Migrant Networks, Greenfield FDI, and Cross-border Mergers and Acquisitions

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Abstract

We study the relationship between international migration and foreign direct investment (FDI), differentiating between the two modes of entry: greenfield FDI and cross-border mergers and acquisitions (M&A). Greenfield FDI is often favored over cross-border M&A (i.e., brownfield FDI) by host countries because it is associated with greater job creation and technology transfers. This implies higher implicit entry barriers for cross-border M&A. Using data on overseas Chinese networks and outward FDI from 2003-2014 to over 100 countries, we estimate a gravity equation for FDI. We find a positive association between overseas Chinese migrant networks and Chinese outward FDI, and importantly, the presence of these migrant networks is more closely associated with M&A than greenfield FDI. Moreover, we find this relationship with FDI to be more pronounced when information asymmetry is stronger, namely, for privately held companies, privately-owned enterprises, in tertiary industries, cross-industry FDI, and in host countries that are more culturally distant from China with tighter regulations. The results are robust to various specifications and estimation methods, including an instrumental variables approach that addresses potential endogeneity concerns.

JEL: F21, F22, F23

Keywords: overseas Chinese networks, migration, foreign direct investment, information

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1 Introduction

Along with significant increases in international trade and cross-border investment, international migration has also reached unprecedented levels with the rise of globalization. It has long been recognized that ethnic and international migrant networks can help overcome informal barriers that accompany international transactions (e.g., Gould, 1994). Existing studies document important evidence on how ethnic or migrant networks promote international trade (e.g., Rauch and Trindade, 2002) and aggregate foreign direct investment (FDI) (e.g., Javorcik et al., 2012).[1] Immigrants can be of great assistance since they are familiar with the language, culture, regulations, and legal framework of both origin and destination countries. They transmit information to match traders and investors with business opportunities, and build trust that enhances contract enforcement and deters opportunism (Rauch, 2001). However, little is known about the potentially different roles of migrant networks on FDI depending on its mode of entry: greenfield versus brownfield investment. In this paper, we examine the effects of international migration on FDI, and in particular, study the impact of overseas Chinese migrant networks on outward greenfield and brownfield FDI from China.

Greenfield FDI refers to cross-border investment in which a parent company establishes new production facilities in the host country, whereas brownfield FDI is typically associated with cross-border mergers and acquisitions (M&A), in which a firm acquires an existing company overseas. While both forms of FDI are conducted to gain access to a foreign market, the entry barriers that each face can be quite different. Greenfield FDI creates job opportunities at new production facilities while brownfield FDI tends to be associated with little job creation (or even job reduction, i.e., through replacing local employees with foreigners). Greenfield FDI also transfers new technology to the host country through positive spillover effects, while brownfield FDI tends to absorb technology from acquired companies. As job creation is the top priority for attracting FDI, followed by technology transfers, host countries generally welcome greenfield FDI more than brownfield FDI (UNCTAD, 2014). Governments may also restrict foreign acquisitions due to concerns of national security, job loss, and the protection of firms in strategic industries (Bertrand et al., 2012; UNCTAD, 2016).[2] Moreover, in addition to skills in communication and execution, sealing a cross-border M&A deal requires a sophisticated understanding of the capabilities, preferences, and potential synergies of both the target's and the acquirer's businesses, along with home and host country characteristics, including their laws, regulations and culture. The information requirements for M&As are arguably greater than those for greenfield investment. Thus, given all of these different factors, the role of

[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."

[2] For example, UNCTAD (2016) lists eight recent examples in which national security and other national interests play a role in the review of cross-border M&A. In contrast, many countries provide incentives like employment grants for qualified greenfield investment projects (e.g., see CMS (2016) for Central and Eastern Europe).

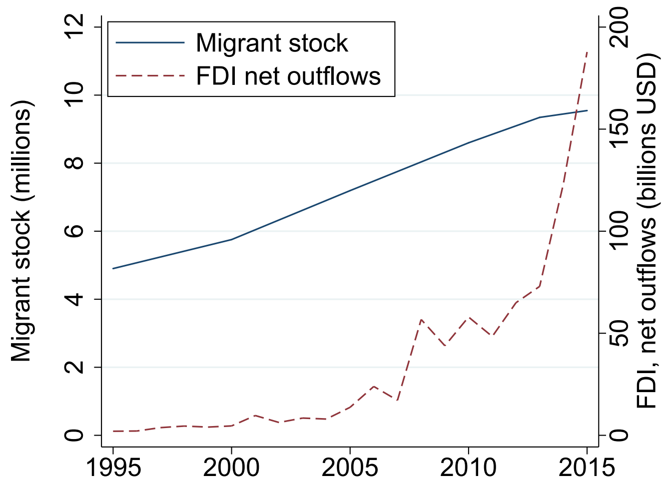
migrants is expected to be larger for cross-border M&As.

Using data on international migrant stocks, this paper empirically studies the relationship between Chinese migrant networks and Chinese outward FDI (OFDI), and importantly, how it varies by investment entry modes.[3] To the best of our knowledge, this is the first paper to individually examine how migrant networks influence greenfield and brownfield cross-border investment. To estimate the impact of migrant networks on greenfield, brownfield, and aggregate FDI, a simple gravity model is employed, controlling for various other host country characteristics.

We find that, all else equal, there is more Chinese investment into countries with larger overseas Chinese networks, and the presence of migrants overseas has large and significant impact on both Chinese greenfield FDI and cross-border M&As. Importantly, our regression results also reveal a strong distinction between the two entry modes, i.e., greenfield versus brownfield, and migrants appear to be more important in alleviating the problems associated with the latter. Both of these findings remain robust when alternative estimation methods are used, even after taking into account the potential endogeneity arising from, for instance, reverse causality, where FDI flows affect migration decisions. In particular, we employ an instrumental variables (IV) strategy, where our instruments include the historical migrant network from 40 years ago, and countries' contemporaneous policy on dual citizenship, immigration strictness, and residents' hostility towards immigrants. We also construct an instrument based on the approach from Burchardi et al. (2016). Using global migration outflows and inflows, migrant shares are predicted starting in 1960, depending on push factors that do not depend on the host-country, and pull factors that are independent of China. Regressions with this IV strongly reinforce the overall results.

This paper also documents new findings that differentiate migrant networks' role in overcoming information asymmetry, and informal and formal barriers to international transactions, including those related to countries' regulations and cultural differences. Using the detailed disaggregate deal-level FDI data, we find substantial heterogeneity across firms, industries, and various host-country dimensions. For example, the effect of migrant networks on OFDI is more pronounced for investment from or between companies that are privately held (i.e., not publicly traded) with more information withheld from the public. It is also larger for privately-owned enterprises, which utilize overseas Chinese networks more actively than state-owned enterprises (CCPIT, 2015). In addition, at the industry level, the positive relationship is stronger in tertiary industries, which are typically more knowledge intensive and face greater foreign ownership restrictions than the secondary or primary industries (Coff, 1999; World Bank, 2010), and for FDI towards a different industry from the investing company. Lastly, cross-border investment increases with the size of migrant networks to a greater extent in host countries that are more culturally distant from China with tighter regulations. Again, we observe stronger effects on

[3]Data on greenfield FDI and M&A are obtained from fDi Intelligence and Thomson-Reuters SDC Platinum, respectively; see Section 2 for details. SDC Platinum is an older database that has been utilized in many papers (e.g. di Giovanni, 2005; Head and Ries, 2008), and the same greenfield FDI data is analyzed by the UN in their annual report on world investment (UNCTAD, 2016).



(a)

Figure 1: Chinese migrant stock abroad and FDI, net outflows. (Sources: UN Global Migration Database and the World Bank World Development Indicators.)

M&A than on greenfield investment. Taken together, the empirical evidence presented strongly suggests that overseas migrants and their networks provide information regarding firms, industries, and countries to facilitate international investment, and is consistent with the anecdotal evidence and idea that brownfield investment face greater information barriers than greenfield FDI.

Despite the large increase in the flow of capital and labor across borders, the link between these two phenomena has been relatively understudied.[4] Due to rising incomes in developing countries such as China and the greater mobility of workers across countries, according to the World Bank World Development Indicators, the global stock of migrants has surged from around 150 million in 1990 to roughly 250 million in 2015. 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%).[5] With exceptional growth in the past decade or so, China has also seen very large movements of labor and capital abroad. As Figure 1 shows, the international Chinese emigrant stock roughly doubled between 1995 and 2015, from 4.9 to 9.5 million. China also has the largest intercontinental movement of migrants worldwide.Furthermore, China has become a huge investor abroad, as net FDI outflows have risen to historic levels, and it has become the third largest investing home economy behind the US and Japan (UNCTAD, 2016). The values of both greenfield and brownfield FDI have also doubled in the last decade. By understanding the linkages between the movements in factors of production, this paper contributes to our understanding of the forces which shape the global economy.

[4]We discuss existing research in the literature review below.

[5]See Annex Table 8 associated with (UNCTAD, 2016).

Literature Review

The role of ethnic and migrant networks in overcoming informal barriers and facilitating economic activity across borders has been studied in various contexts, beginning with international trade (e.g., Gould, 1994; Head and Ries, 1998; Combes et al., 2005). These papers provide evidence that migrants promote cross-border trade, and primarily highlight migrants' role in reducing information asymmetry to facilitate the matching of buyers and sellers. Focusing on overseas Chinese ethnic networks, Rauch and Trindade (2002) further show that in addition to contract enforcement, the information channel is particularly important for differentiated commodities as opposed to homogeneous goods, suggesting that ethnic networks provide thicker information to match heterogeneous sellers and buyers. Recent work by Burchardi and Hassan (2013) also shows how social ties increase economic development by examining links between West and East Germany after the fall of the Berlin Wall.

Our work contributes most directly to the literature on migration and FDI. Much on this literature 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.[6] Importantly, they address the endogeneity issue by using an instrumental variables approach.[7] More recently, Burchardi et al. (2016) and Cohen et al. (2016) utilize the historical geographic distribution of ethnic groups to address endogeneity. Using a simple 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 across the US. Similarly, Cohen et al. (2016) exploit the formation of Japanese internment camps in World War II to isolate exogenous shocks to local ethnic populations, and show that firms today trade more with and acquire more firms from countries that have a large resident population near their firm headquarters.

There have been few studies that have examined our research question for other countries like China, despite the large numbers of emigrants coming from these countries.[8] 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.[9] In this paper, we use data on Chinese outward migration and *outward* FDI beginning in 2003, the period in which Chinese emigration rates rise, and account for the potential endogeneity of migration. Most importantly, we contribute to this area of research by using deal-level FDI data to differentiate between greenfield and brownfield

[6]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.

[7]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.

[8]Buch et al. (2006) study German inward FDI, and find more FDI into states with a large foreign population from the same origin country.

[9]Rauch and Trindade (2002) originally draw the data from Poston et al. (1994), and Tong (2005) use supplementary data to expand the sample by 11 countries. 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 underperform nonethnic Chinese FDI firms, but do not distinguish between the two modes of entry.

FDI, and provide new evidence on the role of migrant networks for each type of investment. Our results on the heterogeneous effects across firms, industries, and host countries also explicitly test and reveal how migrants might promote FDI by alleviating problems associated with information asymmetry and other barriers that hinder cross-border investment.

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, including economic size, geographic distance, as well as other country-level factors such as cultural distance, the strength of institutions, relative endowments of skilled and unskilled labor, and trade and investment agreements (e.g., Blonigen and Piger, 2014).[10] Furthermore, our paper complements existing empirical evidence on the choice of foreign market entry mode (e.g., Hennart and Park, 1993; Nocke and Yeaple, 2008), as well as theoretical predictions on how this choice is affected by changes in FDI policy and trade liberalization at the country level (Qiu and Wang, 2011; Stepanok, 2015). Lastly, our work adds to the recent growing empirical research on Chinese OFDI. Both country and firm-level factors have been found to drive firms' investment abroad.[11] In particular, 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). Recently, 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. While firm heterogeneity is a key theme in these papers, again, the distinction between Chinese greenfield and brownfield OFDI has received little attention. However, the results of the present study indicates that the impact of a factor such as the presence of migrant networks can be substantially different depending on multinationals' mode of entry.

The rest of paper is organized as follows. In Section 2, we describe the data sources and present some descriptive statistics. Section 3 outlines the empirical framework and presents the empirical results, including robustness checks and instrumental variables estimates. Lastly, Section 4 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 Intelligence and Thomson-Reuters Security Data Company (SDC) Platinum, respectively.[12] Both datasets are commonly used to analyze cross-border greenfield and brownfield investment. For example, UNCTAD (2016) rely on fDi Intelligence for their annual report on world investment, and the

[10]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); Lee (2016).

[11]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.

[12]Specifically, fDi Intelligence provides the number and value of announced greenfield FDI projects, while SDC Platinum records both completed cross-border M&A deals.

M&A data in SDC Platinum has been examined in numerous papers (e.g., Rossi and Volpin, 2004; di Giovanni, 2005; Head and Ries, 2008).[13] We limit our sample to the years from 2003 to 2014, because 2003 is the earliest year that fDi Intelligence recorded greenfield investments. Overall, our sample includes 3184 greenfield investment projects across 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).[14]

The distribution of greenfield FDI projects and M&A deals across host countries is listed in Appendix Table 1 and displayed as histograms in Appendix Figure 1. 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.[15] 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 brownfield, they are: Hong Kong, US, Australia, Canada, and Germany.

Next, Figure 2 displays the time-series variation in the number and total value of greenfield and brownfield investments. Over this decade, both greenfield FDI and M&A exhibit a rising trend, especially after the 2007 global financial crisis. Panel (a) shows that 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. In terms of total transaction value as plotted in Panel B, brownfield OFDI sometimes exceeds that of greenfield OFDI, which implies that the size of brownfield projects is, on average, greater than greenfield projects.

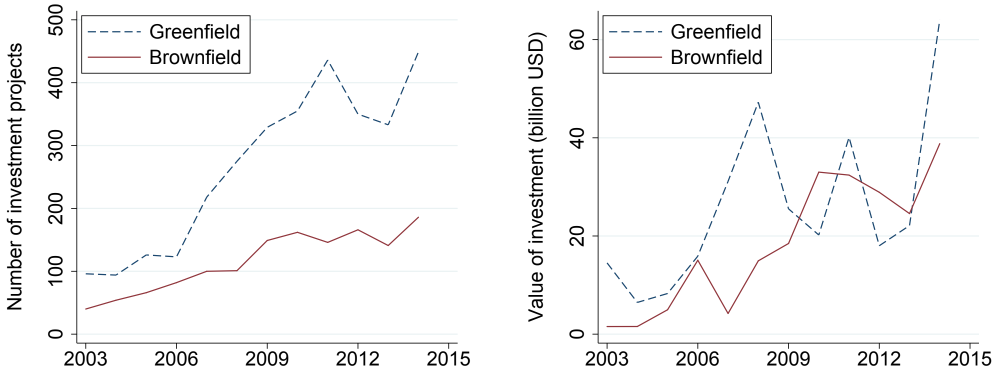
Due to the large state-sector in the Chinese economy, the decomposition between state-owned enterprises (SOE) and privately-owned enterprises (POE) is interesting to examine. In Section 3.5.1, this dimension will also be studied to understand the effect of migrants for different types of firms. For each investing (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 state-owned enterprise (SOE) if at least 25.01% of its ownership belongs ultimately to the Chinese government, and a privately-owned enterprise (POE) otherwise.[16] Decomposing OFDI by the ownership structure of Chinese investors, we

[13]UNCTAD (2016) 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 (2016) 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 (2016), and 40 to 276% of the value.

[14]For both the greenfield FDI and M&A data, 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, the data provider, fDi Intelligence, estimates the value of the deal if it is not disclosed by the investing company. However, estimates for the values of M&A investments are not included.

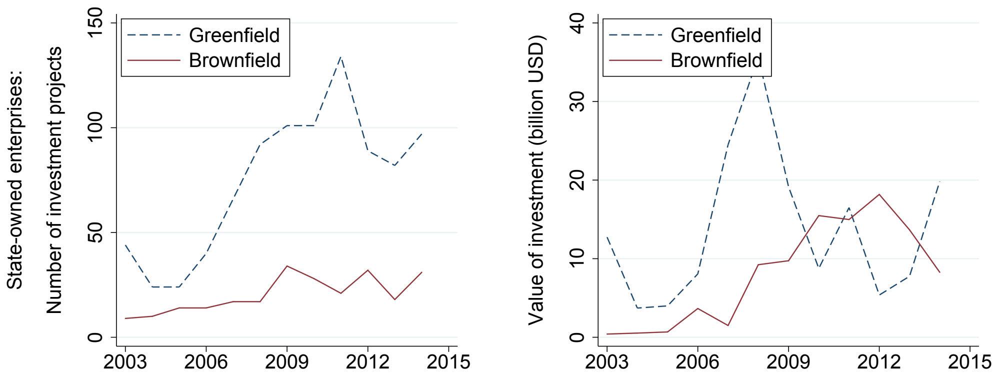
[15]These statistics are computed using the sample of host countries with strictly positive greenfield or brownfield FDI. There are 81 countries with both greenfield and brownfield Chinese investment activity, 55 countries with only greenfield investments and 9 countries with only brownfield investments.

[16]Our results in Section 3.5.1 are robust to changing the equity threshold of the global ultimate owner to 50.01%.

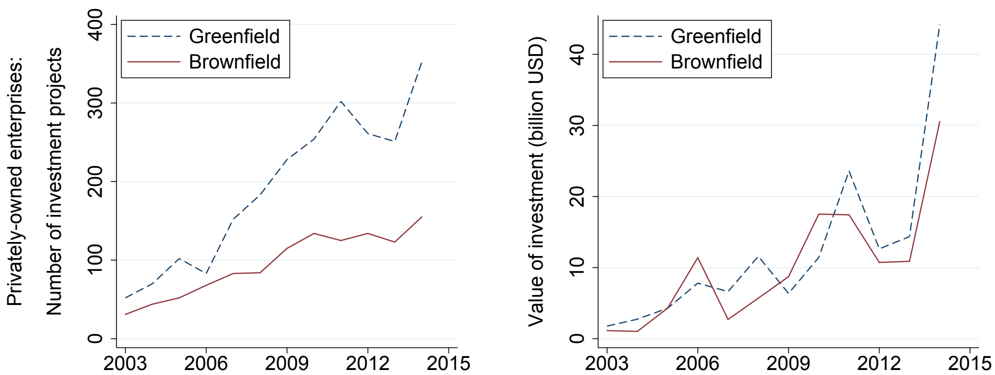


(a) (b)

Figure 2: Panels (a) and (b) plot the time-series of the number and value of Chinese greenfield and brownfield investment projects, respectively.



(a) (b)



(c) (d)

Figure 3: Panels (a) and (b) plot the time-series of the number and value of Chinese greenfield and brownfield investment projects from state-owned enterprises, respectively. Panels (c) and (d) plot the time-series of the number and value of Chinese greenfield and brownfield investment projects from privately-owned enterprises, respectively.

observe in Figure 3 a similar pattern that there is a larger number of greenfield projects of smaller size relative to brownfield investments, regardless of whether the OFDI originates from SOEs or POEs. Moreover, while there tends to be more investment projects from POEs, the value of their projects is generally smaller than those from SOEs.

In the empirical analysis, we also employ a measure of aggregate cross-border investment flows from UNCTAD Bilateral FDI Statistics. The sample contains FDI outflows from China to over 200 host economies between 2003 and 2012. These three complementary datasets of FDI will allow for separate examinations of aggregate and disaggregate FDI by mode of entry.

2.2 Bilateral migrant stock data

Data on bilateral migration are obtained from the Global Migration Database provided by the UN Department of Economic and Social Affairs. 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 host country j 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. Because of the small within-country time variation, the regression estimates are almost identical if we interpolate linearly the values for the years in which the data is unavailable. Thus, 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 time. The temporal variation of migrant shares is very low. The simple average (across all countries) of the standard deviation of migrant shares across 12 years is around 0.06%. For comparison, the mean migrant share across all countries and years is close to 0.9%.

Two previous papers, Gao (2003) and Tong (2005), have examined the relationship between Chinese *ethnic* networks abroad and aggregate FDI using data on ethnic Chinese populations in 1990. A comparison can be made between this dataset and the UN database for the overlapping year of 1990. As Figure 4 illustrates, the correlation between the two variables is very high (at 0.684). One would expect, if the data is collected accurately, that the ethnic populations are larger than the number of migrants. This is true for 36 out of 49 observations. For observations below the 45 degree, this suggests either the ethnic population was underestimated or the migrant population was overestimated.

2.3 Other data

In the regression analysis described in the next section, we include a set of control variables to mitigate the concern of omitted variable bias. The control variables include many host country characteristics that have been found to be important determinants of FDI. These include

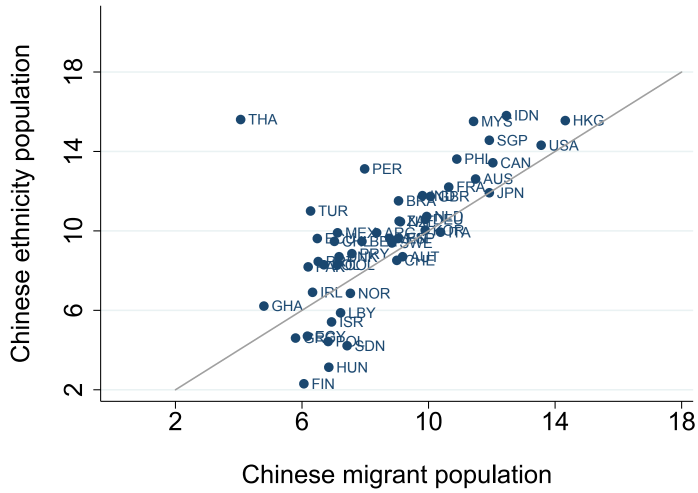


Figure 4: This figure plots the population of Chinese ethnicity against Chinese migrants for 49 countries in 1990.

traditional gravity variables like market size (as proxied by GDP) and geographic distance.[17] To account for the market-seeking and growth-seeking motives of Chinese OFDI (e.g., Deng, 2004; Buckley et al., 2011), we control for income (as measured by GDP per capita) and real GDP growth in the host country; both variables are drawn from the WDI. To control for cultural similarity that makes cross-border investments more likely, we add a dummy 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 for a common legal system origin that equals to 1 if the host country shares the same legal framework with China. The former is obtained from CEPII (along with distance), and the latter from La Porta et al. (1999).

Furthermore, 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. Financial development is included since it can potentially facilitate the international expansion of firms through FDI (e.g., Desbordes and Wei, 2014); it is measured by private credit from deposit money banks and other financial institutions divided by GDP (Beck et al., 2000). Lastly, 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. The definition and sources of variables used in this paper are listed in Appendix Table 2, and summary statistics are provided in Appendix Table 3,

[17] An alternative measure of market size is population. In unreported regressions, we confirm our results are robust to this measure.

3 Empirical framework and results

3.1 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). The gravity equation can be specified as follows:

$$FDI_{ij} = b_0 \; GDP_i^{\beta_1} \; GDP_j^{\beta_2} \; Dist_{ij}^{\beta_3} \; \exp(\beta_{\boldsymbol{X}} \boldsymbol{X}_{ij} + \varepsilon_{ij}),$$

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. Lastly, ε_{ij} is the error term. For each year, the gravity equation is log-transformed:

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

To examine the heterogeneous effects at the aggregate and disaggregate level by mode of entry, our dependent variable includes the number and value of greenfield investment projects (*#GF*, *GF*), the number and value of cross-border M&A deals (*#BF*, *BF*) from China to the host country, and aggregate FDI outflows. 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 3.4, we validate our results with an instrumental variables strategy to address potential endogeneity issues.

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

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

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. If Chinese migrants overseas do help Chinese investors overcome informal and formal barriers and increase the amount of FDI, then α_3 should 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.

3.2 Baseline results

Table 1 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. This subset of control variables allows countries such as Macau to be included in the estimation sample, as is done in Table 2 below for comparison. Throughout the empirical analysis, we exclude tax haven countries such as Panama, the British Virgin Islands, the Cayman Islands. Table 1 also excludes both Macau and Hong Kong, which have unique status as special administrative regions of China, while in Table 2, we compare regressions with and without these two countries. Thus, in Table 1, the sample contains 135 countries between the years 2003 and 2014 in columns 1 to 4, and 124 countries from 2003 to 2012 in column 5.

Consistent with the hypothesis that cross-border migrant networks help overcome barriers associated with international transactions, we find that $Migrant\ share$ is positively and significantly associated with different measures of OFDI: both greenfield and brownfield FDI, and both for counts and values. This is the first key result, which we confirm below with alternative estimation methods and an IV strategy. 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 raises the count measures *#GF* and *#BF* by roughly 10.7% and 18.0%, respectively, and increases the investments value measures *GF* and *BF* by 43.6%, 90.3%, respectively.

Table 1 also shows that the positive relation between migrants networks and OFDI exhibits substantial heterogeneity depending on the mode of entry. We hypothesize that the positive migrant effect is stronger for brownfield FDI compared to greenfield FDI because of the higher barriers encountered for cross-border M&A. This second key result is indeed confirmed in Table 1. Specifically, the coefficient of $Migrant\ share$ in the regression of column 3 (4) is larger than that in column 1 (2). 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). However, both χ^2-statistics are substantially higher when more control variables are included in Table 4 below. Thus, the results generally suggest that overseas Chinese stocks are more closely related to brownfield OFDI than to greenfield OFDI. Intuitively, cross-border M&As require intensive knowledge and information of the capabilities, preferences, and potential synergies of the acquiring and target firms that are from different cultural backgrounds, therefore, benefit more from the presence of overseas Chinese networks that bridge the gap.

Lastly, in Table 1 column 5, we rely on aggregate FDI statistics obtained from the UN for

Table 1: Overseas Chinese Migrant Networks and Chinese Outward FDI

Dependent variable	log (FDI + 1)				
	# GF	GF	# BF	BF	UN FDI
	(1)	(2)	(3)	(4)	(5)
Migrant share	14.590***	59.781***	24.703***	123.696***	82.551***
	(4.056)	(19.787)	(7.679)	(34.557)	(29.578)
(log) GDP	0.231***	1.233***	0.113***	0.569***	0.904***
	(0.024)	(0.084)	(0.021)	(0.082)	(0.096)
(log) GDP per capita	-0.067***	-0.526***	0.005	0.048	-0.810***
	(0.025)	(0.128)	(0.014)	(0.081)	(0.163)
(log) Distance	-0.163**	-1.078***	-0.052	-0.242	-1.294***
	(0.066)	(0.349)	(0.052)	(0.329)	(0.416)
Language	0.230	2.189*	-0.167	-0.381	-0.130
	(0.225)	(1.149)	(0.336)	(1.368)	(1.175)
Legal system	-0.038	0.407	-0.111**	-0.650**	-0.231
	(0.095)	(0.500)	(0.047)	(0.287)	(0.629)
Year fixed effects	Y	Y	Y	Y	Y
Number of countries	135	135	135	135	124
Observations	1,483	1,483	1,483	1,483	1,240
R-squared	0.511	0.455	0.387	0.298	0.391

Notes: The dependent variables are Chinese outward FDI measured by (log) one plus the number and $10,000 plus the value of greenfield investment projects (*#GF* and *GF*), likewise for M&A (*#BF* and *BF*), and $10,000 plus the value of aggregate FDI (*UN FDI*). 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 dependent variable. Due to data availability, the sample is slightly shorter from 2003 to 2012. However, it is clear that the positive relationship between FDI and outward migration continues to hold at the aggregate level.

Next, we examine how the results vary depending on the selection of countries into our sample. Figure 5 reveals two countries, Macau and Hong Kong, have very high migrant shares (above 30%) compared with the rest of the sample. These potential outliers were excluded in our baseline regression. 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 business strategies. Therefore, their FDI inflows from China may be motivated by different reasons. Thus, in Table 2, we compare the results with and without Macau and/or Hong Kong. All regressions include the same set of control variables, but for space considerations, we present the coefficient estimates of our key explanatory variable, $Migrant\ share$. In Panel A, the inclusion of both cities essentially removes the positive association between migrant networks and greenfield or brownfield FDI. Examining Panels B and C, it is clear that the insignificance is due to the presence of Macau. The positive relationship generally holds with Hong Kong included and Macau excluded, with statistical significance at the 1% level in 3 out of 4 columns. With the sample in Panel C, a one-standard deviation (2.79%) increase in Chinese migrant shares raises greenfield and brownfield FDI counts (values) by roughly 9.2% and 24.4% (8.2% and 75.4%), respectively.[18] This sharp contrast between the

[18]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*

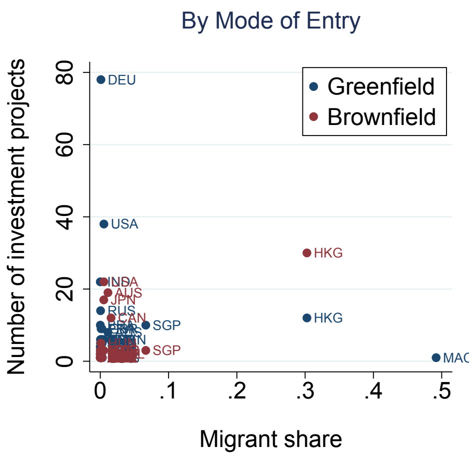


Figure 5: Number of Chinese greenfield and brownfield investment projects in 2010.

inclusion of Macau and Hong Kong is not surprising given the lack of FDI towards Macau as exhibited in Figure 5. In fact, in 2010, there were zero FDI projects invested in Macau by Chinese companies, and only one single M&A.

3.3 Robustness

We perform a series of additional tests that demonstrate our main results are robust to alternative specifications. First, in Table 3, we estimate our baseline regression equation using two different methods. Again, all regressions include a set of control variables, but are not reported for the sake of space. In Panel A, 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 B, 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. With the exception of the number of greenfield projects in Panel B column 1, which is positive but not precisely estimated, the association between the size of the migrant network and FDI remains statistically significant. Thus, even though the magnitudes of the coefficients differ from the OLS estimates, the general findings are consistent. There is a positive relationship between migration and OFDI from China, and it is stronger for brownfield investment as opposed to greenfield investment.

Our results could potentially be driven by unobserved heterogeneity, where, for instance, certain countries tend to attract both foreign investment and immigration. In Section 3.4 below, we will employ an instrumental variables strategy with historical migrant shares from 40 years ago as an instrument. Since China opened up itself to the world in the late 1970s, early 1980s, whereas outward migration from China was taking place before that period, it is unlikely for

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: Sample Selection with and without Macau and Hong Kong

	Panel A: With Macau and Hong Kong				
	# GF	GF	# BF	BF	UN FDI
	(1)	(2)	(3)	(4)	(5)
Migrant share	-0.798	-4.660*	0.365	0.388	5.379
	(1.311)	(2.683)	(2.667)	(9.588)	(4.429)
Observations	1,507	1,507	1,507	1,507	1,507
R-squared	0.508	0.454	0.360	0.282	0.452

	Panel B: With Macau and without Hong Kong				
	# GF	GF	# BF	BF	UN FDI
	(1)	(2)	(3)	(4)	(5)
Migrant share	-1.462**	-5.412***	-1.036	-3.532	3.752
	(0.580)	(2.051)	(1.019)	(5.696)	(2.687)
Observations	1,495	1,495	1,495	1,495	1,495
R-squared	0.497	0.445	0.316	0.247	0.437

	Panel C: With Hong Kong and without Macau				
	# GF	GF	# BF	BF	UN FDI
	(1)	(2)	(3)	(4)	(5)
Migrant share	3.284***	2.925	8.735***	27.019***	17.728***
	(0.728)	(3.676)	(1.111)	(7.559)	(3.880)
Observations	1,495	1,495	1,495	1,495	1,495
R-squared	0.524	0.459	0.476	0.322	0.455

Notes: The dependent variables are Chinese outward FDI measured by (log) one plus the number and $10,000 plus the value of greenfield investment projects (*#GF* and *GF*), likewise for M&A (*#BF* and *BF*), and $10,000 plus the value of aggregate FDI (*UN FDI*). 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.

FDI to have driven migration. For now, we address this issue with the standard method of including destination fixed effects in the regression. However, recall that the migrant share is only available in 2000, 2005, 2010, and 2013. Thus far, we have carried forward the value of migrant share where data is missing, which means there is no time variation within each interval. Hence, in Table 3 Panel C, we create a panel limited to the years in which migrant share is available (i.e., 2003, 2005, 2010, and 2013), so that we should observe more within-country variation over the these longer intervals.

Results in Table 3 Panel C are supportive of our previous findings (note, Distance, Language, and Legal system are omitted due to perfect collinearity). Although the coefficients in columns 2 and 4 are less precisely estimated, the qualitative results suggest a stronger association between brownfield FDI and the migrant network, controlling for unobserved time-invariant characteristics in destinations. Because of the lack of time variation, we also employ the commonly used Hausman-Taylor model for estimating the effects of time-invariant regressors. As Panel D indicates, we obtain similar findings.

If migrant shares were time-invariant, the relationship between migrant networks and FDI could not be jointly estimated with destination fixed effects due to perfect collinearity. While migrant shares are not completely time-invariant, their variation over time within a country is

Table 3: Robustness Checks with Alternative Estimation Methods

	Panel A: OLS			
Dependent variable	log (FDI)			
	# GF	GF	# BF	BF
	(1)	(2)	(3)	(4)
Migrant share	15.531***	39.082***	29.887***	61.504***
	(3.045)	(12.056)	(10.429)	(11.341)
Observations	554	554	287	202
R-squared	0.504	0.237	0.352	0.288
	Panel B: Poisson pseudo-maximum-likelihood (PPML)			
Dependent variable	FDI			
	# GF	GF	# BF	BF
	(1)	(2)	(3)	(4)
Migrant share	11.286	18.173**	76.713**	100.989***
	(8.716)	(7.824)	(37.970)	(22.061)
Observations	1,483	1,483	1,483	1,483
R-squared	0.527	0.324	0.693	0.335
	Panel C: Destination fixed effects			
Dependent variable	log (FDI + 1)			
	# GF	GF	# BF	BF
	(1)	(2)	(3)	(4)
Migrant share	27.893*	86.477	33.486*	147.633
	(14.817)	(64.545)	(19.623)	(99.030)
Observations	499	499	499	499
R-squared	0.766	0.706	0.688	0.532
	Panel D: Hausman-Taylor			
Dependent variable	log (FDI + 1)			
	# GF	GF	# BF	BF
	(1)	(2)	(3)	(4)
Migrant share	28.449**	92.062	34.194***	151.842**
	(11.410)	(72.443)	(9.286)	(72.075)
Observations	492	492	492	492
	Panel E: Estimated destination fixed effects			
Dependent variable	log (FDI + 1)			
	# GF	GF	# BF	BF
	(1)	(2)	(3)	(4)
Migrant share	7.276	17.131	29.603***	147.095***
	(5.018)	(24.003)	(10.133)	(43.097)
Observations	1,376	1,376	1,376	1,376
R-squared	0.545	0.479	0.406	0.310

Notes: The dependent variables are Chinese outward FDI measured by (log) number and value of greenfield investment projects (*#GF* and *GF*), and likewise for M&A (*#BF* and *BF*) in Panel A, number and value of greenfield investment projects and likewise for M&A in Panel B, and (log) one plus the number and \$10,000 plus the value of greenfield investment projects, and likewise for M&A in Panels C to E. The sample in Panels C and D are years 2003, 2005, 2010, and 2013. 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.

small. Thus, in Panel E, instead of including fixed effects directly into the estimating equation, we use a proxy, following, for example, Crozet and Hinz (2016). Specifically, using the UN aggregate bilateral FDI data from 2003 to 2012 for all host and source countries available, we first estimate the following equation:

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

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 destination fixed effects in the regression where only Chinese outward FDI is examined. In Panel E, the results are shown to be similar when we include these proxies. Thus, for the remainder of the analysis, we treat the sample as pooled cross-sections with year fixed effects to account for common shocks across countries in each year. Endogeneity concerns are addressed with the inclusion of additional regressors, as well as using an instrumental variable strategy.

To address endogeneity arising from omitted variable bias, in Table 4, we include in our regression equation measures of growth, financial development, institutional quality, and trade openness. 38 countries are lost as a result.[19] However, as Table 4 shows, the inclusion of these previously omitted variables reveals even stronger differences for greenfield and brownfield FDI. 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 9.98 (< 0.01), and likewise, for columns 2 and 4, the Wald test χ^2 statistic (p-value) is 34.4 (< 0.01).

In Table 4, while the coefficients of the control variables are not statistically significant across all of the specifications, some general results emerge, and are consistent with the literature. The estimates suggest that larger countries with lower GDP per capita receives less greenfield investment and fewer M&A with Chinese companies (column 4). This 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).[20] Furthermore, markets with higher financial development generally attract more Chinese OFDI. We utilize this full set of control variables for the remainder of our analysis.

[19]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, technology, and natural resource abundance. (log) Remoteness is measured as GDP weighted distance, while technology is captured by the number of patent applications (by residents and non-residents) from the WDI, and natural resource abundance is computed as 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.

[20]"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`

Table 4: Robustness Checks with Additional Regressors

Dependent variable	log (FDI + 1)			
	# GF	GF	# BF	BF
	(1)	(2)	(3)	(4)
Migrant share	11.937**	32.823	35.087***	181.961***
	(5.608)	(25.807)	(10.658)	(42.853)
(log) GDP	0.364***	1.813***	0.128***	0.590***
	(0.038)	(0.134)	(0.029)	(0.130)
(log) GDP per capita	-0.266***	-1.287***	-0.081**	-0.104
	(0.054)	(0.255)	(0.035)	(0.222)
(log) Distance	0.004	-0.519	0.021	-0.075
	(0.090)	(0.432)	(0.076)	(0.470)
Language	0.177	1.893*	-0.189	-0.560
	(0.220)	(1.072)	(0.411)	(1.803)
Legal system	0.126	0.647	0.053	0.001
	(0.123)	(0.601)	(0.068)	(0.425)
GDP growth	0.000	0.016	0.001	0.011
	(0.002)	(0.017)	(0.002)	(0.014)
Financial development	0.002	0.003	0.003**	0.010**
	(0.001)	(0.004)	(0.001)	(0.005)
Institution quality	0.032	0.111	0.014	-0.001
	(0.025)	(0.117)	(0.017)	(0.099)
Trade openness	0.132	0.821**	-0.149	-0.854*
	(0.080)	(0.372)	(0.101)	(0.450)
Year fixed effects	Y	Y	Y	Y
Number of countries	96	96	96	96
Observations	1,021	1,021	1,021	1,021
R-squared	0.575	0.466	0.459	0.331

The dependent variables are Chinese outward FDI measured by (log) one plus the number and $10,000 plus the value of greenfield investment projects (*#GF* and *GF*), and likewise for M&A (*#BF* and *BF*). 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.

Thus far, we have used the Chinese migrant population as a proportion of destination's total population as a measure of the migrant network size. However, it may be that the absolute size of the migrant stock matters. Therefore, in Appendix Table 4, we replace the share of Chinese migrants with the stock Chinese migrant population (in logarithms). This 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 number (value) of greenfield and brownfield projects by 0.08 and 0.13% (0.17 and 0.33%), respectively.

3.4 Instrumental variables strategy

3.4.1 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 brownfield investment or 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 and use a set of instruments which predict Chinese migrant shares well, thereby meeting the relevance criteria, and also appear to be exogenous with respect to FDI, satisfying the exclusion restriction.

First, following the approach of Javorcik et al. (2012), we use a measure of the historical Chinese migrant network as an instrument. As Javorcik et al. (2012) explain, 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 creates a strong pull factor for future migration. We expect large Chinese migrant populations to have the effect of encouraging future migration. 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. While the two datasets are not identical, the correlation between them is extremely high for the overlapping years of 1990 and 2000 at 0.977. Therefore, our first instrument is the share of Chinese migrants in 1960 and 1970, essentially a 40-year lag, which is longer than the 30-year lag employed in Javorcik et al. (2012). Because this supplementary data is available every decade, we split our sample between 2003 and 2014 in half and assign the 1960 values for the first half of the sample, and 1970 values for the second half. For comparison, we also repeat the estimation with a 30-year lag and show the results are also robust.

Furthermore, as an alternative to lagged migrant shares, we take advantage of the bilateral structure of the data and construct an instrumental variable following the logic of Burchardi et al. (2016).[21] The method utilizes information on global migration outflows and inflows which capture the push and pull factors of migration, respectively. First, we predict the stock of migrants in a particular destination j if country j received an inflow of Chinese immigrants (in percentage terms) equal to the rest of the world. Second, we adjust this inflow based on the proportion of non-Chinese immigration relative to the rest of the world, such that countries which receive more (non-Chinese) immigrants overall will also experience a larger influx of Chinese migrants. Denote $Migrant^{CHN}_{j,t}$ as the stock of Chinese migrants in country j time t. Then, the first step computes the push factor as the percentage change in the flow of Chinese

[21]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.

migrants to all destinations other than j:

$$Push_{j,t} = \frac{Migrant^{CHN}_{-j,t}}{Migrant^{CHN}_{-j,t-1}} - 1 \equiv \frac{Migrant^{CHN}_{WLD,t} - Migrant^{CHN}_{j,t}}{Migrant^{CHN}_{WLD,t-1} - Migrant^{CHN}_{j,t-1}} - 1$$

This global outflow of Chinese migrants captures the push factor that does not depend on factors in destination j. In the second step, the push factor is adjusted by the inflow of immigrants relative to the rest of the world by the factor:

$$Pull_{j,t} = \left(\frac{Migrant^{-CHN}_{j,t}}{Migrant^{-CHN}_{j,t-1}} - 1\right) \div \left(\frac{Migrant^{-CHN}_{WLD,t}}{Migrant^{-CHN}_{WLD,t-1}} - 1\right)$$

For example, if the pull factor is larger than 1, then the increase in foreign population in destination j is larger than the global rise in migrant population. Combining these two steps, the predicted migrant stock in destination j time t is then

$$\widehat{Migrant}^{CHN}_{j,t} = \begin{cases} \widehat{Migrant}^{CHN}_{j,t-1} \times \Big(1 + Push_{j,t} \times Pull_{j,t}\Big) & \text{if } Push_{j,t} > 0, \\ \widehat{Migrant}^{CHN}_{j,t-1} \times \Big(1 + \frac{Push_{j,t}}{Pull_{j,t}}\Big) & \text{otherwise.} \end{cases}$$

In this step, the foreign population inflow into the US originating outside of China (relative to the world) captures the pull factor for which China is irrelevant. If the push factor is negative, it is divided by the pull factor because the destination country should be losing fewer Chinese migrants if it attracts more immigrants in general. Since 1960 is the earliest year available, the actual migrant stock is used as opposed to the predicted, i.e., $\widehat{Migrant}^{CHN}_{j,1960} = Migrant^{CHN}_{j,t}$. We then repeat this calculation for all destinations and for every interval in which migration data is available (i.e., 1970, 1980, 1990, 1995, 2000, 2005, and 2010). The predicted values for the years 2000, 2005, and 2010, divided by the destination country's population in the respective years, are used as instruments for $Migrant\ share$.

Taking the US from 1960-70 as an example, the Chinese-born population of US in 1960 and 1970 are 105,384 and 220,531, respectively. The global stock of Chinese migrants in 1960 and 1970 are 4,803,292 and 4,448,338, respectively. Hence, the push and pull factors are equal to

$$Push_{US,1970} = \frac{4,448,338 - 105,384}{4,803,292 - 220,531} - 1 = -0.100$$
$$Pull_{US,1970} = \left(\frac{11,973,797 - 220,531}{10,825,585 - 105,384} - 1\right) \div \left(\frac{105,509,001 - 4,448,338}{92,825,210 - 4,803,292} - 1\right) = 0.651$$

If the growth rates of immigrants in the US is larger than the world, then we predict the growth rate of Chinese immigrants should be as well. After this proportional adjustment, the predicted migrant stock for 1970 is

$$\widehat{Migrant}^{CHN}_{US,1970} = 105,384 \times \left(1 - \frac{0.100}{0.651}\right) = 89,174.$$

In addition to exploiting the variation from historical migrant shares and flows, we also employ contemporaneous instruments that influence migration patterns but not the movement of capital. In particular, we utilize variables which reflect countries' immigration policies purely. Specifically, we first obtain data on whether countries recognize dual citizenship from the MACIMIDE Global Expatriate Dual Citizenship Dataset (Vink et al., 2015).[22] Second, 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.[23] Thus, the immigration strictness variable ranges from 0 to 1.

Lastly, since immigration policies may not fully reflect how welcoming a nation is towards immigrants, we use data from the World Values Survey to measure countries' hostility towards foreign residents. The Survey includes a question which asks respondents whether they "would not like to have as neighbors: Immigrants/foreign workers", and is available for three waves of the survey (1999, 2005, and 2010) and a total of 87 countries. Thus, the variable $Immigrant\ hostility$ captures the average hostility towards immigrants for each country, as a fraction between 0 and 1.

3.4.2 Instrumental variables estimation results

Tables 5 reports the two-stage least squares (2SLS) estimation results with the 40-year lagged migrant share as one of the instruments. The dependent variable in the first-stage regression is always 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. This suggests that dual citizenship is a pull factor on all origin countries, since Chinese citizens cannot accrue its benefits because they must renounce their Chinese nationality if they wish to be a citizen of a foreign country. Not surprisingly, more strict immigration policies are associated with less Chinese immigrants. The estimate in Panel D also shows that the hostility of host countries' residents towards immigrants is negatively correlated with migrant shares, and this effect is statistically significant.

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

[22]Dual citizenship is recognized if acquiring foreign citizenship does not lead to an automatic loss of citizenship of the origin country. In our regression sample, this policy is constant for all countries except Belgium, Luxembourg, and the Slovak Republic.

[23]The original data contains two additional fields: labor migration and co-ethnics. We exclude these fields because the former relates to existing labor market conditions, such as the quality of migrants accepted, while the latter is already captured in part by historical migrant shares.

Table 5: IV Estimation with Two-stage Least Squares- 40-year Lagged Migrant Shares

Panel A

	Stage I	Stage II			
Dependent variable:	Migrant share	# GF	GF	# BF	BF
	(1)	(2)	(3)	(4)	(5)
Migrant share (40-year lag)	0.382***				
	(0.023)				
Migrant share		13.697***	47.908**	22.816***	123.934***
		(4.337)	(20.698)	(3.804)	(17.023)
Underidentification test (p)		< 0.01	< 0.01	< 0.01	< 0.01
Observations	1,009	1,009	1,009	1,009	1,009
R-squared	0.818				

Panel B

	Stage I	Stage II			
Dependent variable:	Migrant share	# GF	GF	# BF	BF
	(1)	(2)	(3)	(4)	(5)
Migrant share (40-year lag)	0.383***				
	(0.023)				
Dual citizenship	0.001***				
	(0.0004)				
Migrant share		13.356***	51.664**	22.681***	123.789***
		(4.318)	(20.460)	(3.806)	(16.915)
Underidentification test (p)		< 0.01	< 0.01	< 0.01	< 0.01
Overidentification test (p)		0.25	0.22	0.55	0.80
Observations	1,009	1,009	1,009	1,009	1,009
R-squared	0.820				

Panel C

	Stage I	Stage II			
Dependent variable:	Migrant share	# GF	GF	# BF	BF
	(1)	(2)	(3)	(4)	(5)
Migrant share (40-year lag)	5.900***				
	(0.382)				
Dual citizenship	-0.0001				
	(0.0001)				
Immigrant strictness	-0.001				
	(0.001)				
Migrant share		2.332	151.573	118.521***	666.083***
		(21.807)	(112.018)	(18.993)	(89.383)
Underidentification test (p)		< 0.01	< 0.01	< 0.01	< 0.01
Overidentification test (p)		0.534	0.433	0.275	0.352
Observations	266	266	266	266	266
R-squared	0.883				

Panel D

	Stage I	Stage II			
Dependent variable:	Migrant share	# GF	GF	# BF	BF
	(1)	(2)	(3)	(4)	(5)
Migrant share (40-year lag)	0.422***				
	(0.042)				
Dual citizenship	0.002***				
	(0.0004)				
Immigrant hostility	-0.003**				
	(0.001)				
Migrant share		5.177	80.221***	22.213***	121.819***
		(6.970)	(26.791)	(7.646)	(29.444)
Underidentification test (p)		< 0.01	< 0.01	< 0.01	< 0.01
Overidentification test (p)		0.09	0.74	0.90	0.63
Observations	380	380	380	380	380
R-squared	0.843				

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 (log) one plus the number and $10,000 plus the value of greenfield investment projects (*#GF* and *GF*), and likewise for M&A (*#BF* and *BF*). 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.

for M&A (i.e., columns 4 and 5) persist, and reinforce the notion that migrants facilitate transactions for the more information-intensive brownfield cross-border investment. Comparing the estimates on $Migrant\ share$ from Table 1 with Table 5 reveal that the OLS coefficients are actually quite close to the IV estimates. Table 6, which uses predicted migrant shares as the IV instead of the lagged migrant share, delivers the same message. Regardless of the set of instruments employed, the second-stage results are similar and reinforces our earlier findings.

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. Only in Tables 5 and 6 Panel D column 2, the p-value is slightly less than 0.1 at 0.09. Lastly, in Appendix Table 5, we estimate the IV version of PPML using 40-year lagged (or predicted) migrant share, dual citizenship, and immigrant hostility as instruments. Our results are generally robust to this specification as well.

3.5 Heterogeneity across firms, industries, and host-country characteristics

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. In particular, we present empirical evidence showing a more pronounced migrant network effect for FDI which faces greater informal barriers such as information asymmetry and cultural differences, as well as formal barriers with regards to countries' regulations. Heterogeneity across firms, industries, and various host-country characteristics are examined separately. With the detailed deal-level greenfield and brownfield FDI data, we first exploit the cross-sectional variation of investment to a given destination across different types of firms, comparing publicly traded versus private companies and privately-owned enterprises (POE) versus state-owned enterprises (SOE). Second, we examine differences between FDI from tertiary industries as opposed to primary and secondary industries, and also FDI into industries that are different from the that of the investing firm. Lastly, we show that the migrant network effect is also stronger in countries with larger implicit barriers in the form of cultural differences, and explicit barriers including capital controls, labor regulations, and administrative requirements. The results are again consistent with the idea that brownfield FDI, or cross-border M&A, are more information-intensive, and therefore this investment entry mode benefits more from the presence of migrants in the host country.

3.5.1 Heterogeneity across firms

First, we test the hypothesis that when information about the investing or invested company is more scarce, the marginal effect of migrant networks on FDI increases. First, companies can be classified by whether or not they are listed on a stock exchange. While measures of a company's

Table 6: IV Estimation with Two-stage Least Squares- Predicted Migrant Shares

Panel A

	Stage I	Stage II			
Dependent variable:	Migrant share	# GF	GF	# BF	BF
	(1)	(2)	(3)	(4)	(5)
Predicted migrant share	0.137***				
	(0.018)				
Migrant share		14.977***	41.423**	22.054***	136.472***
		(3.557)	(19.183)	(3.954)	(22.760)
Underidentification test (p)		< 0.01	< 0.01	< 0.01	< 0.01
Observations	984	984	984	984	984
R-squared	0.779				

Panel B

	Stage I	Stage II			
Dependent variable:	Migrant share	# GF	GF	# BF	BF
	(1)	(2)	(3)	(4)	(5)
Predicted migrant share	0.138***				
	(0.018)				
Dual citizenship	0.001***				
	(0.0004)				
Migrant share		14.719***	46.924**	21.786***	135.760***
		(3.562)	(19.329)	(3.935)	(22.580)
Underidentification test (p)		< 0.01	< 0.01	< 0.01	< 0.01
Overidentification test (p)		0.27	0.28	0.60	0.68
Observations	984	984	984	984	984
R-squared	0.781				

Panel C

	Stage I	Stage II			
Dependent variable:	Migrant share	# GF	GF	# BF	BF
	(1)	(2)	(3)	(4)	(5)
Predicted migrant share	0.274***				
	(0.045)				
Dual citizenship	0.001***				
	(0.000)				
Immigration strictness	-0.005***				
	(0.002)				
Migrant share		-12.635	215.116	72.213**	440.868**
		(36.558)	(165.119)	(29.259)	(198.794)
Underidentification test (p)		< 0.01	< 0.01	< 0.01	< 0.01
Overidentification test (p)		0.482	0.406	0.222	0.198
Observations	266	266	266	266	266
R-squared	0.419				

Panel D

	Stage I	Stage II			
Dependent variable:	Migrant share	# GF	GF	# BF	BF
	(1)	(2)	(3)	(4)	(5)
Predicted migrant share	0.100***				
	(0.019)				
Dual citizenship	0.002***				
	(0.0004)				
Immigrant hostility	-0.009***				
	(0.002)				
Migrant share		4.862	93.603**	24.972***	134.171***
		(7.695)	(38.862)	(7.985)	(42.508)
Underidentification test (p)		< 0.01	< 0.01	< 0.01	< 0.01
Overidentification test (p)		0.09	0.76	0.87	0.61
Observations	380	380	380	380	380
R-squared	0.773				

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 (log) one plus the number and $10,000 plus the value of greenfield investment projects (*#GF* and *GF*), and likewise for M&A (*#BF* and *BF*). 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.

transparency are difficult to obtain, the general public typically has more information about a company that is listed or publicly traded. For instance, besides potentially greater name recognition, the listed company must disclose certain financial details and file earnings reports. As argued by Erel et al. (2012), information asymmetry is likely to be a larger problem for private targets as opposed to public targets for cross-border M&As. Thus, we expect migrants to have a larger role in facilitating FDI for privately held (i.e., unlisted) as opposed to publicly traded companies .

To identify whether the parent company of greenfield FDI is a private or publicly traded firm, we match our deal-level data to Datastream. For M&A, we consider the status of both the acquirer from China and the target in the host country. Following Erel et al. (2012), an acquirer or target firm is listed if its public status is "Public" or non-missing. We separately aggregate to the country level the values of our dependent variables (i.e., $\#GF$, GF, $\#BF$, and BF) for the different statuses, $s =$ private or public. Hence, the following equation is estimated at the country-status level:

$$\begin{aligned}\log(FDI_{sjt}+1) = {} & \gamma_0 + \gamma_1 \log(GDP_{j,t-1}) + \gamma_2 \log(Dist) + \gamma_3 Migrant\ share_{j,t-1} \\ & + \gamma_4 Migrant\ share_{j,t-1} \times Private_s + \gamma_5 Private_s + \gamma_{\boldsymbol{X}} \boldsymbol{X}_{j,t-1} + \nu_{sjt},\end{aligned} \tag{3}$$

where $Private_s$ is an indicator variable equal to 1 if the FDI is associated with private companies and zero otherwise. If the coefficient γ_4 is positive, this would corroborate the idea that overseas migrants can help resolve the barrier of information asymmetry. The estimation results are presented in Table 7 Panel A, where in columns 1 and 2, greenfield FDI originating from private parent companies is considered; in columns 3 and 4 (5 and 6), the link between migrant networks and brownfield FDI from private acquirers (to private targets) is examined. As before, the effect on brownfield investment remains larger than on greenfield FDI (whether by count or value), regardless of whether the investment is originating from a firm that is private or publicly traded. 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.

Next, we consider the differences between state-owned enterprises (SOE) and privately-owned enterprises (POE). The business practices of these types of firms can vary widely. In particular, according to a survey on Chinese outward direct investment 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 while this number is 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.[24]. Thus, whether migrants play a larger role for state-owned or private enterprises

[24]For example, in 2012, former Canadian Prime Minister Stephen Harper approved the sale of Canada's oil

Table 7: Heterogeneity Across Firms

	Panel A					
Private company	Parent		Acquirer		Target	
	# GF	GF	# BF	BF	# BF	BF
	(1)	(2)	(3)	(4)	(5)	(6)
Migrant share	5.583	24.311	20.192***	136.454***	22.494***	159.693***
	(4.153)	(24.778)	(5.861)	(37.809)	(8.133)	(42.367)
Migrant share × Private	5.382**	20.750***	11.381**	42.899**	8.036***	15.346***
	(2.167)	(6.776)	(5.607)	(19.210)	(2.195)	(5.422)
Private	0.354***	2.194***	0.150***	0.802***	0.197***	0.795***
	(0.041)	(0.191)	(0.025)	(0.159)	(0.031)	(0.142)
Observations	1,770	1,770	1,600	1,600	1,600	1,600
R-squared	0.468	0.401	0.382	0.268	0.377	0.281

	Panel B			
	# GF	GF	# BF	BF
	(1)	(2)	(3)	(4)
Migrant share	6.214	12.696**	40.459*	100.638***
	(4.005)	(6.030)	(23.155)	(35.127)
Migrant share × Privately-owned	8.076***	20.637***	16.483*	80.231***
	(2.189)	(5.873)	(8.574)	(18.189)
Privately-owned	0.222***	0.098***	0.829***	0.398***
	(0.040)	(0.028)	(0.194)	(0.139)
Observations	2,038	2,038	2,038	2,038
R-squared	0.459	0.364	0.389	0.249

Notes: The dependent variables are Chinese outward FDI measured by (log) one plus the number and $10,000 plus the value of greenfield investment projects (*#GF* and *GF*), and likewise for M&A (*#BF* and *BF*). 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.

is theoretically ambiguous.

In Table 7 Panel B, we run a similar regression to Equation (4), but instead of status, FDI is aggregated up to the country level depending on different ownership types, POE or SOE. Hence, $Private_s$ is replaced by an indicator for POEs. Empirically, 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, which suggests that companies with private ownership benefit more from migrant networks in the host country than SOEs.

3.5.2 Heterogeneity across industries

We now examine heterogeneity across different industries. First, the problem of asymmetric information is especially severe for knowledge-intensive business such as information technology, engineering, and research and development (Coff, 1999). With their know-how and comparative advantage in combining resources from both sides of the border more efficiently, overseas Chinese are expected to add more value to industries with greater knowledge-intensity. Furthermore, a report by the World Bank (2010) also found fewer restrictions on foreign ownership in primary

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.)

and manufacturing sectors, but stricter limits in services. Migrants are thus expected to mitigate informal problem associated with information as well as more formal barriers.

To aggregate the total number and value of greenfield and brownfield projects to the industry level, we 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.[25] The number or value of FDI projects is aggregated up to this broader industry definition, i.e., s = primary, secondary, or tertiary, in the following specification:

$$\begin{aligned}\log(FDI_{sjt}+1) = g_0 + g_1\log(GDP_{j,t-1}) + g_2\log(Dist) + g_3 Migrant\ share_{j,t-1} \\ + g_4 Migrant\ share_{j,t-1} \times Tertiary_s + g_5 Tertiary_s + \gamma_{\boldsymbol{X}}\boldsymbol{X}_{j,t-1} + v_{sjt},\end{aligned} \tag{4}$$

where $Tertiary_s$ is an indicator variable equal to one if s = tertiary, and zero otherwise.[26] In Table 8 Panel A, we see that the largest effects are indeed observed for the knowledge-intensive tertiary industries. Note that even within an industry, the positive relationship is more pronounced for M&A. Thus, consistent with our hypothesis, the evidence suggests that the positive relationship between overseas Chinese networks and Chinese OFDI is mostly driven by the investment in the tertiary or service industries. Appendix Table 6 reports the regression estimates of the baseline specification for each group of industries. Consistent with the findings in Table 8, for primary industries, the migrant network effect is not statistically different from zero, while the effect is positive for secondary industries, and largest for tertiary industries.

While knowledge-intensity may vary across sectors, 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 8 Panel B. For greenfield investment, while the SIC code for the parent company can be obtained, the industry to which the FDI project itself is not coded. We assign the project a SIC 2-digit code based on information provided from fDi Intelligence 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, brownfield FDI 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., s = same industry or cross-industry). Subsequently, an indicator for cross-industry FDI is interacted with $Migrant\ share$. As Table 8 Panel B shows, consistent with idea that migrants promote FDI through an information channel, the marginal

[25]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.

[26]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.

Table 8: Heterogeneity Across Industries

	Panel A			
	# GF	GF	# BF	BF
	(1)	(2)	(3)	(4)
Migrant share	-5.639	-39.825	15.373**	102.938***
	(4.804)	(24.906)	(6.212)	(36.871)
Migrant share × Tertiary	17.964***	111.715**	14.755***	70.678***
	(6.327)	(50.539)	(2.496)	(7.155)
Tertiary	-0.261***	-2.350***	-0.042	-0.433*
	(0.055)	(0.411)	(0.039)	(0.223)
Observations	1,513	1,513	1,513	1,513
R-squared	0.408	0.376	0.344	0.240
	Panel B			
	# GF	GF	# BF	BF
	(1)	(2)	(5)	(6)
Migrant share	7.013	21.914	22.034***	129.555***
	(4.597)	(25.414)	(7.443)	(41.234)
Migrant share × Cross-industry	2.066**	13.244**	9.883***	68.656***
	(0.881)	(5.102)	(1.825)	(5.601)
Cross-industry	0.061**	0.095	0.020	0.014
	(0.023)	(0.165)	(0.015)	(0.120)
Observations	1,770	1,770	1,600	1,600
R-squared	0.458	0.373	0.373	0.270

Notes: The dependent variables are Chinese outward FDI measured by (log) one plus the number and $10,000 plus the value of greenfield investment projects (*#GF* and *GF*), and likewise for M&A (*#BF* and *BF*). 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.

effect of the size of migrant networks on FDI is more pronounced for cross-industry FDI.

3.5.3 Host-country characteristics

Lastly, we consider how the effect of migrant networks vary with host-country characteristics. In particular, we provide further evidence that emigrant networks matter more when the barriers to international transactions, whether formal or informal, are larger. The results of this analysis are presented in Table 9. First, in Panel A, in addition to the full set of control variables, we include an interaction term between *Migrant share* and the common language indicator variable. The estimates show that for both greenfield and brownfield OFDI, 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, smaller cultural gap, and greater trust between the countries, migrants' role in facilitating international investment transactions is expected to shrink. Indeed, the empirical evidence validates this hypothesis.[27]

To provide further insight on the role of migrants for either alleviating information frictions or overcoming regulation barriers, we employ a similar method to examine the heterogeneous

[27] Dunlevy (2006) find the immigrant effect on trade to be less important when Spanish or English is the language of the origin country, and when the origin country's political system is more corrupt.

Table 9: Heterogeneity across Host Countries- Barriers to Entry

	Panel A			
	# GF	GF	# BF	BF
	(1)	(2)	(3)	(4)
Migrant share	44.228*	205.689**	116.789***	523.288***
	(26.263)	(89.564)	(29.248)	(90.869)
Migrant share × Language	-38.503	-207.433**	-96.864***	-405.228***
	(26.149)	(90.948)	(28.972)	(91.049)
Language	0.362***	2.833***	0.297***	1.451***
	(0.111)	(0.547)	(0.077)	(0.445)
Observations	1,019	1,019	1,019	1,019
R-squared	0.581	0.474	0.538	0.370

	Panel B			
	# GF	GF	# BF	BF
	(1)	(2)	(3)	(4)
Migrant share	5.503	4.623	24.446***	142.969***
	(3.477)	(12.188)	(3.759)	(21.467)
Migrant share × Capital controls	58.967***	240.422***	128.723***	466.271***
	(15.731)	(86.096)	(16.632)	(80.399)
Capital controls	-0.056	-0.378	-0.133***	-0.573**
	(0.076)	(0.370)	(0.041)	(0.243)
Observations	970	970	970	970
R-squared	0.590	0.478	0.547	0.364

	Panel C			
	# GF	GF	# BF	BF
	(1)	(2)	(3)	(4)
Migrant share	7.046*	15.308	28.426***	158.351***
	(4.057)	(17.550)	(6.510)	(29.348)
Migrant share × Labor regulations	34.979**	147.715**	85.114***	317.872***
	(13.964)	(70.344)	(18.498)	(82.100)
Labor regulations	-0.081	-0.263	-0.160**	-0.456
	(0.079)	(0.403)	(0.066)	(0.293)
Observations	907	907	907	907
R-squared	0.585	0.464	0.502	0.344

	Panel D			
	# GF	GF	# BF	BF
	(1)	(2)	(3)	(4)
Migrant share	8.732*	17.644	29.761***	163.608***
	(4.568)	(17.805)	(7.199)	(32.506)
Migrant share × Administrative requirements	16.531	134.696*	78.037***	269.166**
	(12.249)	(78.602)	(23.357)	(110.062)
Administrative requirements	0.035	0.255	-0.140*	-0.180
	(0.070)	(0.383)	(0.071)	(0.325)
Observations	907	907	907	907
R-squared	0.583	0.465	0.492	0.340

Notes: The dependent variables are Chinese outward FDI measured by (log) one plus the number and $10,000 plus the value of greenfield investment projects (*#GF* and *GF*), and likewise for M&A (*#BF* and *BF*). 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.

effects across countries with different regulations and laws. 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.[28] All of these variables are converted 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. Again, the share of Chinese migrants is interacted with these dummy variables. When regulations on the international flow of capital, labor market, business practices are higher, migrants have a stronger role in increasing the OFDI from their origin country, especially for M&A.[29]

4 Conclusion

Using data on Chinese migrant stocks across many countries and Chinese outward FDI, this paper provides empirical evidence that migration and cross-border investment are closely linked. We find migrant networks to be an important determinant of FDI at the aggregate level, as well as the disaggregate level by mode of entry, i.e., greenfield and brownfield FDI. Moreover, 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 face greater information asymmetry and other informal and formal barriers, the results indicate overseas Chinese networks are more closely associated with brownfield FDI than greenfield FDI. We also provide evidence that migrant networks facilitate cross-border investment by alleviating information frictions and cultural barriers. The relationship between overseas Chinese networks and OFDI is more pronounced for private as opposed to publicly traded companies, privately-owned as opposed to state-owned enterprises, for the knowledge-intensive tertiary industries compared to secondary and primary industries, for cross-industry FDI, and in host-countries with smaller Chinese-speaking populations and tighter regulations.

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. Furthermore, while Chinese OFDI is certainly large among developing countries, other countries at similar stages of development are also increasingly investing abroad. For example, FDI outflows are 2.5 and 6 times larger for India and South Africa 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

[28] 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)."

[29] Note that the magnitude of the coefficients on $Migrant\ share$ can become quite large because of the split in sample: the maximum value of $Migrant\ share$ for countries that have strict capital controls is 1.9%, while for those that do not, it is 7.2%.

becomes even more integrated, understanding their linkages is key in the future research agenda.

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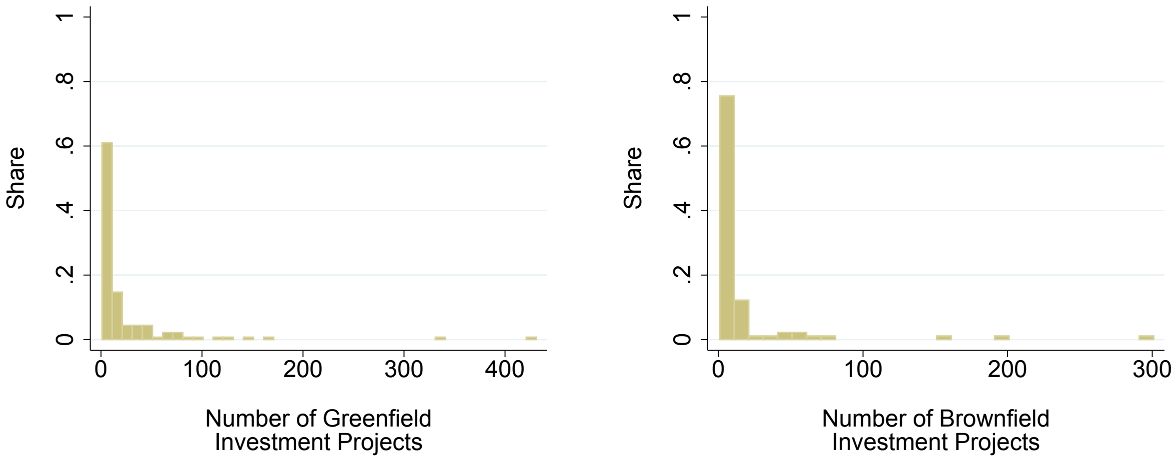
Appendix

Appendix Table 1: Number of Investment Projects by Country between 2003 and 2014

			Both Greenfield (GF) and Brownfield (BF)					
Country	#GF	#BF	Country	#GF	#BF	Country	#GF	#BF
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 (GF)					
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 Brownfield (BF)					
Country		#BF	Country		#BF	Country		#BF
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



(a) (b)

Appendix Figure 1: Panels (a) and (b) plot histograms of the number of Chinese greenfield and brownfield investment projects over the whole sample from 2003-2014, respectively. The bin size for both panels is 10.

Appendix Table 2: Variable Definitions

Variable	**Definition**	**Source**
#GF	Number of Chinese outward greenfield investment projects	fDi intelligence
GF	Total investment value of Chinese outward greenfield projects	fDi intelligence
#BF	Number of cross-border M&A deals in host country with Chinese firms as the acquirers	SDC Platinum
BF	Total transaction value of cross-border M&A deals in host country with Chinese firms as the acquirers	SDC Platinum
UN FDI	Aggregate Chinese outward foreign direct investment flows	UNCTAD Bilateral FDI Statistics
Migrant share	Chinese emigrant population in host country as a share of host country's population	UN Global Migration Database & WDI
(log) GDP	(log) GDP in USD	WDI
(log) GDP per capita	(log) GDP per capita in USD	WDI
Distance	Geographic distance between China and host country	CEPII
Language	Dummy variable equal to 1 if at least 9% of population in host country speaks same language as China; zero otherwise	CEPII
Legal System	Dummy variable equal to 1 if host country has same legal origin as China (i.e., socialist)	La Porta et al. (1999)
GDP growth	Annual real GDP growth rate	WDI
Financial Development	Private credit by deposit money banks and other financial institutions divided GDP	Beck et al. (2000)
Institutional Quality	Sum of corruption, law and order, and bureaucratic quality indices (see Bekaert et al. (2004))	ICRG
Trade Openness	Sum of imports and exports divided by GDP	WDI
Migrant share (40-year lag)	Chinese migrant population in host country as a share of host country's population, from 1960-70	World Bank
Dual citizenship	Dummy variable equal to 1 if acquiring foreign citizenship does not lead to automatic loss of origin country's citizenship	MACIMIDE
Immigration strictness	Strictness of immigration policy associated with family reunification, asylum and refugees, and control of immigration	Helbling et al. (forthcoming)
Immigrant hostility	Share of population that do not want immigrants/foreign workers as neighbors	WVS
Capital controls	Dummy variable equal to 1 if capital controls are more strict than sample median	Gwartney et al. (2015)
Labor regulations	Dummy variable equal to 1 if hiring and firing regulations are less flexible than sample median	Gwartney et al. (2015)
Administrative requirements	Dummy variable equal to 1 if administrative requirements are more burdensome than sample median	Gwartney et al. (2015)

Notes: WDI = World Bank World Development Indicators. ICRG = International Country Risk Guide. WVS = World Values Survey.

Appendix Table 3: 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
# BF	3.50	2.00	4.83	1.00	36
BF (billion USD)	887	169	1530	0.02	8430
UN FDI (billion USD)	158	467	18.01	0.49	4808
Migrant share	0.002	0.0003	0.01	0	0.07
(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
Dual citizenship	0.67	1	0.47	0	1
Immigration strictness	0.42	0.39	0.10	0.26	0.76
Immigrant hostility	0.23	0.19	0.16	0.02	0.67

Appendix Table 4: Robustness Check with (log) Migrant Stocks

	# GF	GF	# BF	BF
	(1)	(2)	(3)	(4)
(log) Migrant stock	0.083***	0.265*	0.129***	0.585***
	(0.030)	(0.151)	(0.036)	(0.158)
(log) GDP	0.304***	1.616***	0.047	0.231
	(0.040)	(0.179)	(0.030)	(0.164)
(log) GDP per capita	-0.251***	-1.210***	-0.062*	-0.002
	(0.056)	(0.253)	(0.032)	(0.213)
(log) Distance	0.070	-0.302	0.119	0.368
	(0.093)	(0.428)	(0.087)	(0.485)
Language	0.311**	2.120***	0.418	2.676
	(0.149)	(0.750)	(0.304)	(1.913)
Legal system	0.177	0.817	0.093	0.111
	(0.124)	(0.585)	(0.079)	(0.460)
GDP growth	0.003	0.045**	0.004	0.033*
	(0.004)	(0.022)	(0.003)	(0.019)
Financial development	0.001	0.001	0.001	0.002
	(0.001)	(0.004)	(0.001)	(0.005)
Institution quality	0.039	0.128	0.032	0.084
	(0.025)	(0.114)	(0.020)	(0.110)
Trade openness	0.175**	0.943***	-0.011	-0.122
	(0.071)	(0.333)	(0.083)	(0.417)
Year fixed effects	Y	Y	Y	Y
Observations	1,016	1,016	1,016	1,016
R-squared	0.585	0.471	0.450	0.312

Notes: The dependent variables are Chinese outward FDI measured by (log) one plus the number and $10,000 plus the value of greenfield investment projects (*#GF* and *GF*), and likewise for M&A (*#BF* and *BF*). 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.

Appendix Table 5: IV Poisson Pseudo-Maximum Likelihood

	Panel A			
Instruments:	Migrant share (40-year lag), Dual citizenship			
	# GF	GF	# BF	BF
	(1)	(2)	(3)	(4)
Migrant share	-5.874	71.929***	103.313	197.146*
	(9.405)	(27.902)	(75.685)	(103.629)
Observations	1,007	1,007	1,007	1,007
	Panel B			
Instruments:	Migrant share (40-year lag), Dual citizenship, Immigration strictness			
	# GF	GF	# BF	BF
	(1)	(2)	(3)	(4)
Migrant share	-19.768	121.463*	158.002***	185.072***
	(45.737)	(62.515)	(25.186)	(33.955)
Observations	266	266	266	266
	Panel C			
Instruments:	Migrant share (40-year lag), Dual citizenship, Immigrant hostility			
	# GF	GF	# BF	BF
	(1)	(2)	(3)	(4)
Migrant share	-18.792	66.758**	51.970	264.163*
	(16.359)	(27.125)	(36.181)	(138.042)
Observations	378	378	378	378
	Panel D			
Instruments:	Predicted migrant share, Dual citizenship			
	# GF	GF	# BF	BF
	(1)	(2)	(3)	(4)
Migrant share	8.215	23.484	30.534	72.510**
	(11.378)	(17.642)	(23.629)	(28.791)
Observations	982	982	982	982
	Panel E			
Instruments:	Predicted migrant share, Dual citizenship, Immigration strictness			
	# GF	GF	# BF	BF
	(1)	(2)	(3)	(4)
Migrant share	-46.535	168.312**	196.758***	165.104***
	(59.945)	(70.974)	(32.659)	(45.189)
Observations	266	266	266	266
	Panel F			
Instruments:	Predicted migrant share, Dual citizenship, Immigrant hostility			
	# GF	GF	# BF	BF
	(1)	(2)	(3)	(4)
Migrant share	-15.104	48.613*	31.317	168.004
	(17.356)	(28.831)	(23.918)	(188.974)
Observations	378	378	378	378

Notes: The estimation method is the IV version of the Poisson pseudo-maximum-likelihood estimator. In all panels, the dependent variables are Chinese outward FDI measured by (log) one plus the number and $10,000 plus the value of greenfield investment projects (*#GF* and *GF*), and likewise for M&A (*#BF* and *BF*). 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.

Appendix Table 6: FDI in Primary, Secondary, and Tertiary Industries

	Panel A: Primary industries			
	# GF	GF	# BF	BF
	(1)	(2)	(3)	(4)
Migrant share	-0.483	23.095	12.159	109.008
	(6.787)	(64.846)	(15.613)	(95.103)
Observations	131	131	131	131
R-squared	0.324	0.366	0.264	0.271
	Panel B: Secondary industries			
	# GF	GF	# BF	BF
	(1)	(2)	(3)	(4)
Migrant share	4.009	31.731	16.697***	94.465***
	(6.061)	(25.181)	(4.981)	(31.601)
Observations	460	460	460	460
R-squared	0.432	0.330	0.367	0.253
	Panel C: Tertiary industries			
	# GF	GF	# BF	BF
	(1)	(2)	(3)	(4)
Migrant share	12.859**	66.120**	30.391***	177.233***
	(5.089)	(30.603)	(8.886)	(41.794)
Observations	922	922	922	922
R-squared	0.478	0.443	0.401	0.298

Notes: The dependent variables are Chinese outward FDI measured by (log) one plus the number and $10,000 plus the value of greenfield investment projects (*#GF* and *GF*), and likewise for M&A (*#BF* and *BF*). 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.