since $\hat{\mu}'(K^*)<0$.

C.6 Total Expenditure

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

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

$$I(w, K^*) = wL + [N - \mu(K^*)MG(K^*)]\Theta(w)z\kappa + \mu(K^*)M \int_{\underline{K}=1}^{K^*} P(w, K)dG(K)$$

The final good market clears such that:

$$\begin{aligned} Y(w, K^*) = I(w, K^*) &+ \mu(K^*)M \int_{\underline{K}}^{K^*} \Theta(w)Z(\kappa + \eta K)dG(K) \\ &+ [1 - \mu(K^*)]M \int_{\underline{K}}^{K^*} \Theta(w)ZKdG(K) + M \int_{K^*}^{\infty} \Theta(w)ZKdG(K) + MG(K^*)\psi, \end{aligned}$$

where $I(w, K^*)$ is defined above. The second, third, and fourth terms represent the profits of M&A and GF firms, and they are repatriated to source country s. The last term is search costs.[63]

C.7 Efficiency

C.7.1 Market Equilibrium K^*

The cutoff condition (equation 15) is

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

where $\Theta(w, Y) = \frac{\sigma-(\sigma-1)\beta}{\sigma} Y^{\frac{1}{\sigma}} \tilde{\Theta}(w, Y)^{\frac{\sigma-1}{\sigma}\beta}$. Using $\tilde{\Theta}(w, Y) = \left[\frac{Y^{1/\sigma}}{w}(\beta(\sigma - 1)/\sigma)\right]^{\frac{\sigma}{(1-\beta)\sigma+\beta}}$ and $Y = \left(\frac{1}{w}\frac{\beta(\sigma-1)}{\sigma}\right)^{\frac{\beta}{1-\beta}} \mathbb{Y}(K^*)^{\frac{\alpha}{1-\beta}}$ (equation 14), $Y^{1/\sigma} = \tilde{\Theta}^{\beta/\sigma}\mathbb{Y}(K^*)^{\frac{1}{\sigma-1}}$. With this function of

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

$Y^{1/\sigma}$ and $L = \tilde{\Theta}(w)\mathbb{Y}(K^*)$ (the labor market clearing condition, equation 18), I can set the following equation that K^* satisfies in equilibrium:

$$\frac{\sigma - (\sigma - 1)\beta}{\sigma}\ \mathbb{Y}(K^*)^{\frac{1}{\sigma-1}-\beta} L^{\beta} \mu(K^*)(1-\chi)[(Z-z)\kappa - Z(1-\eta)K^*] = \psi.$$

Using equations (7) and (18), the labor demand for each type of firms can be represented as $\ell_\omega = \frac{L Z_\omega K_\omega}{\mathbb{Y}(K^*)}$ in equilibrium.

C.7.2 Social Planner's Problem

I solve the social planner's problem:

$$\max_{\hat{K}, \ell_\omega}\ Y - MG(\hat{K})\psi,$$

subject to the resource constraint, $L = \int \ell_\omega d\omega$. The problem can be divided into two steps: (i) the search decision and (ii) the allocation of workers given the search outcome. I solve the question backwards.

First, from equation (4), the labor decision problem is

$$\max_{\ell_\omega}\ Y = \left[\int_\Omega (Z_\omega^\alpha K_\omega^\alpha \ell_\omega^\beta)^{\frac{\sigma-1}{\sigma}} d\omega\right]^{\frac{\sigma}{\sigma-1}},$$

subject to the resource constraint, $L = \int \ell_\omega d\omega$.

Let λ be the Lagrange multiplier of the constraint. Then,

$$L = \left[\int_\Omega (Z_\omega^\alpha K_\omega^\alpha \ell_\omega^\beta)^{\frac{\sigma-1}{\sigma}} d\omega\right]^{\frac{\sigma}{\sigma-1}} + \lambda(L - \int \ell_\omega d\omega).$$

The first-order condition on ℓ_ω is

$$Y^{\frac{1}{\sigma}}(Z_\omega K_\omega)^{\left(1-\frac{\sigma-1}{\sigma}\beta\right)} \ell_\omega^{\left(\frac{\sigma-1}{\sigma}\beta - 1\right)} \beta = \lambda$$
$$\leftrightarrow \ell_\omega = \left(\frac{Y^{1/\sigma}\beta}{\lambda}\right)^{\frac{\sigma}{\sigma-(\sigma-1)\beta}} Z_\omega K_\omega$$

Using the resource constraint,

$$\int_{\Omega} \ell_{\omega} d\omega = \left(\frac{Y^{1/\sigma}\beta}{\lambda}\right)^{\frac{\sigma}{\sigma-(\sigma-1)\beta}} \int_{\Omega} Z_{\omega} K_{\omega} d\omega$$
$$\leftrightarrow \left(\frac{Y^{1/\sigma}\beta}{\lambda}\right)^{\frac{\sigma}{\sigma-(\sigma-1)\beta}} = \frac{L}{\int_{\Omega} Z_{\omega} K_{\omega} d\omega}$$

because $L = \int_{\Omega} \ell_{\omega} d\omega$. Therefore, the solution is

$$\ell_{\omega} = \frac{L Z_{\omega} K_{\omega}}{\int_{\Omega} Z_{\omega} K_{\omega} d\omega}.$$

Since we can consider $\int_{\Omega} Z_{\omega} K_{\omega} d\omega = \mathbb{Y}(\hat{K})$, the labor allocation is identical to the market equilibrium if $\hat{K}$ is equal to K^{*}. If this is the case, the amount of M&A and GF investments that the local economy receives is the same as the one in the market equilibrium.

Second, the social planner solves the search decision problem:

$$\max_{\hat{K}} \ Y - MG(\hat{K})\psi = \left[\int_{\Omega} (Z_{\omega} K_{\omega})^{\frac{\sigma-1}{\sigma}} d\omega\right]^{\frac{\sigma}{\sigma-1}-\beta} L^{\beta} - MG(\hat{K})\psi.$$

The first-order condition is

$$\frac{\sigma-(\sigma-1)\beta}{\sigma-1} \mathbb{Y}(\hat{K})^{\frac{1}{\sigma-1}-\beta} L^{\beta} \mu(MG(\hat{K}))$$
$$\times \left([(Z-z)\kappa - Z(1-\eta)\hat{K}] - \frac{\mu'(MG(\hat{K}))MG(\hat{K})}{\mu(MG(\hat{K}))} \int_{\underline{K}}^{\hat{K}} [Z(1-\eta)(\hat{K}-K)]dG(K)\right) = \psi,$$

where I use $\mu(\hat{K}) = \mu(MG(\hat{K}))$.

The solution is

$$\frac{\sigma-(\sigma-1)\beta}{\sigma-1} \mathbb{Y}(\hat{K})^{\frac{1}{\sigma-1}-\beta} L^{\beta} \mu(\hat{K})$$
$$\times \left((1-\xi(\hat{K}))[(Z-z)\kappa - Z(1-\eta)\hat{K}] - \frac{\xi(\hat{K})}{G(\hat{K})} \int_{\underline{K}}^{\hat{K}} [Z(1-\eta)(\hat{K}-K)]dG(K)\right) = \psi,$$

where $\xi(\hat{K})$ is the elasticity of the matching function:

$$\xi(\hat{K}) = -\frac{\mu'(MG(\hat{K}))MG(\hat{K})}{\mu(MG(\hat{K}))}.$$