FDI on the Move: the Facilitation of Greenfield FDI and Cross-border M&A by Migrant Networks

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Abstract

This paper empirically investigates the heterogeneous roles of migrant networks in facilitating foreign direct investment (FDI). The impact of migrant networks varies depending on the entry mode of FDI, either greenfield or merger and acquisition (M&A), as well as the barriers associated with each. Using deal-level data on Chinese outward FDI and Chinese migrant stocks in 135 countries from 2003-2014, we find that migrant networks have a positive and significant impact on FDI, which is larger for M&A than greenfield FDI. Additional findings provide strong evidence of migrants' role in overcoming informal and formal informational barriers. The positive relationship is more pronounced for investment from non-listed companies and privately-owned enterprises, for cross-industry FDI, in service industries, and in host countries with tighter regulations and culturally more distant from China. We also provide evidence consistent with learning-by-investing, where the impact of migrant networks declines with the investors' experience. Our results are robust to various specifications and estimation methods, including an instrumental variables approach that addresses potential endogeneity concerns.

JEL: F21, F22, F23

Keywords: Chinese migrant networks, greenfield, mergers and acquisitions, foreign direct investment, information barriers

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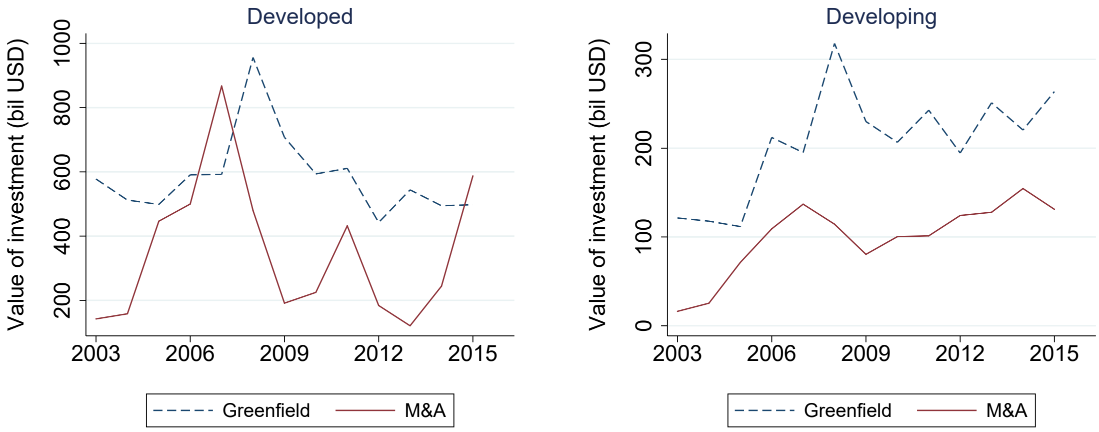
1 Introduction

Social networks formed by ethnic ties and migration facilitate international trade (e.g., Rauch, 2001; Gould, 1994; Rauch and Trindade, 2002) as well as foreign direct investment (FDI) (e.g., Javorcik et al., 2012; Burchardi et al., 2016).[1] However, what cross-border barriers can be efficiently dealt with by migrant networks remains an open question, especially in the context of FDI. These networks may be effective in resolving frictions like language barriers, but less helpful when managing frictions such as political conflicts. Moreover, their impact may change over time as multinational enterprises (MNE) accumulate knowledge and experience overseas. Understanding these informational and the investment barriers migrant networks alleviate provides important insights on the international comovements of labor and capital. In this paper, we focus on the two modes of FDI entry, greenfield FDI and mergers and acquisitions (M&A), to study the heterogeneous roles of migrant networks in facilitating cross-border investment.

Greenfield FDI refers to investment in which a parent company establishes new production facilities overseas, while with M&A, a firm acquires an existing company in a foreign country. Investing companies often face many frictions when moving their capital abroad. Formal barriers include laws and regulations, whereas informal obstacles may arise from asymmetric information or differences in culture and management. At times, the barriers encountered may also be entry mode-specific. For example, while greenfield FDI is challenged with regulations on startup procedures (World Bank, 2010), M&A require deep knowledge on the capacity and preference of both the target and acquirer to close deals. This heterogeneity in investment barriers may drive the patterns of greenfield FDI and M&A worldwide. It is well-known that M&A dominate capital *inflows* for developed countries. Yet, Figure 1 shows that greenfield FDI is more prevalent for capital *outflows* from both developed and developing countries. Second, over the period from 2003 to 2015, M&A from developing countries grows more rapidly than greenfield FDI (806% versus 217%). At the same time, labor mobility across countries has risen dramatically. The global stock of migrants has increased from 160 to 250 million since 1995, and for a large developing country like China, its emigrant stock has roughly doubled from 4.9 to 9.5 million (see Figure 2). With expertise both in their countries of birth and residence, migrant networks provide valuable information to investors to alleviate many of the regulatory barriers and informational frictions encountered. However, depending on the type of FDI, the informational barriers faced at entry and therefore the role of informational networks may vary.

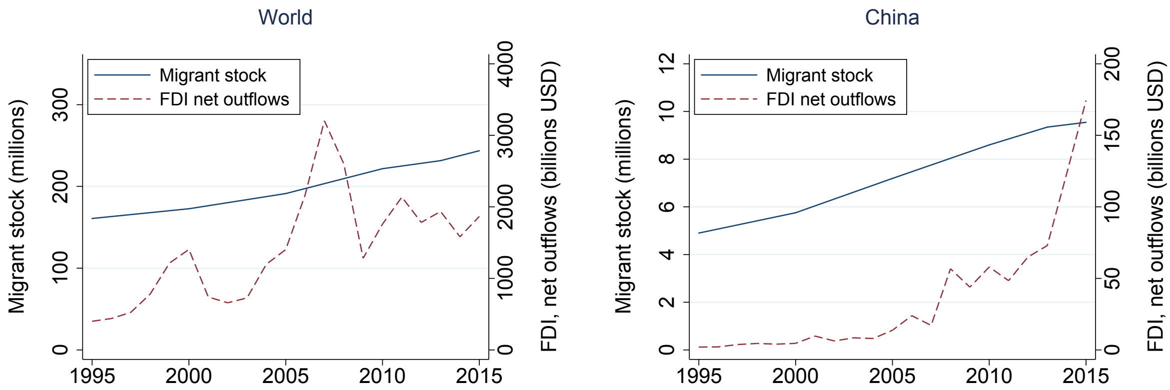
Aggregating deal-level data on Chinese outward FDI and overseas Chinese migrant stocks in 135 countries between 2003 and 2014, we find that migrant networks have a positive and significant impact on both greenfield FDI and cross-border M&A. This is observed both at the extensive and intensive margin (i.e., the number and value of investment projects, respectively).

[1] The UN Conference on Trade and Development (UNCTAD) defines foreign direct investment as an "investment made to acquire lasting interest in enterprises operating outside of the economy of the investor", and requires that the "single foreign investor either owns 10 per cent or more of the ordinary shares or voting power of an enterprise ... or owns less than 10 per cent of the ordinary shares or voting power of an enterprise, yet still maintains an effective voice in management."



(a) (b)

Figure 1: Outward greenfield FDI and M&A from (a) developed and (b) developing countries. (Source: UNCTAD (2017).)



(a) (b)

Figure 2: Migrant stock abroad (left y-axis) and FDI net outflows (right y-axis) for (a) the world and (b) China. (Sources: UN Global Migration Database and the World Bank World Development Indicators.)

Importantly, the association between the presence of migrants and FDI tends to be stronger for M&A compared to greenfield FDI. These findings remain robust with an instrumental variables (IV) strategy to address endogeneity concerns, where our instruments include the historical migrant network from 40 years ago and countries' contemporaneous policy on dual citizenship. We also construct an instrument based on Burchardi et al. (2016), where, using global bilateral migration flows, migrant shares are predicted from push factors that do not depend on the host-country, and pull factors that are independent of China. Regressions from the IV strategy strongly reinforce our baseline results.

Second, we explore the role of migrants as informational networks in alleviating specific informational barriers by entry mode. We exploit the detailed dataset to classify investing companies by firm or sector characteristics, and also utilize the variation in host countries characteristics. At the firm-level, migrants' impact is stronger for investment from non-listed as well as privately-owned enterprises. Furthermore, migrant networks better promote FDI in service industries, which are typically more knowledge intensive (Coff, 1999), and FDI in industries that are different from investors core business in home country. We also find substantial heterogeneity across different country characteristics by interacting the migrant networks with other determinants of bilateral investment. In particular, a larger impact is observed for culturally distant host countries with tighter regulations (capital controls, labor regulations, administrative requirements) for both greenfield FDI and M&A, and more startup time and procedures for greenfield FDI (but not the monetary cost). Another channel through which social networks may influence cross-border transactions is contract enforcement (Chaney, 2016). However, we find no evidence that migrant networks help MNEs in countries with weak contract enforcement. Thus, the empirical results strongly support the idea of migrants as informational networks facilitating the entry of cross-border investment. Throughout, the effects also tend to be more pronounced for M&A.

Lastly, we provide new evidence that there is "learning-by-investing" for MNEs by showing that the impact of migrants declines with the experience of MNEs investing overseas. Specifically, we find that the migrant network effect is largest for the investor's first project into a country. In fact, for all subsequent investment projects, migrants' impact disappears entirely for greenfield FDI, though it remains significant for M&A. These results also hold when we include, as a control in the regression, cumulative Chinese FDI by entry mode into a host country from the past. This reveals that the relationship between migrant networks and firms is in fact dynamic. The contribution of migrants is important only when investors are uninformed about the host nation's economic environment; through knowledge spillovers and experience, MNEs rely less on migrants over time.

The three sets of results presented all indicate that the role of migrants in facilitating cross-border investment does differ depending on the mode of entry. In particular, migrant networks are more valuable for M&A compared to greenfield FDI. This is in fact consistent with Figure 1, where outward FDI is dominated by greenfield investment as opposed to M&A. In addition, coinciding with an increase in worldwide labor mobility, the flow of M&A is catching up to greenfield FDI.

The role of informational networks in overcoming informational barriers and facilitating economic activity across borders has been studied in various contexts, most notably in international trade for ethnic and migrant networks (e.g., Head and Ries, 1998; Rauch and Trindade, 2002; Combes et al., 2005; Chaney, 2014; Parsons and Vézina, forthcoming). Focusing on overseas Chinese ethnic networks, Rauch and Trindade (2002) show heterogeneous effects depending on the goods being traded (i.e., differentiated commodities versus homogeneous goods). Our work contributes most directly to the literature on migration and FDI. Much of it has focused on immigration into the US. For example, Javorcik et al. (2012) find a positive relationship between immigrant shares in the US and FDI towards the migrants' origin countries for 1990 and 2000, especially for more educated immigrants.[2] Importantly, they address the endogeneity issue by using an instrumental variables approach.[3] More recently, Burchardi et al. (2016) and Cohen et al. (2016) utilize the historical geographic distribution of ethnic groups in the US to address endogeneity. In particular, using a reduced-form model of migration based on push and pull forces, Burchardi et al. (2016) construct an instrument by relying on the ancestry composition of migrants.

We contribute to this area of research by differentiating between greenfield FDI and M&A, and provide direct evidence on the migrants' role in overcoming informal and formal informational barriers to support the information channel hypothesis. While previous papers examine *whether* migrant networks promote cross-border investment, relatively little has been said on *how* they do it. Our paper answers affirmatively to the first question, and also presents evidence with heterogeneous FDI to support the idea that migrants use local knowledge about firms, industries, and host countries to alleviate information frictions for investments from their country of origin. Moreover, despite the large numbers of emigrants from countries such as China, there have been relatively few studies examining this research question for them.[4]

Our paper also complements the theoretical work on the choice of foreign market entry mode, including how it is affected by changes in FDI policy and trade liberalization (Qiu and Wang, 2011; Stepanok, 2015), as well as existing empirical evidence (e.g., Hennart and Park, 1993; Nocke and Yeaple, 2008). Using the same greenfield FDI dataset and a related database on M&A, Davies et al. (2015) find that M&A in the world are more sensitive to geographic and cultural barriers and short-run variations like a currency crisis, while greenfield FDI is affected more by long-run factors such as institutional development.[5] Meanwhile, Desbordes and Wei (2017) finds financial development to have a positive effect on both modes of FDI. Our findings contribute to this strand of literature by highlighting the benefits of social networks as another potential factor in the choice of the optimal entry mode. More broadly, our paper informs studies that examine the determinants of FDI. Our empirical analysis controls for many of the various factors which have been empirically identified to be correlated with multinational activity (e.g., Blonigen and Piger, 2014).[6] Lastly, our work adds to the recent growing empirical

[2]Earlier work by Bhattacharya and Groznik (2008) also found US outward FDI to a particular destination to be correlated with the size of the immigrant group from the same country. Kugler and Rapoport (2007) document a similar pattern over time, but also show a negative contemporaneous correlation.

[3]Their instruments for immigrant entry into the US are the cost of obtaining a passport in the origin country, the historical share of migration, distance to the EU, the presence of a US military base, and dual citizenship.

[4]Using the ethnic Chinese population data in 1990 from Rauch and Trindade (2002), Gao (2003) and Tong (2005) show that overseas Chinese ethnic networks have a positive correlation with Chinese inward FDI and bilateral investment, respectively. Huang et al. (2013) also analyze Chinese inward FDI, but focus on the performance of industrial firms with investment originating from ethnically Chinese economies (Hong Kong, Macau, Taiwan) versus other countries. They find that ethnic Chinese FDI firms under-perform non-ethnic Chinese FDI firms. Buch et al. (2006) study German inward FDI, and find more FDI into states with a large foreign population from the same origin country. Recent work by Burchardi and Hassan (2013) shows how social ties increase economic development and investment by examining links between West and East Germany after the Berlin Wall fell.

[5]Cuadros et al. (2016) also utilize the same dataset for greenfield FDI to show positive correlation between migrants and bilateral FDI, which is mitigated by financial constraints. For M&A, Davies et al. (2015) and Desbordes and Wei (2017) rely on the database Zephyr from Bureau van Dijk.

[6]Other papers in this large literature include Bevan and Estrin (2004), Portes and Rey (2005), Bénassy-Quéré et al. (2007), Head and Ries (2008), Chang (2014), and Lee (2016).

research on Chinese outward FDI (OFDI).[7] Using data on FDI from Zhejiang province, Chen et al. (2016) find privately-owned multinationals to be discriminated in the domestic Chinese market and thus engage in investment and production abroad.

The rest of paper is organized as follows. Section 2 describes the data sources and presents some stylized facts about Chinese OFDI. Section 3 outlines the main empirical framework. In Section 4, we present the empirical results. Lastly, Section 5 concludes.

2 Data

2.1 FDI data

We draw data from a variety of sources. First, transaction-level data on Chinese outward greenfield FDI and cross-border M&As are obtained from Financial Times Ltd. fDi Markets and Thomson-Reuters Security Data Company (SDC) Platinum, respectively.[8] Both datasets are commonly used to analyze cross-border greenfield investment and M&A. For example, UNCTAD (2017) rely on fDi Markets for their annual report on world investment, and M&A data from SDC Platinum has been examined in numerous papers (e.g., Rossi and Volpin, 2004; di Giovanni, 2005; Head and Ries, 2008).[9] We limit our sample to the years from 2003 to 2014, because 2003 is the earliest year that fDi Markets recorded greenfield investments. In this period, China has greenfield investment projects in 136 host countries (with an average of 265 projects and total valuation of 26 billion USD annually), and 1393 cross-border M&A deals in 90 countries (with an average of 116 deals and reported transaction value of 18 billion USD per year).

Throughout the regression analysis, we exclude tax haven countries such as Panama, the British Virgin Islands, the Cayman Islands, as well as the cities of Macau and Hong Kong. Both cities have unique status as special administrative regions of China, and have very high migrant shares (over 30%) compared to the rest of the sample. Moreover, these two special administrative regions are contiguous to Mainland China, and while they possess their own independent legal system, the companies in these cities are often conduits for Chinese businesses. Therefore, their FDI inflows from China may be motivated by different reasons, and we consider them potential outliers in the analysis.

The UNCTAD Bilateral FDI Statistics also provide data on bilateral aggregate cross-border investment flows between 2003 and 2012. Since the interest of this paper is on the heterogeneous

[7]For example, Buckley et al. (2011), Kolstad and Wiig (2012), and Huang and Wang (2011, 2013) find that Chinese OFDI is asset-driven and attracted towards big markets with natural resources and advanced technology. As well, firm productivity has been shown to increase the likelihood and size of investment overseas (e.g., Chen and Tang, 2014; Wang et al., 2016; Tian and Yu, 2015).

[8]fDi Markets records announced greenfield FDI projects, and we use the completed cross-border M&A deals from SDC Platinum. For both greenfield FDI and M&A, the value of transactions is not reported in some instances due to confidentiality. Thus, while transaction counts can be always computed, deal valuations are not available for all transactions. In the case of greenfield FDI, fDi Markets estimates the deal value if it is not disclosed by the investing company. Estimates for the values of M&A investments are not included.

[9]UNCTAD (2017) also maintains a database of (non-bilateral) cross-border M&A purchases at the country level. For both the number and value of Chinese M&A purchases, SDC Platinum and UNCTAD (2017) are highly correlated at 0.91 and 0.85, respectively. SDC Platinum captures 38 to 80% of the number of M&A deals in UNCTAD (2017), and 40 to 276% of the value.

impact of migrant networks on FDI depending on mode of entry, we do not make use of this dataset in the main context. However, we did confirm that the positive relationship between FDI and outward migration also holds for aggregate FDI.[10]

2.2 Bilateral migrant stock data

Data on bilateral migration are obtained from the Global Migration Database provided by the United Nations Department of Economic and Social Affairs (2015).[11] Statistics on bilateral migrant stocks are available every five years from 1990 to 2015, with an additional year in 2013. Our key explanatory variable is the share of Chinese migrants in the host country, i.e., the number of Chinese emigrants to the host country in a particular year normalized by the host country's population. Data on the host country's population is retrieved from the World Bank World Development Indicators (WDI). For years in which the migration data are not available, we carry the value of migrant share forward until the new data becomes available. For example, the migrant share in 2006 to 2009 will take the same value as 2005. Since there are no sudden surges in emigration to a particular destination, Chinese migrant shares are relatively stable over a short time period, and the regression estimates are almost identical if we use linear interpolation instead. The simple average (across all countries) of the standard deviation of migrant shares across 12 years is around 0.15%. For comparison, the standard deviation in the entire sample is 0.73%.

2.3 Other data

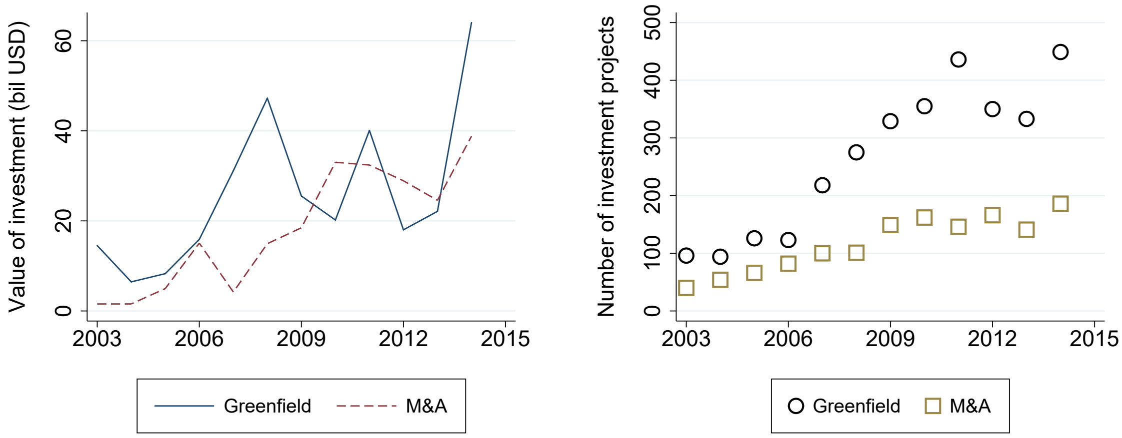
In our regressions, we control for host country characteristics that might influence FDI and migration patterns. These include traditional gravity variables like market size (as proxied by GDP), income (i.e., GDP per capita), and geographic distance.[12] Data on GDP are drawn from the WDI, and distance comes from CEPII. To control for cultural similarity that makes cross-border investments more likely (e.g., Dunlevy, 2006; Davies et al., 2015), we add a dummy variable for common language that equals to 1 if at least 9% of the population in the host country speaks the same language with China, and a dummy variable for a common legal system origin. The former is obtained from CEPII, and the latter from La Porta et al. (1999).

To further mitigate concerns of omitted variable bias, we include other determinants of bilateral investment. To account for the market-seeking and growth-seeking motives of Chinese

[10] These results are available upon request.

[11] As stated in the UN's documentation: "Most of the data used to estimate the international migrant stock by country or area were obtained from population censuses. Additionally, population registers and nationally representative surveys provided information on the number and composition of international migrants. In estimating the international migrant stock, international migrants have been equated with the foreign-born population whenever this information is available, which is the case in most countries or areas." More information is available at `http://www.un.org/en/development/desa/population/migration/data/estimates2/estimates15.shtml`. Moreover, Gao (2003) and Tong (2005) examine the relationship between Chinese *ethnic* networks abroad and aggregate FDI using data on ethnic Chinese populations in 1990. For the overlapping year of 1990, there is a large positive correlation between the population of ethnic Chinese and Chinese migrants from the UN database (0.684).

[12] An alternative measure of market size is population. In unreported regressions, we confirm our results are robust to this measure. These results are available upon request.



(a)

(b)

Figure 3: Chinese greenfield FDI and M&A in terms of the (a) value and (b) number of investment projects.

OFDI (e.g., Buckley et al., 2011), we control for real GDP growth in the host country. We also include financial development, which can potentially facilitate the international expansion of firms through FDI (e.g., Desbordes and Wei, 2017); it is measured by private credit from deposit money banks and other financial institutions divided by GDP (Beck et al., 2000). We follow Rossi and Volpin (2004) and Bekaert et al. (2004), among others, and use the sum of indices for corruption, law and order, and bureaucratic quality from the International Country Risk Guide (ICRG) as a proxy for institutional quality. Lastly, following Blonigen et al. (2007), we use trade openness, the ratio of exports plus imports to GDP (from WDI), to control for the degree of business interactions with the rest of the world. Summary statistics are provided in Appendix Table 1,

2.4 Stylized facts on Chinese outward FDI

In this section, we document some simple stylized facts regarding Chinese outward FDI. First, the distribution of greenfield FDI projects and M&A deals across host countries is listed in Appendix Table 2. The number of greenfield projects for any given host country is typically larger than the number of cross-border M&A deals, with notable exceptions being Australia and Canada. Between 2003 and 2014, over 60% of host countries receive less than a total of 10 greenfield FDI investment projects from China, and close to 80% see less than 10 M&A with Chinese companies.[13] There are, however, some host countries that China invests heavily in. Specifically, the five most popular destinations for Chinese greenfield OFDI over this decade are Germany, US, UK, Hong Kong, and India; likewise, for M&A, they are: Hong Kong, US, Australia, Canada, and Germany.

[13]These statistics are computed using the sample of host countries with strictly positive greenfield FDI or M&A. There are 81 countries with both greenfield Chinese investment and M&A activity, 55 countries with only greenfield investments and 9 countries with only M&A.

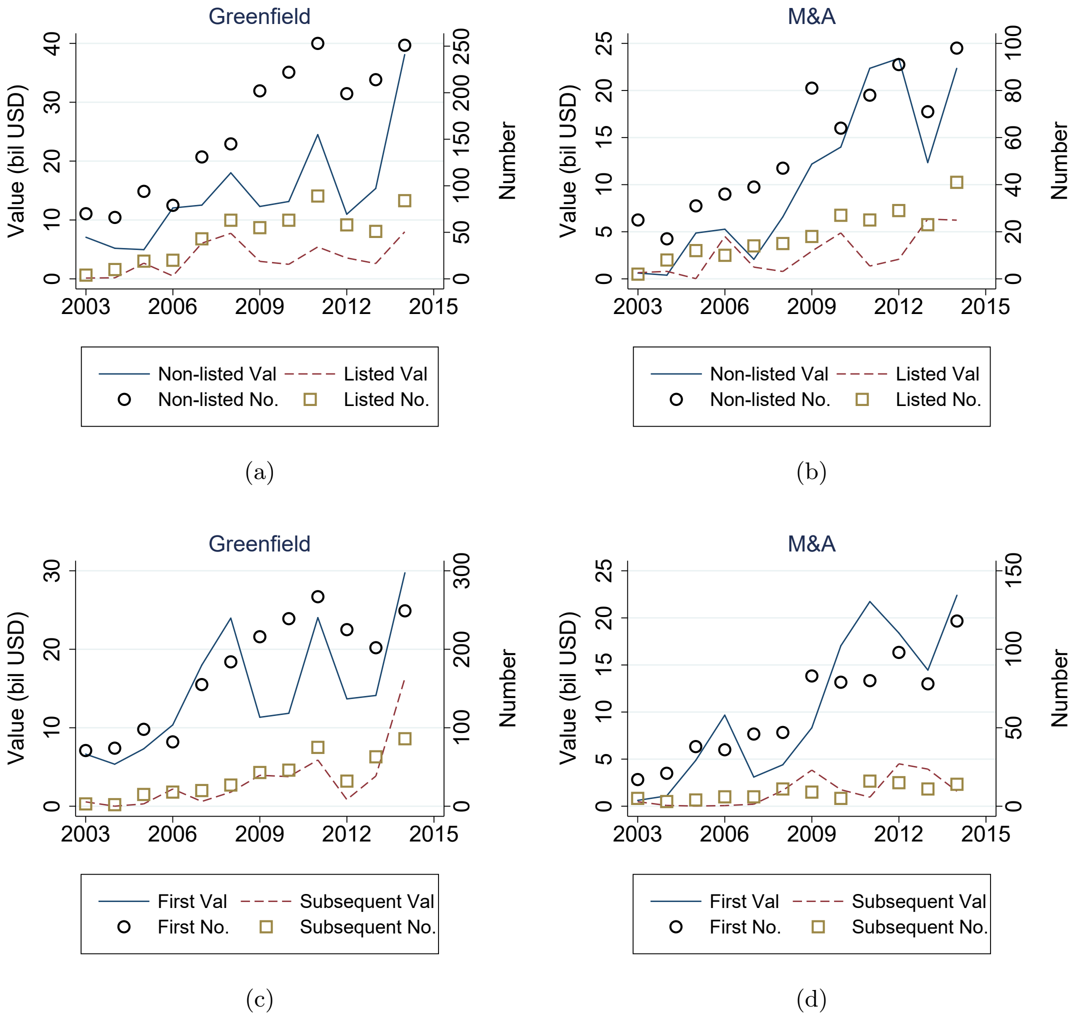


Figure 4: The value and number of Chinese greenfield FDI/M&A from (a/b) non-listed and listed companies; (c/d) companies' first and subsequent investment projects abroad.

Next, Figure 3 shows that the aggregate value and number of investment projects for both greenfield FDI and M&A are rising over this period. The total number of Chinese greenfield investment projects is consistently around two to three times larger than the number of cross-border M&A deals (Panel (b)). However, in terms of size of transactions (Panel (a)), M&A are on average greater than greenfield projects. As with M&A from other developing countries (Figure 1(b)), the value of Chinese M&A has increased more rapidly than greenfield FDI.

These aggregate time trends, although disaggregated by entry mode, still masks some of the heterogeneity that exists within each entry mode. As a preview to the regression analysis in Section 4 below, in Figure 4, we consider two characteristics. First, we classify FDI as either originating from a non-listed or listed firm. Since these companies have different information released to the public, the information intensity for investment also varies. To identify whether the parent company of greenfield FDI is a listed firm, we match our deal-level data to Datastream; for M&A, we follow Erel et al. (2012) and label an acquirer as listed if its public status is "Public" or non-missing. Panels (a) and (b) show that, on average, most of the outward FDI from China is conducted by non-listed companies. Importantly, there has also been significant growth investment from non-listed as opposed to listed firms.

Second, in Panels (c) and (d), we decompose total FDI depending on whether or not the investment is the company's first established enterprise or deal in a particular country. We make this classification separately for greenfield investment and M&A. For example, if a Chinese company has previously had a M&A in the United States, all M&A deals after this first deal to the United States are considered "subsequent" deals. Since firms investing in subsequent projects have acquired experience, we expect initial investment into a host country to be more information intensive. While the M&A data dates back to 1982, the greenfield FDI data is available since 2003. Therefore, we supplement our information on foreign investment with official FDI data from the Ministry of Commerce in China, which reports FDI transactions since 1982, though the value of investment is not released. We find the English names of the Chinese companies, and match them with our own greenfield FDI data to determine whether there were investments made before 2003. From 2003 to 2014, roughly 80 to 85% of either the value or number of Chinese greenfield investment and M&A are first time investment projects to a particular country. Furthermore, as Figure 4 indicates, initial investment by companies continues to increase over time, even relative to subsequent projects in countries. Thus, Figure 4 illustrates that over this period, the arguably more knowledge intensive investment from non-listed companies and first-time investors is growing faster and diverging from their counterparts.

We document some additional facts by exploiting the within-firm variation across transactions in Table 1. For each company, we now count the number of investment projects made prior to the current transaction in *any* country of the world, for both greenfield FDI and M&A, separately. This gives us the "project number" for the current transaction. In Table 1, we run deal-level regressions to examine how investment behavior correlates with the experience of investing abroad. In Panel A, host countries' migrant share is regressed on the project number. The results show that, for both greenfield FDI and M&A, companies tend to start in countries with larger Chinese migrant networks. As companies gain more experience and the number of investment projects abroad increases, they move their capital to countries with fewer Chinese migrants. The results hold for the full sample of deals (columns 1 and 2), and also when the sample is restricted to companies with multiple investments outside of China (columns 3 and 4). Finally, in Panel B, we regress the value of the investment deal (in logarithms) on the firm's project number, and the estimates show a positive correlation between the two variables. As companies' foreign operations expand, the value of those investment deals tends to also increase.

3 Empirical framework

Following the literature on international trade and the determinants of FDI, we utilize a simple gravity model for bilateral FDI. The gravity equation has been reasonably successful in fitting the observed data of cross-country trade and FDI flows (e.g., Bénassy-Quéré et al., 2007; Blonigen and Piger, 2014). After logarithmic transformation, the gravity equation can be

Table 1: Migrant Shares and Valuation over Project Number

	Panel A			
	Dependent variable: Migrant share			
Sample:	Full		Multiple projects only	
	GF	MA	GF	MA
	(1)	(2)	(3)	(4)
Project number	-0.0019***	-0.0417*	-0.0027***	-0.0588***
	(0.0006)	(0.0213)	(0.0008)	(0.0214)
Year fixed effects	Y	Y	Y	Y
Observations	2,702	945	1,814	402
R-squared	0.010	0.019	0.015	0.037

	Panel B			
	Dependent variable: log (Value)			
Sample:	Full		Multiple projects only	
	GF	MA	GF	MA
	(1)	(2)	(3)	(4)
Project number	0.0118***	0.5193***	0.0020	0.3357***
	(0.0040)	(0.0661)	(0.0018)	(0.0681)
Year fixed effects	Y	Y	Y	Y
Observations	3,020	560	2,061	239
R-squared	0.050	0.144	0.022	0.127

Notes: The dependent variables are the migrant share of the host country and the (log) value of the investment project in Panels A and B, respectively. All regressions include year fixed effects. Standard errors in parentheses are clustered by the investing or acquiring company. ***, **, * denote significance level at 1%, 5% and 10% respectively.

specified as follows:

$$\log(FDI_{ijt}) = \beta_0 + \beta_1 \log(GDP_{it}) + \beta_2 \log(GDP_{jt}) + \beta_3 \log(Dist_{ij}) + \beta_{\boldsymbol{X}} \boldsymbol{X}_{ijt} + \varepsilon_{ijt},$$

where FDI_{ij} is investment from country i to country j, GDP captures market size, and $Dist_{ij}$ is the geographic distance between the two countries. To mitigate concerns of omitted variable bias, $\boldsymbol{X}_{ij}$ is a vector that includes other potential determinants of cross-border investment, which are either bilateral or host/home-country specific. ε_{ij} is the error term.

To examine the heterogeneous effects of migrant networks by FDI mode of entry, our dependent variable includes the value and number of greenfield investment projects (*GF*, *#GF*) and the number and value of cross-border M&A deals (*MA*, *#MA*) from China to the host country. We also consider the average size of transactions, *Ave GF* and *Ave MA*. Since China only has positive investment into a subset of host countries every year, we apply a very standard approach to deal with zero FDI flows. In our baseline specification, the dependent variable $\log(FDI_{ijt})$ is replaced with $\log(FDI_{ijt}+1)$, i.e., a value of zero FDI projects would be replaced by one FDI project, and a value of zero FDI flows becomes \$10,000 USD, which is the smallest value of FDI observed in the data. In robustness checks, we demonstrate our findings are robust to alternative estimation methods, including OLS without replacing zeros with ones, as well as the Poisson pseudo-maximum-likelihood (PPML) estimator. Furthermore, to mitigate the concern of reverse causality, all the time-varying explanatory variables are lagged by one year (e.g., Chang, 2014). In Section 4.3, we validate our results with an instrumental variables strategy to address potential endogeneity issues.

Thus, focusing on OFDI from China, the following baseline specification is estimated to study the impact of overseas Chinese migration networks on different types of OFDI:

$$\log(FDI_{jt}+1) = \alpha_0 + \alpha_1 \log(GDP_{j,t-1}) + \alpha_2 \log(Dist_j) + \alpha_3 Migrant\ share_{j,t-1} + \alpha_{\boldsymbol{X}} \boldsymbol{X}_{j,t-1} + \epsilon_{jt}. \tag{1}$$

Our regressor of interest is $Migrant\ share$, defined as the number of overseas Chinese migrants in host country j as a ratio of the total population in country j. The coefficient α_3 is expected to be positive. The vector $\boldsymbol{X}_{j,t-1}$ also includes year fixed effects to absorb time-specific changes in FDI flows common to all countries. Standard errors of the estimated coefficients allow for clustering of observations by host country.

4 Empirical results

4.1 Baseline results

Table 2 reports the baseline regression results from estimating Eq. (1) with OLS. The regressors consist of standard gravity equation variables (i.e., (log) GDP, (log) GDP per capita, (log) Distance, Common language, and Common legal system) and year fixed effects. The sample contains 135 countries between the years 2003 and 2014.

Consistent with the hypothesis that cross-border migrant networks help overcome barriers associated with international transactions, we find that the size of the migrant network has a positive and statistically significant impact on both greenfield FDI and M&A, and both for values and counts. The magnitudes of the coefficients are also large and economically meaningful. All else equal, a one-standard deviation increase (0.73%) in the share of Chinese migrants in the host country's population increases the investment value *GF* and *MA* by 43.6%, 90.3%, respectively, and raises the counts of investment projects *#GF* and *#MA* by roughly 10.7% and 18.0%, respectively.[14]

Importantly, Table 2 also shows that the positive relation between migrants networks and OFDI exhibits substantial heterogeneity depending on the mode of entry. The coefficient of $Migrant\ share$ in the regression of column 3 (4) is larger than that in column 1 (2). This implies that the positive impact of migrant networks is stronger for M&A compared to greenfield FDI, at both the extensive and intensive margin. The difference of the marginal effects is statistically significant at 5% level with a χ^2-statistic (and associated p-value) of 4.17 (0.04) for values, while the difference for counts is less precisely estimated with a χ^2-statistic of 2.66 (0.10). Thus, the results suggest that the facilitation of overseas Chinese migrants is more important to M&A than greenfield OFDI. We argue, and provide supportive evidence in Sections 4.6 and 4.7, that cross-

[14]While no direct comparison exists in the literature on emigration and outward FDI *flows*, the results from Gao (2003) are perhaps the most relatable. He finds that a one percentage point increase in Chinese *ethnicity* shares, with Hong Kong as a FDI source country included, is associated with a 6% increase in Chinese *inward* FDI. For both Javorcik et al. (2012) and Tong (2005), the dependent variable is FDI *stock*.

Table 2: Overseas Chinese Migrant Networks and Chinese Outward FDI

Dependent variable	log (FDI + 1)					
	GF	# GF	Ave GF	MA	# MA	Ave MA
	(1)	(2)	(3)	(4)	(5)	(6)
Migrant share	0.598***	0.146***	0.452***	1.237***	0.247***	0.990***
	(0.198)	(0.041)	(0.164)	(0.346)	(0.077)	(0.271)
(log) GDP	1.233***	0.231***	1.003***	0.569***	0.113***	0.457***
	(0.084)	(0.024)	(0.066)	(0.082)	(0.021)	(0.064)
(log) GDP per capita	-0.526***	-0.067***	-0.459***	0.048	0.005	0.043
	(0.128)	(0.025)	(0.107)	(0.081)	(0.014)	(0.069)
(log) Distance	-1.078***	-0.163**	-0.915***	-0.242	-0.052	-0.190
	(0.349)	(0.066)	(0.293)	(0.329)	(0.052)	(0.291)
Language	2.189*	0.230	1.959**	-0.381	-0.167	-0.213
	(1.149)	(0.225)	(0.942)	(1.368)	(0.336)	(1.050)
Legal system	0.407	-0.038	0.444	-0.650**	-0.111**	-0.539**
	(0.500)	(0.095)	(0.417)	(0.287)	(0.047)	(0.250)
Year fixed effects	Y	Y	Y	Y	Y	Y
Observations	1,483	1,483	1,483	1,483	1,483	1,483
R-squared	0.455	0.511	0.421	0.298	0.387	0.261

Notes: The dependent variables are Chinese outward FDI measured by the (log) value, number, and project average value of greenfield FDI (*GF*, *#GF*, and *Ave GF*), and likewise for M&A (*MA*, *#MA*, and *Ave MA*). All time-variant explanatory variables are lagged by one year. Standard errors in parentheses are clustered by host country. ***, **, * denote significance level at 1%, 5% and 10% respectively.

border M&A are more information intensive than greenfield FDI. Intuitively, by crossing both national and organizational boundaries, M&A requires intensive knowledge and information of the capabilities, preferences, and potential synergies of the acquiring and target firms that are from different cultural backgrounds. Therefore, they seem to benefit more from the presence of overseas Chinese networks that bridge the gap.

The total effect of migrant networks on FDI can be decomposed along the extensive and intensive margins, as done in Desbordes and Wei (2017). The extensive margin is measured by the number of FDI projects (columns 2 and 5), while the intensive margin is captured by the average size of FDI projects (columns 3 and 6), where, for example, $Ave\ GF = GF/\#GF$. While the size of migrant networks has an impact on FDI both margins for both modes of entry, a comparison between columns 2 and 3 and columns 5 and 6 show a stronger impact on intensive margin. Specifically, for greenfield FDI, three-quarters (0.452/0.598) of the total impact appears to occur at the intensive margin. For M&A, the contribution of the intensive margin is even larger at 80% (0.990/1.237). Intuitively, as migrant networks reduce investment barriers, not only does each investor increases the size of investment, but also new and less profitable FDI projects get to enter the foreign market. Our findings suggest that investors that own relatively profitable projects to begin with are more sensitive to the presence of migrant networks than investors with less profitable projects. In their decomposition of the effect of financial development on greenfield FDI, Desbordes and Wei (2017) also find the intensive margin is more important in accounting for two-thirds of the total effect.

Furthermore, some patterns can be observed with regards to the control variables in Table 2. The estimates suggest that larger countries receive more FDI from China, and more greenfield investment is made in poorer countries that are closer to China. This latter finding is consistent with Chinese multinationals' strategy of going abroad –"encircling the cities from the rural areas"– a pragmatic business strategy that calls for building capacity and the accumulation of wealth in markets with low competition (rural areas) first before moving to developed markets to undertake competition (cities).[15]

4.2 Robustness

First, as a placebo test on the importance of country-specific social ties, in Table 3 Panel A, we replace the share of Chinese migrants with the share of migrants from all other countries. For space considerations, we only present the coefficient of interest. If information can be transmitted by any foreigner to Chinese investors, then the impact of the non-Chinese migrant network should remain positive. However, the coefficient is statistically insignificant across all columns. This suggests that the overseas Chinese population is crucial in facilitating the outward FDI from China, and all other immigrants only provide limited assistance, if any.

In the remainder of Table 3, we present a series of additional regressions that demonstrate our main results are robust to alternative specifications. In Panel B, we replace the share of Chinese migrants with the absolute size of the migrant stock (in logarithms). Both can be argued as a suitable measure for the size of the migrant network overseas. The change has no qualitative effect on the positive relationship between migrant networks and outward FDI, and the coefficients also remain statistically significant. A 1 percent increase in the stock of Chinese migrants abroad raises the value (number) of greenfield FDI and M&A by around 0.23 and 0.44% (0.07 and 0.10%), respectively.

To address endogeneity arising from omitted variable bias, in Table 3 Panel C, we include in our regression equation measures of growth, financial development, institutional quality, and trade openness. The sample is thus restricted to 96 countries.[16] The inclusion of these previously omitted variables reveals even starker differences between greenfield investment and M&A. With this specification, the null hypothesis that the $Migrant\ share$ coefficient in columns 1 and 3 are equal is rejected with χ^2 statistic (p-value) of 34.4 (< 0.01), and likewise, for columns 2 and 4, the Wald test χ^2 statistic (p-value) is 9.98 (< 0.01). We maintain this list of control variables for the remainder of the analysis.

Next, we show our results are not driven by unobserved heterogeneity at the country level. For instance, certain countries may tend to attract both foreign investment and immigration,

[15] "Encircling the cities from the rural areas" was initially a military strategy developed by Mao Zedong, the founding Chairman of China. Guided by this strategy, the Communist party established revolutionary bases in rural areas that were largely ignored by the Kuomintang party and gradually accumulated arms forces and wealth to fight with Kuomintang party in cities. This strategy is thought to be crucial for the victory of the Communist party in the domestic war. The strategy also provides important guidelines for business practices, see for example, `http://english.cctv.com/2016/07/11/VIDEaFG3eAExf0417rKdqkGV160711.shtml`

[16] Other potential factors include proximity to large markets, and technology or natural resource seeking motives. In unreported results, we confirm that our findings hold qualitatively when we further augment the list of control variables by including measures of remoteness (GDP weighted distance), technology (number of patent applications from the WDI), and natural resource abundance (agricultural raw materials, fuel, and ores and metals exports as a share of merchandise exports from the WDI) (e.g., Huang and Wang, 2013). The sample is substantially reduced to 666 observations and 79 countries in these regressions.

Table 3: Robustness Checks

	Panel A: Share of other migrants			
Dependent variable	log (FDI + 1)			
	GF	# GF	MA	# MA
	(1)	(2)	(3)	(4)
Share of other migrants	0.010	0.003	0.034	0.010
	(0.023)	(0.005)	(0.028)	(0.006)
Observations	1,483	1,483	1,483	1,483
R-squared	0.450	0.501	0.259	0.338
	Panel B: Migrant stock			
Dependent variable	log (FDI + 1)			
	GF	# GF	MA	# MA
	(1)	(2)	(3)	(4)
(log) Migrant stock	0.229**	0.069***	0.444***	0.101***
	(0.112)	(0.026)	(0.122)	(0.028)
Observations	1,477	1,477	1,477	1,477
R-squared	0.455	0.515	0.389	0.289
	Panel C: Additional controls			
Dependent variable	log (FDI + 1)			
	GF	# GF	MA	# MA
	(1)	(2)	(3)	(4)
Migrant share	0.310	0.118**	1.820***	0.352***
	(0.258)	(0.056)	(0.429)	(0.107)
Observations	1,019	1,019	1,019	1,019
R-squared	0.467	0.575	0.331	0.459
	Panel D: Additional controls and estimated destination fixed effect			
Dependent variable	log (FDI + 1)			
	GF	# GF	MA	# MA
	(1)	(2)	(3)	(4)
Migrant share	0.064	0.085	1.743***	0.350***
	(0.265)	(0.056)	(0.423)	(0.104)
Observations	1,016	1,016	1,016	1,016
R-squared	0.478	0.581	0.333	0.459
	Panel E: OLS			
Dependent variable	log (FDI)			
	GF	# GF	MA	# MA
	(1)	(2)	(3)	(4)
Migrant share	0.226	0.050	0.869***	0.334***
	(0.148)	(0.062)	(0.216)	(0.098)
Observations	473	473	176	248
R-squared	0.265	0.538	0.386	0.439
	Panel F: Poisson pseudo-maximum-likelihood			
Dependent variable	FDI			
	GF	# GF	MA	# MA
	(1)	(2)	(3)	(4)
Migrant share	0.036	-0.139	1.027***	0.484*
	(0.132)	(0.094)	(0.314)	(0.277)
Observations	1,016	1,016	1,016	1,016
R-squared	0.344	0.648	0.439	0.727

Notes: The dependent variables are Chinese outward FDI measured by the (log) value and number of greenfield FDI (*GF* and *#GF*) and likewise for M&A (*MA* and *#MA*) in Panels A to D, the (log) value and number of greenfield FDI and likewise for M&A in Panel E, and the value and number of greenfield FDI and likewise for M&A in Panel F. All regressions include the set of gravity equation control variables as described in the text and year fixed effects. All time-variant explanatory variables are lagged by one year. Standard errors in parentheses are clustered by host country. ***, **, * denote significance level at 1%, 5% and 10% respectively.

due to factors that we have not controlled for. In Section 4.3 below, we will also employ an instrumental variables strategy to tackle this problem. If migrant shares were time-invariant, the relationship between migrant networks and FDI could not be jointly estimated with host country fixed effects due to perfect collinearity. While migrant shares are not completely time invariant, recall that the variable is only available in 2000, 2005, 2010, and 2013 due to data constraints. We have carried forward the value of migrant share where data is missing, which means there is no time variation within each interval. To address this problem, instead of including fixed effects directly into the estimating equation, we use a proxy, following, for example, Crozet and Hinz (2016). Specifically, using aggregate data from UNCTAD Bilateral FDI Statistics between 2003 and 2012 for all host and source countries available, we first estimate the following equation:

$$\begin{aligned}\log(FDI_{ijt}+1) = b_0 &+ b_1\log(GDP_{i,t-1}) + b_2\log(GDP_{j,t-1}) + \alpha_3\log(Dist_{ij}) \\ &+ \alpha_4 Migrant\ share_{i,t-1} + \alpha_5 Migrant\ share_{j,t-1} \\ &+ \alpha_{\boldsymbol{X}}\boldsymbol{X}_{ij,t-1} + c_i + c_j + c_t + \epsilon_{ijt}.\end{aligned} \tag{2}$$

Therefore, we rely on FDI data not only from China, but all bilateral pairs, and $Migrant\ share_{i,t-1}$ and $Migrant\ share_{j,t-1}$ are the Chinese migrant shares of source country i and host country j, respectively. The estimated coefficients, $\hat{c}_j$, provide proxies for host country fixed effects in the regression where only Chinese outward FDI is examined. Results are shown in Table 3 Panel D. Compared to the baseline regression estimates, the coefficients on $Migrant\ share$ remain positive in all columns, and are quantitatively similar and statistically significant for M&A.

Lastly, we consider alternative estimation methods. In Panel E, we use simple OLS, without replacing zeros in the dependent variable with ones. The sample size is reduced considerably as a result, but the results are similar both qualitatively as well as quantitatively. Moreover, in Panel F, we deal with zero or missing FDI flows in the data using another standard method. Specifically, we apply the Poisson pseudo-maximum-likelihood (PPML) estimator from Santos Silva and Tenreyro (2006), which simultaneously deals with the problem of zeros in the dependent variable and is consistent in the presence of heteroskedasticity. The association between the size of the migrant network and FDI remains statistically significant for M&A, but not greenfield. Although results for the impact of migrants on greenfield FDI is more mixed Table 3, this is actually consistent with our baseline result and interpretation that M&A require more information and hence benefit more from migrant networks.

4.3 Instrumental variables strategy

4.4 Instruments

So far, we have documented a significant and positive relationship between overseas Chinese migrant networks and Chinese OFDI. Moreover, across all specifications, such a linkage is consistently stronger for cross-border M&A in comparison to greenfield investment. However, one may be concerned of potential endogeneity issues between migration and cross-border investment. As discussed by Javorcik et al. (2012), reverse causality may exist where FDI drives migration instead. For instance, the presence of multinationals from cross-border investment generates greater economic activity, possibly encouraging the inflow of migrants. More directly, overseas migrant networks may be formed by FDI, as employees from the home country are transferred to the host country, and this in turn facilitates the movement of more emigrants to that location. To address this concern, we employ an instrumental variables (IV) approach.

The determination of bilateral migration can be analyzed by push factors that encourage labor movement out of an origin country, and pull factors that make a particular destination more attractive. Conceptually, these push and pull factors can be time variant or time invariant. Since our empirical setting focuses on one origin country, China, we cannot examine time-invariant push factors. For time-variant push factors, these are controlled for by the inclusion of time fixed effects as in the previous specifications. On the other hand, a destination, for instance, may be more appealing in certain years, and it may also attract more migrants compared to other countries across all years.

Thus, we consider various pull factors of migration into a destination that are uncorrelated with the FDI flows of today. First, following Javorcik et al. (2012), we employ historical migrant shares as an instrument. Migration is likely to be correlated over time, as families reunite and established networks in a foreign country lower the cost of immigration. Therefore, this encourages future migration from China to the host country. Because our primary database for Chinese migrants abroad, the UN Global Bilateral Migration Database, is available from 1990, the longest lag that can be created is 10 years. In this case, there may be concerns that the exclusion restriction for a valid instrument is not satisfied. Hence, we supplement our data with the World Bank Global Bilateral Migration Database, which has data from 1960 to 2000 in 10 year intervals. This 40-year lag is longer than the 30-year lag employed in Javorcik et al. (2012). While the UN and World Bank datasets are not identical, the correlation between them is extremely high for the overlapping years of 1990 and 2000 at 0.977. For China, although its open-door policy beginning in 1978 marked a dramatic change in economic policy, China's OFDI only rises significantly at the turn of the 21st century (e.g., see Figure 2). However, for various historical reasons, the overseas Chinese community had always been sizable, and so the size of the network 40 years ago would be difficult to attribute to cross-border movements in capital. In addition, to control for destination-specific unobserved heterogeneity that may drive migration and FDI, we continue our approach from Table 3 Panel D and include the estimated host-country fixed effects.

Next, as discussed in Javorcik et al. (2012), dual citizenship provides benefits to foreigners that is likely to encourage cross-border migration. Thus, it is expected to be a good predictor of migrants' presence in the host country. Arguably, dual citizenship benefits are a pull factor that also influence migration patterns but not the movement of capital. We obtain data on whether countries recognize dual citizenship from the MACIMIDE Global Expatriate Dual Citizenship Dataset (Vink et al., 2015). In our regression sample, this variable is constant for all countries except Belgium, Luxembourg, and the Slovak Republic. Hence, we do not include estimated host-country fixed effects in the IV regressions where dual citizenship is an instrument.

One concern with using the aforementioned historical migrant share as an instrument is the potential for bilateral China-destination specific factors that could induce both investment and labor flows. Note that dual citizenship does not suffer from such a problem because the recognition of more than one citizenship is not China-specific. Hence, to further alleviate concerns regarding the validity of our IV strategy, we construct an alternative instrument for time-variant pull factors that utilizes information on global migration flows to the destination independent of Chinese migration. Specifically, we instrument Chinese migrant shares with *Other migrant share*, defined as the (lagged) total migrant stock from the world excluding China to the host country i at year $t-1$ normalized by the host country's total population. This instrument captures the attractiveness of the host country j as an emigration destination, and is expected to predict Chinese migrant shares well and meet the relevance criteria. Although these other non-Chinese immigrants may have good knowledge about the host market, they lack the understanding and information on the Chinese market. Therefore, this prevents them from effectively and directly matching Chinese outward investment with host market opportunities or overcoming investment barriers specific to Chinese investors. Therefore, this instrument is likely to satisfy the exclusion restriction. As before, we estimate this both with the estimated destination fixed effects for one specification, and without them when we use dual citizenship as a second instrument. To test the validity of our instruments, we conduct two diagnostic tests. The underidentification test is performed by examining the Kleibergen-Paap rank Lagrange multiplier statistic, and the test for overidentifying restrictions is provided by the Hansen J statistic.

In the Online Appendix, we include IV regressions with alternative instruments that confirm the robustness of our results. Specifically, we take advantage of the bilateral structure of the data and construct an instrumental variable following the logic of Burchardi et al. (2016).[17] This method utilizes information on global migration outflows and inflows which capture the push and pull factors of migration, respectively, independent of Chinese migration since 1960. In addition., we also employ contemporaneous instruments reflect countries' immigration policies purely. Since immigration policies may also influence FDI, we are careful to select policies that should only affect labor mobility. We draw data from a new dataset on the strictness of immigration policies from IMPIC for 33 OECD countries from 1980 to 2010 (Helbling et al., forthcoming). The index employed covers policies from three different fields: family reunification, asylum and refugees, and control of immigration; we normalize the range of this immigration strictness variable to be from 0 to 1. Lastly, from the World Values Survey, we utilize a measure of countries' attitudes towards foreign residents.

4.5 Instrumental variables results

Table 4 reports the two-stage least squares (2SLS) estimation results, with a different set of instruments in each panel. The dependent variable in the first-stage regression is always

[17]We found that applying the method of Burchardi et al. (2016) directly here yields extreme predictions of migrant stocks. This is in part due to the decreasing stocks observed in countries, driving some migrant stocks, which were already small to begin with, to be negative.

the Chinese migrant share in the host country, *Migrant share*, and the regressors are the instrument(s), the full set of control variables, and year fixed effects. Note that the first-stage regression as well as estimating sample are identical regardless of the second stage dependent variable. As indicated in column 1 across all panels, the chosen instruments are all significantly correlated with the endogenous variable. For instance, the historical migrant network is a strong positive predictor of the migrant share today, despite it reflecting the share of Chinese migrants roughly 40 years ago. Dual citizenship is also positively correlated with the current share of Chinese migrants in Panel B, though it is still positive but imprecisely estimated in Panel D. This suggests that dual citizenship may be a pull factor on all origin countries, since Chinese citizens cannot accrue its benefits and must renounce their Chinese nationality if they wish to be a citizen of another country.

The second-stage IV results in columns 2 to 5 corroborate the OLS estimates and the previous robustness checks. The second-stage results reveal overseas Chinese migrant networks are a strong determinant of Chinese outward FDI. Importantly, the strong positive effects for M&A (i.e., columns 4 and 5) persist, and reinforce the notion that migrants facilitate transactions for the more information-intensive cross-border M&A investment. Comparing the estimates on *Migrant share* from Table 3 Panels C and D with Table 4 reveals that the OLS coefficients are not too different from the IV estimates. Furthermore, corroborating the previous findings, the coefficients in regressions with the value of FDI (columns 2 and 4) remain substantially larger than that with the number of FDI projects (columns 3 and 5).

The diagnostic tests also indicate that, in general, the instruments chosen are valid. The p-values associated with the Kleibergen-Paap rank Lagrange multiplier statistic from the underidentification test and the Hansen J statistic from a test of overidentifying restrictions are reported. For the former, p-values are all very small, rejecting the null hypothesis that the excluded instruments are not relevant. For the latter, the p-values are generally greater than 0.1, suggesting that the exclusion restriction is satisfied and the instruments are uncorrelated with the error term.

4.6 Information and barriers to investment

4.6.1 Potential barriers to greenfield FDI and M&A

Having established the positive link between migrant networks and FDI, we now explore the different channels through which overseas migrants might facilitate cross-border investment. While certain information such as laws and regulations are publicly available, knowledge about the economic environment, its firms, and industries, are not so easily obtained by foreign firms. First, at the firm-level, the lack of information either held by or about companies may deter FDI. This is more likely to affect, for instance, firms that are non-listed as opposed listed. The latter typically have more resources at their disposal and greater name recognition. Moreover, listed companies are more transparent because they must disclose financial details and file earnings reports. Therefore, information asymmetry is likely to be a larger problem for non-listed targets as opposed to public targets for cross-border M&As (Erel et al., 2012). Although

Table 4: IV Estimation with Two-stage Least Squares

Panel A	Stage I	Stage II			
Dependent variable:	Migrant share	GF	# GF	MA	# MA
	(1)	(2)	(3)	(4)	(5)
Migrant share (40-year lag)	0.374***				
	(0.022)				
Migrant share		0.189	0.096**	1.065***	0.212***
		(0.220)	(0.045)	(0.179)	(0.039)
Underidentification test (p)		< 0.01	< 0.01	< 0.01	< 0.01
Estimated destination FE	Y	Y	Y	Y	Y
Observations	1,004	1,004	1,004	1,004	1,004
Shea partial R-squared	0.577				
Panel B	Stage I	Stage II			
Dependent variable:	Migrant share	GF	# GF	MA	# MA
	(1)	(2)	(3)	(4)	(5)
Migrant share (40-year lag)	0.382***				
	(0.023)				
Dual citizenship	0.058***				
	(0.017)				
Migrant share		0.507**	0.133***	1.235***	0.227***
		(0.207)	(0.043)	(0.170)	(0.038)
Underidentification test (p)		< 0.01	< 0.01	< 0.01	< 0.01
Overidentification test (p)		0.108	0.364	0.779	0.484
Estimated destination FE	N	N	N	N	N
Observations	1,004	1,004	1,004	1,004	1,004
Shea partial R-squared	0.605				
Panel C	Stage I	Stage II			
Dependent variable:	Migrant share	GF	# GF	MA	# MA
	(1)	(2)	(3)	(4)	(5)
Other migrant share	0.021***				
	(0.003)				
Migrant share		1.065	0.315**	2.427***	0.616***
		(0.873)	(0.124)	(0.669)	(0.119)
Underidentification test (p)		< 0.01	< 0.01	< 0.01	< 0.01
Estimated destination FE	Y	Y	Y	Y	Y
Observations	1,004	1,004	1,004	1,004	1,004
Shea partial R-squared	0.077				
Panel D	Stage I	Stage II			
Dependent variable:	Migrant share	GF	# GF	MA	# MA
	(1)	(2)	(3)	(4)	(5)
Other migrant share	0.017***				
	(0.003)				
Dual citizenship	0.018				
	(0.022)				
Migrant share		0.762	0.267*	2.300***	0.641***
		(1.032)	(0.146)	(0.779)	(0.131)
Underidentification test (p)		< 0.01	< 0.01	< 0.01	< 0.01
Overidentification test (p)		0.114	0.301	0.636	0.225
Estimated destination FE	N	N	N	N	N
Observations	1,004	1,004	1,004	1,004	1,004
Shea partial R-squared	0.052				

Notes: In all panels, the dependent variable of the first stage regression is *Migrant share*. The second stage dependent variables are Chinese outward FDI measured by the (log) value and number of greenfield FDI (*GF* and *#GF*), and likewise for M&A (*MA* and *#MA*). All regressions include the full set of control variables as described in the text and year fixed effects. All time-variant explanatory variables are lagged by one year. Standard errors in parentheses are clustered by host country. ***, **, * denote significance level at 1%, 5% and 10% respectively. The p-values associated with the Kleibergen-Paap rank Lagrange Multiplier (Hansen J) statistic for the underidentification (overidentification) test are reported.

acquirers search for high synergy with suitable targets, there may be adverse selection as targets know their value better than the acquirers.

The business practices of a firm may also influence its difficulty in investing abroad. For example, we can compare the operations of privately-owned enterprises (POE) and state-owned enterprises (SOE) in China. According to a survey by the China Council for the Promotion of International Trade, 51.1% POEs turn to the overseas Chinese Chamber of Commerce in dealing with investment risk, while only 38.6% for SOEs ask for this assistance (CCPIT, 2015, Figure 6.11). The survey also shows that 93.5% POEs highly values opinions from their overseas employees as opposed to 80.7% for SOEs (CCPIT, 2015, Figure 6.8). This evidence suggests that POEs are more open to utilizing overseas Chinese networks than SOEs. However, because SOEs are affiliated with foreign governments, their investment deals are more heavily scrutinized and may face higher entry barriers and greater restrictions from the host-country.[18]. Thus, whether migrants play a larger role for state-owned or privately-owned enterprises is theoretically ambiguous.

Conducting FDI requires substantial knowledge about foreign markets, and information intensity may also vary by industry. While roughly half of global foreign direct investment, whether greenfield or M&A, is made in the tertiary or service industries, the problem of asymmetric information is arguably more severe for cross-border transactions in these industries.[19]. Compared to farming and manufacturing, industries such as information technology, engineering, and research and development are all more human-capital-intensive (e.g., Coff, 1999).[20] Again, asymmetric information is an impediment, especially for M&A.

Furthermore, multinationals must learn about and comply with specific host-country laws and regulations. In the case of greenfield FDI, money, time, and resources must be dedicated to the startup of a new production facility. New businesses also encounter more formal barriers in the form of mandatory procedures, licensing and permit requirements, and difficulties in securing access to industrial land (World Bank, 2010). In addition to crossing organizational boundaries, cross-border M&A must also confront the challenges associated with operations in a different country, just as greenfield FDI. Companies must obtain knowledge about and comply with the administrative requirements and red tape which govern their operating activities, with regards to both output (i.e., sales) or inputs (e.g., labor markets).

Culture has also been shown to be an important determinant of international transactions. For instance, Dunlevy (2006) shows that cultural differences lessens trade, although the effect is mitigated by the presence of migrants. Furthermore, Davies et al. (2015) find that M&A are negatively affected by cultural barriers, by not greenfield FDI. The culture of a country is often reflected in the business operations of an enterprise, including its organization and

[18]For example, in 2012, former Canadian Prime Minister Stephen Harper approved the sale of Canada's oil company Nexen to China's state-owned energy giant China National Offshore Oil Corporation (CNOOC), but restricted foreign SOEs to minority stakes in the future except in "exceptional circumstances". (See "Canada OK's foreign energy takeovers, but slams door on any more", *Reuters*, Dec. 8, 2012.)

[19]See Annex Tables 14 and 20 from (UNCTAD, 2017)

[20]A report by the World Bank (2010) also found fewer restrictions on foreign ownership in primary and manufacturing sectors, but stricter limits in services, which reinforces the migrant effect.

management (e.g., Kogut and Singh, 1988). Migrants familiar with local markets have a comparative information advantage over their foreign peers due to the lack of information mobility across linguistic and cultural borders.[21] Therefore, problems arising from differences in culture may be alleviated by the presence of migrant networks. Evidence from Rauch and Trindade (2002) suggests that aside from reducing information barriers, informational networks can deter contract violations in international trade as well. Similar contract enforcement difficulties may exist for cross-border investment, as multinationals must deal with product procurement, and in the case of M&A, the possibility of the opposing party reneging on any agreements made.

4.6.2 Heterogeneity across firms

Using the detailed deal-level FDI data, we exploit firm, industry, and country-level variation to examine how the migrant network effect changes with investment barriers. To provide evidence that migrants have an information advantage that facilitates FDI, we first explore the heterogeneity across firms. As in Section 2.4, we classify companies by whether or not they are listed on a stock exchange. We separately aggregate to the country level the values of our dependent variables (*GF*, *#GF*, *MA*, and *#MA*) for FDI from non-listed and listed companies. Since non-listed companies typically possess less resources and information, and less is known about them, the information barrier for FDI from these companies should be higher. Hence, we generate an indicator variable $\mathbb{I}(info)_k$ equal to 1 if k is the more information intensive category, i.e., non-listed companies. The following equation is estimated:

$$\begin{aligned} \log(FDI_{jkt}+1) = \gamma_0 + \gamma_1 \log(GDP_{j,t-1}) + \gamma_2 \log(Dist_j) + \gamma_3 Migrant\ share_{j,t-1} \\ + \gamma_4 Migrant\ share_{j,t-1} \times \mathbb{I}(info)_k + \gamma_5 \mathbb{I}(info)_k + \gamma_{\boldsymbol{X}} \boldsymbol{X}_{j,t-1} + \nu_{jkt}. \end{aligned} \tag{3}$$

If the coefficient γ_4 is positive, this would corroborate the idea that overseas migrants help resolve information asymmetry. The estimation results are presented in Table 5 Panel A, where in columns 1 and 2, greenfield FDI originating from non-listed parent companies is considered; in columns 3 and 4 (5 and 6), the link between migrant networks and M&A from non-listed acquirers (to non-listed targets) is examined. As before, the effect on M&A investment remains larger than on greenfield FDI, by value and number, regardless of whether the investment is originating from a firm that is listed or not. Moreover, as hypothesized, γ_4 is positive and statistically significant across all columns, suggesting migrants are more important in facilitating cross-border investment when less information is available about either one of the involved parties. Although one might argue that non-listed companies are smaller, and the differential impact of migrants is due to the size of investment, Figure 4 indicates that the scale of investment is actually comparable for both types of companies. In fact, the computed average value of projects from non-listed Chinese firms is actually larger than that of listed firms. Thus, this interpretation does not seem valid.

In Table 5 Panel B, we compare investment from privately-owned enterprises (POE) and

[21] For instance, Dvořák (2005) show that in portfolio investment, that domestic investors earn higher profits than foreign investors.

Table 5: Heterogeneity Across Firms

	Panel A: Non-listed versus Listed Firms					
Non-listed company	Parent		Acquirer		Target	
	GF	# GF	MA	# MA	MA	# MA
	(1)	(2)	(3)	(4)	(5)	(6)
Migrant share	0.261	0.066	1.277***	0.189***	1.494***	0.209***
	(0.247)	(0.042)	(0.361)	(0.057)	(0.412)	(0.079)
Migrant share × Non-listed	0.260***	0.062***	0.452**	0.118**	0.179***	0.086***
	(0.075)	(0.023)	(0.187)	(0.055)	(0.054)	(0.021)
Non-listed	1.894***	0.306***	0.616***	0.114***	0.616***	0.152***
	(0.184)	(0.037)	(0.129)	(0.021)	(0.117)	(0.026)
Observations	2,038	2,038	2,038	2,038	2,038	2,038
R-squared	0.417	0.469	0.271	0.381	0.283	0.372
	Panel B: Privately-owned versus State-owned Enterprises					
	GF	# GF	MA	# MA		
	(1)	(2)	(3)	(4)		
Migrant share	0.405*	0.062	1.006***	0.127**		
	(0.232)	(0.232)	(0.351)	(0.060)		
Migrant share × POE	0.165*	0.081***	0.802***	0.206***		
	(0.086)	(0.022)	(0.182)	(0.059)		
POE	0.829***	0.222***	0.398***	0.098***		
	(0.194)	(0.040)	(0.139)	(0.028)		
Observations	2,038	2,038	2,038	2,038		
R-squared	0.389	0.459	0.249	0.364		

Notes: The dependent variables are Chinese outward FDI measured by the (log) value and number of greenfield FDI (*GF* and *#GF*), and likewise for M&A (*MA* and *#MA*). Non-listed (POE) is a dummy variable that equals to 1 if the company is not listed in any stock exchange (a privately-owned enterprise) and zero otherwise. All regressions include the full set of control variables as described in the text and year fixed effects. All time-variant explanatory variables are lagged by one year. Standard errors in parentheses are clustered by host country. ***, **, * denote significance level at 1%, 5% and 10% respectively.

state-owned enterprises (SOE). For each investing or acquiring company, we collect its ownership structure from Orbis, a database managed by Bureau van Dijk which contains information on 200 million companies worldwide. A firm is classified as a SOE if at least 25.01% of its ownership belongs ultimately to the Chinese government, and a POE otherwise.[22] For both greenfield FDI and M&A, while there tends to be more investment projects from POEs, the value of their projects is generally smaller than those from SOEs. We run a similar regression to Equation (3), where FDI is now aggregated up to the country level according to ownership type, POE or SOE. Panel B shows that migrant shares have a stronger relationship to investment from private companies as opposed to those with government support. The coefficient on the interaction term is positive and statistically significant, corroborating the idea that companies without government support can utilize the networks abroad to help overcome barriers associated with international transactions.

[22] We confirm our regression results are also robust when we change the equity threshold of the global ultimate owner to 50.01%.

4.6.3 Heterogeneity across industries

Overseas Chinese migrants are also expected to add more value to industries with greater knowledge-intensity, namely, the tertiary industries. These include, for instance, financial services and information technology. Thus, we aggregate the total number and value of greenfield projects and M&A to the industry level, and rely on Orbis to provide the industry of the parent company for greenfield FDI, and SDC Platinum itself for the acquirer's industry. We classify industries as either primary (SIC two-digit code 1-14), secondary (15-39), or tertiary (40-99). Primary industries are related to agriculture or natural resources, secondary industries are generally manufacturing, and tertiary industries include services for the most part.[23] The number or value of FDI projects is aggregated up to this broader industry definition, i.e., k = primary, secondary, or tertiary. We define $\mathbb{I}(info)_k$ to be 1 if k = tertiary, and zero otherwise.[24] In Table 6 Panel A, we see that the largest effects are indeed observed for the service industries. Even within an industry, the positive relationship is more pronounced for M&A.

A company that invests outside the industry it operates in may also find the environment to be less familiar and encounter information barriers. Thus, the migrant network effect is expected to be larger for FDI in industries that are different from that of the investing company. This hypothesis is tested in Table 6 Panel B. For greenfield investment, while the SIC code for the parent company can be easily obtained, the industry of the FDI project itself is not coded. We assign the project a SIC 2-digit code based on information provided from fDi Markets regarding the industry sector, sub-sector, and industry activity. If this code is different from that of the parent company, we refer to this as cross-industry FDI. Meanwhile, M&A is classified as cross-industry if the industry code of the acquirer and target companies are different. Similar to the previous specifications, aggregate FDI at the country level is computed separately for investment in the same industry and across different industries (i.e., k = same industry or cross-industry). Subsequently, an indicator for cross-industry FDI is interacted with $Migrant\ share$. Consistent with idea that migrants promote FDI through an information channel, Table 6 Panel B shows that the marginal effect of the size of migrant networks on FDI is more pronounced for cross-industry FDI.

4.6.4 Heterogeneity across host countries

In this section, we exploit variation in host-country characteristics to examine informational barriers such as regulatory obstacles. First, in Table 7 Panels A and B, we examine the costs associated with starting a business. Since new production facilities are created only in the case of greenfield FDI, we expect migrant networks to facilitate more cross-border investment

[23] Specifically, primary industries are Agriculture, Forestry, Fishing, Mining; secondary industries are Construction and Manufacturing; and tertiary industries are Transportation, Communications, Electric, Gas, Sanitary Services, Wholesale Trade, Retail Trade, Finance, Insurance, Real Estate, Services, and Public Administration. While the original classification is SIC 4-digit, the number of projects within such a narrow code is typically small, so we use broader classifications.

[24] In unreported results, we also included an additional indicator variable for secondary industries and its interaction with $Migrant\ share$. The results are qualitatively and quantitatively similar. The same is true when the estimation is made separately for primary, secondary, and tertiary industries.

Table 6: Heterogeneity Across Industries

	Panel A: Tertiary versus Primary and Secondary			
	GF	# GF	MA	# MA
	(1)	(2)	(3)	(4)
Migrant share	0.180	0.031	0.881**	0.134**
	(0.136)	(0.028)	(0.341)	(0.056)
Migrant share × Tertiary	0.679**	0.133***	0.775***	0.160***
	(0.282)	(0.039)	(0.114)	(0.032)
Tertiary	0.624***	0.070***	0.179**	0.035**
	(0.172)	(0.024)	(0.085)	(0.015)
Observations	3,057	3,057	3,057	3,057
R-squared	0.261	0.298	0.210	0.294
	Panel B: Cross-Industry FDI			
	GF	# GF	MA	# MA
	(1)	(2)	(3)	(4)
Migrant share	0.273	0.086*	1.210***	0.209***
	(0.258)	(0.047)	(0.406)	(0.074)
Migrant share × Cross-industry	0.134***	0.022**	0.680***	0.098***
	(0.048)	(0.009)	(0.047)	(0.017)
Cross-industry	0.080	0.052**	-0.003	0.014
	(0.143)	(0.020)	(0.094)	(0.012)
Observations	2,038	2,038	2,038	2,038
R-squared	0.401	0.468	0.276	0.377

Notes: The dependent variables are Chinese outward FDI measured by the (log) value and number of greenfield FDI (*GF* and *#GF*), and likewise for M&A (*MA* and *#MA*). All regressions include the full set of control variables as described in the text and year fixed effects. All time-variant explanatory variables are lagged by one year. Standard errors in parentheses are clustered by host country. ***, **, * denote significance level at 1%, 5% and 10% respectively.

when the mode of entry is greenfield but not M&A. Moreover, we expect their assistance to be more important when startup procedures are more burdensome, but not necessarily when the monetary cost is higher.

Thus, we draw data on three variables from the World Bank Doing Business Reports on starting a business: time, number of procedures, and monetary cost (as a percentage of income per capita). To distinguish non-monetary from monetary costs, we combine startup time and procedures into an index by normalizing the variable between the maximum and minimum values observed in the sample. Furthermore, to contrast countries with tight versus loose regulations, we convert each of these variables to indicator variables that take the value of 1 if the measure of the country's barrier is stronger than the median value across the sample, and zero otherwise. Quantitatively similar results are also obtained with the mean instead of the median. Thus, in addition to the full set of control variables, we include an interaction term between $Migrant\ share$ and these dummy variables. The results confirm our hypotheses: there is a more pronounced effect of migrant networks on greenfield FDI when the non-monetary costs of starting a business are higher (Panel A columns 1 and 2). No such effect is observed when monetary costs are higher (Panel B columns 1 and 2), and when M&A are involved (Panels A and B columns 3 and 4).

Next, in Panels C to E, we consider various regulations on capital inflow and the operations

Table 7: Heterogeneity Across Host Countries- Barriers to Entry

	GF	# GF	MA	# MA
Panel A	(1)	(2)	(3)	(4)
Migrant share	0.147	0.107**	1.870***	0.363***
	(0.244)	(0.050)	(0.467)	(0.112)
Migrant share × Startup time and procedures	3.870***	0.902***	-0.703	0.197
	(1.269)	(0.272)	(1.198)	(0.249)
Startup time and procedures	-0.597	-0.026	-0.349	-0.088
	(0.390)	(0.095)	(0.349)	(0.065)
Observations	895	895	895	895
R-squared	0.472	0.597	0.347	0.482
Panel B	(1)	(2)	(3)	(4)
Migrant share	0.252	0.106*	1.783***	0.350***
	(0.263)	(0.056)	(0.433)	(0.109)
Migrant share × Startup cost	1.125	0.376	1.082	0.159
	(1.142)	(0.278)	(0.932)	(0.145)
Startup cost	-0.183	-0.108	-0.945**	-0.120*
	(0.491)	(0.096)	(0.411)	(0.071)
Observations	980	980	980	980
R-squared	0.457	0.577	0.335	0.462
Panel C	(1)	(2)	(3)	(4)
Migrant share	0.046	0.055	1.430***	0.244***
	(0.122)	(0.035)	(0.215)	(0.038)
Migrant share × Capital controls	2.404***	0.590***	4.663***	1.287***
	(0.861)	(0.157)	(0.804)	(0.166)
Capital controls	-0.378	-0.056	-0.573**	-0.133***
	(0.370)	(0.076)	(0.243)	(0.041)
Observations	970	970	970	970
R-squared	0.478	0.590	0.364	0.547
Panel D	(1)	(2)	(3)	(4)
Migrant share	0.153	0.070*	1.584***	0.284***
	(0.175)	(0.041)	(0.293)	(0.065)
Migrant share × Labor regulations	1.477**	0.350**	3.179***	0.851***
	(0.703)	(0.140)	(0.821)	(0.185)
Labor regulations	-0.263	-0.081	-0.456	-0.160**
	(0.403)	(0.079)	(0.293)	(0.066)
Observations	907	907	907	907
R-squared	0.464	0.585	0.344	0.502
Panel E	(1)	(2)	(3)	(4)
Migrant share	0.176	0.087*	1.636***	0.298***
	(0.178)	(0.046)	(0.325)	(0.072)
Migrant share × Administrative requirements	1.347*	0.165	2.692**	0.780***
	(0.786)	(0.122)	(1.101)	(0.234)
Administrative requirements	0.255	0.035	-0.180	-0.140*
	(0.383)	(0.070)	(0.325)	(0.071)
Observations	907	907	907	907
R-squared	0.465	0.583	0.340	0.492
Panel F	(1)	(2)	(3)	(4)
Migrant share	2.057**	0.442*	5.233***	1.168***
	(0.896)	(0.263)	(0.909)	(0.292)
Migrant share × Language	-2.074**	-0.385	-4.052***	-0.969***
	(0.909)	(0.261)	(0.910)	(0.290)
Language	2.833***	0.362***	1.451***	0.297***
	(0.547)	(0.111)	(0.445)	(0.077)
Observations	1,019	1,019	1,019	1,019
R-squared	0.474	0.581	0.370	0.538

Notes: The dependent variables are Chinese outward FDI measured by the (log) value and number of greenfield FDI (*GF* and *#GF*), and likewise for M&A (*MA* and *#MA*). All regressions include the full set of control variables as described in the text and year fixed effects. All time-variant explanatory variables are lagged by one year. Standard errors in parentheses are clustered by host country. ***, **, * denote significance level at 1%, 5% and 10% respectively.

of MNEs upon entry. From the Economic Freedom of the World database of (Gwartney et al., 2015), we obtain measures of capital controls, labor regulations involved with hiring and firing employees, and business regulations from administrative requirements issued by the government that companies have to comply with.[25] In Panels C to E, we find that when regulations on the international flow of capital, labor market, business practices are tighter, migrants have a stronger role in increasing the OFDI from their origin country, especially for M&A.

In Panel F, to test for the role of migrants in overcoming informal barriers related to cultural differences, we interact $Migrant\ share$ with common language indicator variable. The estimates show that for both greenfield OFDI and M&A, the effect of migrants is larger for countries that only have a small percentage of its population speaking Chinese, i.e., when $Language$ is equal to 0. This contrast is stronger for M&A. Since sharing a common language implies a lower language barrier and smaller cultural gap between the countries, migrants' role in facilitating international investment transactions is expected to shrink. Indeed, the empirical evidence validates this hypothesis.

In Table 8, we explore whether migrant networks promote more investment when the contracting environment is weak. From the World Bank Doing Business Reports, we construct a measure of the contract enforcement cost by averaging indices of the time and number of procedures to enforce contracts. As shown in Panel A, unlike regulatory barriers, we do not find evidence for a stronger effect of migrant networks when resolving disputes is more costly, for either greenfield FDI or M&A. This contrasts with the findings from Rauch and Trindade (2002) for international trade. In Table 8 Panel B, we draw another variable from the World Values Survey for a measure of social trust, following, for example, Pevzner et al. (2015). The aggregate level of trust in the country is measured by the share of individuals answering the survey question, "most people can be trusted" as opposed to "can't be too careful". However, there is also no significant effect of migrant networks alleviating distrust in cross-border investment deals.

4.7 Learning-by-investing

Lastly, we present evidence that is consistent with the idea that companies learn by investing abroad. Ideally, to capture learning-by-investing, one would need to measure how easily a company can invest in the host country. For example, for greenfield investment, ease of investment may be measured by the length of time to start a business, secure land, hire employees, establish a distribution network, etc. The World Bank (2010) notes that the number of days and procedures required to start a business for foreign companies can be significantly higher

[25] Gwartney et al. (2015) compiles data from various sources. The International Monetary Fund, Annual Report on Exchange Arrangements and Exchange Restrictions reports on up to 13 types of international capital controls. The zero-to-10 rating is the percentage of capital controls not levied as a share of the total number of capital controls listed, multiplied by 10. Hiring and firing regulations and administrative requirements are both based on questions from the World Economic Forum Global Competitiveness Report. The questions, respectively, are "The hiring and firing of workers is impeded by regulations (= 1) or flexibly determined by employers (= 7)." and "Complying with administrative requirements (permits, regulations, reporting) issued by the government in your country is (1 = burdensome, 7 = not burdensome)."

Table 8: Heterogeneity Across Host Countries- Contract Enforcement

	GF	# GF	MA	# MA
Panel A	(1)	(2)	(3)	(4)
Migrant share	0.182	0.122**	1.827***	0.365***
	(0.246)	(0.051)	(0.450)	(0.117)
Migrant share × Contract enforcement	1.558	0.134	1.229	0.209
	(1.202)	(0.355)	(1.142)	(0.146)
Contract enforcement	-0.954**	-0.191***	-0.566	-0.148**
	(0.406)	(0.070)	(0.384)	(0.062)
Observations	895	895	895	895
R-squared	0.474	0.596	0.349	0.488
Panel B	(1)	(2)	(3)	(4)
Migrant share	0.538	0.019	1.817***	0.396***
	(0.491)	(0.108)	(0.534)	(0.116)
Migrant share × Trust	-0.126	0.029	-0.026	-0.013
	(0.282)	(0.049)	(0.485)	(0.091)
Trust	0.421	0.262*	1.617***	0.355***
	(0.712)	(0.139)	(0.578)	(0.122)
Observations	407	407	407	407
R-squared	0.444	0.627	0.401	0.555

Notes: The dependent variables are Chinese outward FDI measured by the (log) value and number of greenfield FDI (*GF* and *#GF*), and likewise for M&A (*MA* and *#MA*). All regressions include the full set of control variables as described in the text and year fixed effects. All time-variant explanatory variables are lagged by one year. Standard errors in parentheses are clustered by host country. ***, **, * denote significance level at 1%, 5% and 10% respectively.

than those of domestic companies. If the foreign MNE gains experience after investing in one economy, future endeavors in the same country should proceed more quickly. Controlling for various firm-level characteristics, one might then expect that, for instance, the time to start a business will decrease with the company's experience in a market. Unfortunately, we do not have such detailed data on the ease of investment by firm. Instead, we rely on the empirical framework thus far and show regression results which are supportive of such a learning-by-investing hypothesis, where there may be knowledge spillovers between migrant networks and foreign investors.

The results are presented in Table 9. In Panel A, following Section 2, we decompose Chinese outward FDI by whether it is the initial project or not. Projects are considered subsequent (i.e., not first) in a country when the company has already invested in that country before. As before, we aggregate all first time deals to a country separately from subsequent transactions, and interact a dummy variable for first time deals with $Migrant\ share$. The interaction term is positive and also statistically significant, which means that the presence of migrants is especially important for a company expanding its operations in the foreign economy for the first time. Thus, the results suggest there is within-firm learning, and companies benefit less in subsequent transactions from the informational networks.

In Panels B to D, we consider an alternative specification to examine this hypothesis. If learning occurs, then the effect of migrants should disappear with sufficient learning. Experience can be measured by cumulative FDI to the same host country. We first run our baseline

Table 9: Learning-by-Investing

	Panel A: First versus Subsequent Entry			
	GF	# GF	MA	# MA
	(1)	(2)	(3)	(4)
Migrant share	-0.199	-0.036	0.877**	0.119**
	(0.202)	(0.039)	(0.362)	(0.055)
Migrant share × First	0.874***	0.215***	0.889***	0.197***
	(0.123)	(0.033)	(0.207)	(0.066)
First	2.411***	0.380***	0.969***	0.179***
	(0.228)	(0.045)	(0.160)	(0.031)
Observations	2,038	2,038	2,038	2,038
R-squared	0.426	0.484	0.275	0.372
	Panel B: Baseline with Restricted Sample			
	GF	# GF	MA	# MA
	(1)	(2)	(3)	(4)
Migrant share	0.293	0.124**	1.862***	0.366***
	(0.257)	(0.057)	(0.455)	(0.112)
Observations	931	931	931	931
R-squared	0.474	0.589	0.346	0.479
	Panel C: Controlling for Cumulative GF			
	GF	# GF	MA	# MA
	(1)	(2)	(3)	(4)
Migrant share	0.221	0.059*	1.845***	0.334***
	(0.205)	(0.035)	(0.440)	(0.098)
(log) Cumulative GF or # GF	0.237***	0.417***	0.057	0.204**
	(0.049)	(0.047)	(0.036)	(0.038)
Observations	931	931	931	931
R-squared	0.504	0.692	0.348	0.528
	Panel D: Controlling for Cumulative MA			
	GF	# GF	MA	# MA
	(1)	(2)	(3)	(4)
Migrant share	0.060	-0.035	1.662***	0.177***
	(0.210)	(0.053)	(0.396)	(0.052)
(log) Cumulative MA or # MA	0.186***	0.316***	0.159***	0.375***
	(0.051)	(0.061)	(0.045)	(0.060)
Observations	931	931	931	931
R-squared	0.494	0.637	0.368	0.612

Notes: The dependent variables are Chinese outward FDI measured by the (log) value and number of greenfield FDI (*GF* and *#GF*), and likewise for M&A (*MA* and *#MA*). All regressions include the full set of control variables as described in the text and year fixed effects. All time-variant explanatory variables are lagged by one year. Standard errors in parentheses are clustered by host country. ***, **, * denote significance level at 1%, 5% and 10% respectively.

specification in Panel B with the restricted sample of Panels C and D to allow for comparisons to be made. Then, we include into our baseline specification the cumulative value or count of greenfield investment projects and M&A into a country (since the beginning of our sample) in Panels C and D, respectively. As before, we take logs and add 0.01 for values and 1 for counts. Cumulative values (counts) are used in columns 1 and 3 (2 and 4).

In Panel C, when we control for Chinese cumulative greenfield investment into a host country, the coefficients on $Migrant\ share$ indeed fall in all four columns. However, the magnitude of the decline is not large. Next, we control for cumulative M&A investment in Panel D, and the decline in the value of the coefficients, and therefore the marginal effect of migrant networks, is much more noticeable. Since we are controlling for aggregate outward FDI from China and not from a particular company, this suggests there may be spillovers across firms within a country from investing companies to future investors. This may be achieved through informal channels or the media. While migrants are still important in facilitating cross-border deals, their impact is reduced when China has acquired experience investing in that particular economy. The coefficients in columns 3 and 4 are 89% and 48% of their initial coefficients in Panel B, suggesting the extensive margin is most impacted. Furthermore, as columns 1 and 2 indicate, greenfield FDI also benefits substantially less from migrant networks when experience is gained from M&A.

5 Conclusion

Using data on Chinese migrant stocks across many countries and Chinese outward FDI, this paper provides empirical evidence that overseas migrants serve as informational networks for foreign investors. We find migrant networks to be an important determinant of FDI, for both modes of entry, greenfield FDI and M&A. The effects are observed at both the extensive and intensive margins, as captured by the number and value of investment projects, respectively. Furthermore, consistent with the idea that M&A is more information intensive, the results indicate that overseas Chinese networks are more closely associated with M&A than greenfield FDI.

We also provide evidence that migrant networks facilitate cross-border investment by alleviating many informational barriers. The relationship between overseas Chinese networks and OFDI is more pronounced for non-listed companies, privately-owned enterprises, for service industries, for cross-industry FDI, and in host-countries with smaller Chinese-speaking populations and tighter regulations. However, we do not find migrants to have a stronger impact for countries with a weaker contracting environment. Lastly, we show empirical support for learning-by-investing, as the marginal effect of migrant networks diminishes with the investor's experience of going abroad.

The growth of international migrant stocks and investment is not unique to China alone. In fact, the largest international migrant stocks all originate from developing countries, namely, India, Mexico, Russia, China, and Bangladesh. With rising incomes in developing countries and greater labor mobility, the global stock of migrants continues to rise. Moreover, this has been accompanied by tremendous growth in the cross-border flow of capital: the outward stock of FDI (as a percentage of GDP) for the world has tripled since 1990 (from 10.1% to 34.0%).[26] For countries like India and South Africa, FDI outflows are 2.5 and 6 times larger, respectively, since 2005. Globalization is a trend that is likely to persist in the near future. As barriers in the international movement of labor and capital fall and the global economy becomes even more integrated, understanding their linkages is key to the future research agenda.

[26] See Annex Table 8 from (UNCTAD, 2017).

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Appendix

Appendix Table 1: Summary Statistics

Variable	Mean	Median	Std Dev	Minimum	Maximum
# GF	4.85	2.00	8.71	1	80
GF (billion USD)	420	95.9	912	0.2	8954
# MA	3.50	2.00	4.83	1.00	36
MA (billion USD)	887	169	1530	0.02	8430
UN FDI (billion USD)	158	467	18.01	0.49	4808
Migrant share	0.21	0.03	0.73	0	7.20
Migrant stock (2003)	28792	924	129790	0	1315072
Growth rate of migrant stock (2003-2014)	524	45.4	4186	-100	45706
(log) GDP	24.2	24.1	2.44	18.6	30.5
(log) GDP per capita	8.68	8.71	1.53	5.25	11.6
(log) Distance	9.01	9.04	0.55	7.06	9.86
Language	0.02	0	0.13	0	1
Legal system	0.18	0	0.38	0	1
GDP growth	3.59	3.71	5.25	-62.1	104
Financial development	0.60	0.42	0.52	9.9×10^{-5}	3.14
Institution quality	9.20	8.5	3.30	2.5	16
Trade openness	0.95	0.85	0.58	0.21	5.27
Migrant share (40-year lag)	0.002	0.0001	0.01	0	0.17
Other migrant share	7.31	3.73	8.72	0.06	49.9
Dual citizenship	0.67	1	0.47	0	1

Appendix Table 2: Number of Investment Projects by Country between 2003 and 2014

Both Greenfield and M&A

Country	#GF	#MA	Country	#GF	#MA	Country	#GF	#MA
Argentina	14	5	Hungary	29	8	Papua New Guinea	3	1
Australia	77	155	India	127	6	Peru	14	5
Austria	1	6	Indonesia	65	13	Philippines	36	1
Azerbaijan	9	3	Iraq	1	2	Poland	33	1
Belarus	11	1	Ireland	11	2	Portugal	5	3
Belgium	27	4	Israel	6	7	South Korea	36	19
Bolivia	1	2	Italy	37	26	Romania	35	1
Brazil	94	15	Jamaica	4	1	Rusia	111	11
Cambodia	14	1	Japan	63	56	Singapore	78	57
Canada	56	73	Jordan	6	1	Slovakia	4	1
Cayman Islands	1	5	Kazakhstan	14	9	South Africa	48	1
Chile	9	2	Kyrgyzstan	5	2	Spain	41	15
Colombia	9	4	Liberia	1	1	Sri Lanka	3	2
Cyprus	2	1	Lithuania	7	1	Sweden	22	8
Czech Republic	13	3	Luxembourg	7	3	Switzerland	13	6
Dem. Rep. of Congo	5	1	Macau, China	7	3	Syrian Arab Republic	3	1
Denmark	24	7	Malaysia	48	12	Taiwan	73	16
Ecuador	6	2	Mexico	33	4	Thailand	48	11
Egypt	17	3	Mongolia	7	11	Tunisia	2	1
Estonia	1	1	Mozambique	3	1	Turkey	22	4
Finland	3	1	Namibia	1	1	Ukraine	7	7
France	82	35	Netherlands	46	2	United Arab Emirates	43	1
Gabon	2	4	New Zealand	8	11	United Kingdom	161	44
Georgia	2	1	Nigeria	11	2	United States	333	191
Germany	43	61	North Korea	6	1	Viet Nam	64	7
Ghana	9	1	Norway	3	4	Zambia	18	1
Hong Kong, China	149	301	Pakistan	28	4	Zimbabwe	7	2

Only Greenfield

Country	#GF	Country	#GF	Country	#GF
Afghanistan	3	Greece	13	Paraguay	2
Algeria	12	Guyana	5	Qatar	5
Angola	1	Haiti	1	Rwanda	4
Antigua and Barbuda	1	Honduras	2	Saudi Arabia	12
Armenia	1	Iran	12	Senegal	3
Bahrain	3	Kenya	11	Serbia	2
Bangladesh	6	Kuwait	4	Slovenia	1
Bosnia and Herzegovina	2	Lao	1	Sudan	4
Botswana	1	Latvia	1	Tajikistan	5
Brunei Darussalam	3	Madagascar	2	Macedonia	1
Bulgaria	16	Micronesia	1	Turkmenistan	5
Ivory Coast	1	Moldova	1	Uganda	5
Cameroon	3	Morocco	3	Tanzania	4
Chad	2	Myanmar	9	Uruguay	3
Costa Rica	1	Nepal	2	Uzbekistan	13
Croatia	1	Nicaragua	2	Venezuela	18
Cuba	2	Niger	2	Yemen	1
Ethiopia	14	Oman	3		
Fiji	1	Panama	5		

Only M&A

Country	#MA	Country	#MA	Country	#MA
Aruba	1	Dominican Republic	1	Republic of the Congo	1
Barbados	4	Eritrea	1	Sierra Leone	3
British Virgin Islands	42	Isle of Man	1	Trinidad and Tobago	2