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Migration and FDI:
The role of job skills*†

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Abstract

Using a multi-country gravity framework, this paper models and quantifies the relevance of migrants' job position in fostering Foreign Direct Investment (FDI). High-skilled migrants are defined as those individuals born in the investors' home/host country occupying managerial or professional positions in the host/home country of investment. Our estimates show that higher shares of migrants with management skills in a given country promote FDI into that country. In contrast, an increase in the share of migrants in non-qualified positions (regardless of their educational attainment) has a negative impact on FDI decisions. These findings highlight that the FDI-enhancing effect of migrants is related to a shift in their skill composition due to their occupation. We test our model on a new global panel data set of Greenfield bilateral investment with a wide variety of specifications, both at the extensive and intensive margins. Additionally, we provide new insights into the mechanisms by which migration influences FDI flows, with particular attention to the relevance of FDI level and activity.

Keywords: Skilled migration; Foreign Direct Investment; Job skills; Gravity equation; Extensive and Intensive Margins.

JEL Classification: F21, F22, F23

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1 Introduction

This paper seeks to explain the role played by migrants with different levels of human capital in cross-border investments. In contrast with previous studies, we focus on migrants' occupational skills rather than on their educational level. Our approach deals with the controversial previous evidence regarding the role played by the educational attainment of migrants as well as with the occupation-education mismatch.

We start the analysis by presenting a model to explain how high-skilled migration can affect FDI both at the intensive and the extensive margins. In our model, a key feature is job heterogeneity within the production process: The affiliate combines headquarters' blueprints (which requires management and coordination skills) with capital and low-skilled jobs to produce goods. The composition of the migrant population in terms of job skills can facilitate this process.

The intuition behind our model may be understood through a historical analogy to the Navajo code talkers during World War II. The United States Marine Corps used the Navajo language to cipher war messages sent to submarines in the Pacific. The complexity of the language made it unintelligible to anyone without extensive exposure and training. At the outbreak of World War II, fewer than 30 non-Navajo could understand the language (Nez and Avila, 2011). To be able to navigate, a submarine requires at least one Navajo code talker to decode the scrambled messages. Increasing the number of Navajo code talkers in the Pacific makes it possible to boost both the number of deployed submarines and the efficiency and ship capacity (e.g., they can work in shifts). The rest of the crew members have no effect on the number or capacity of submarines, thus, the crew is a *submarine* fixed effect. Now, let us imagine there is a particular submarine where most of the crew is ethnically Navajo, but unable to speak the Navajo language. This particular submarine faces higher search costs to identify the one and only true Navajo code talker. Taken to the extreme, when all the crew is unskilled in terms of Navajo language, the submarine will not be able to navigate.

Certain elements of this historical example operate in similar ways in FDI. The relevant component in this example is the specific ability to speak Navajo. Similarly, in our context, high-skilled migrants are defined as those individuals born in the investor's home/host country occupying managerial or professional positions in the host/home country of investment. These individuals acquire management or professionals skills which enable them to manage the relationship with headquarters, like the Navajo code talkers. Therefore, abundant stocks of skilled migrants should have a positive effect on both the extensive and intensive margins of FDI, similarly to the Navajo's effect on the number and submarine capacity.

Low-skilled migrants are defined as those individuals born in the investor's home/host country occupying non-qualified job positions in the host/home country, regardless of their educational attainment. Their wage is pegged to host country unskilled wages and consequently the stock of non-qualified migrants, like the non-code talkers, should have no significant effect on FDI. However, previous empirical results challenged this prediction, finding that an increase in low-skilled migrants has a negative and significant impact on FDI flows. In our model, the negative coefficient for low-skilled migration is capturing the effect of an increase in the ratio of low-skilled migrants to high-skilled migrants: The costs of high-skilled labor for the affiliate increase as management skills become relatively less abundant. In other words, the negative coefficient is capturing the effect of a decrease in the share of high-skilled migrants.

To the best of our knowledge, our study constitutes a novel attempt to fill some gaps in the literature on heterogeneous migrant skills and FDI. First, we incorporate job skills into a standard model of heterogeneous firms, which delivers a tractable FDI gravity equation with sharp predictions regarding migration and FDI. Second, we employ a panel dataset of OECD host countries to estimate the impact of the migrant job composition on FDI margins, using a structural gravity approach. Third, we uncover which specific job skills have more influence on several activity sectors and at different investment levels. An additional contribution is that we clarify the relevance of accounting for the direction of migration and refining the mechanism by which high-skilled migration has an effect on FDI. An abundant share of managers in the migrant stock may reduce specific high-skilled labor costs (communication, search, wages) for foreign affiliates. In line with our theoretical expectations, estimates suggest that a higher share of migrant decision-makers has the largest positive effect on FDI.

The rest of the paper is organized as follow. Section 2 provides an overview of the relevant literature. Section 3 presents the model. Section 4 describes the data and the econometric specification. Section 5 details the results and section 6 concludes.

2 Background

"An efficient way to organize multinational production across locations (...) is to hire talented workers who are able to carry out production activities with very little supervision" (Cristea, 2015, p. 257). Therefore, hiring talented migrants may constitute a mechanism for mitigating communication costs between headquarters and their foreign affiliates. As stated by De Smet, "The ease of hiring skilled expatriates is one of the factors that are taken into consideration in the location decision of multinationals. When the required expertise cannot be sourced in the hosting country, skilled immigrants are necessary to start-up new subsidiaries and train workers"

(2013, p. 4).

By acting as an information-revealing network, migrants may reduce transactions costs, encouraging bilateral investments. They understand the language, culture, values and practices of their home as well as their host country. The positive association between ethnic networks and FDI has already been found by previous papers (see Buch et al., 2006; Burchardi et al., 2016; Federici and Giannetti, 2010; Foad, 2012; Gao, 2003; Kugler and Rapoport, 2007 and Murat and Pistoresi, 2009 among others). The main mechanisms through which this association takes place are the demand and the information channels. The former may occur when people living abroad demand products or services from their home country and companies try to satisfy these needs by investing abroad. The information channel is less straightforward but it seems to be particularly relevant for FDI decisions: Foreign investment implies a long-term investment and therefore requires a wide variety of information about the legal framework and business structure in the host country (Javorcik et al., 2011). FDI also involves higher risk of expropriation and thus information about the investment environment is more valuable (Leblang, 2011).

Migrants can also foster trust, especially in countries where the rule of law is uncertain and doing business with foreigners entails a degree of insecurity (Mundra, 2014). As stated by Burchardi et al. (2016), individuals who have social ties may generate a competitive advantage for the firms at which they work and the regions where they live by reducing information frictions. Migrants may open new channels for profitable investment through their networks with fellow professionals from their home country. They can help companies to identify business opportunities, local tastes and foreign preferences, and can even help investors find joint venture partners. Accordingly, migrant networks seem to matter more for bilateral FDI than for trade (Javorcik et al., 2011; Tong, 2005). Daude and Fratzscher (2008) emphasized that FDI flows are more sensitive to information frictions than investment portfolio equity and debt securities. Cuadros et al. (2016) highlighted the role of migrants as suppliers of financial information about their homeland. This type of knowledge may be particularly relevant during periods of financial distress. The results obtained indicate that migrants eased the credit constraints foreign investors faced during the 2007 financial crisis.

As information exchange is crucial for investment decisions, migrants' personal characteristics come to the forefront of the analysis, as they explain how migrants participate in channeling this information. The existing migration-FDI studies that controlled for migrants' skills heterogeneity (which are summarized in Table 1) focused on educational attainment.[1] The main idea highlighted by the studies shown in Table 1 is that high-skilled migrants are expected to have a greater influence on FDI as they bring with them higher levels of information and influence (Docquier and Lodigiani, 2010). Well-educated individuals may have specialized knowledge about how to conduct business with investors of their own particular ethnicity. They also have the language skills and cultural sensitivity that would promote collaboration with business developers in host countries. Skilled migrants are likely to have a more in-depth understanding of customer behavior and to be able to provide insights about the type of products that would generate higher levels of demand. This type of migrants may even be personally involved in investments from their country of origin, boosting capital flows (Foley and Kerr, 2013).

[Table 1 about here.]

However, the role played by migrants' educational attainment is controversial, to say the least. Thus, Felbermayr and Jung (2009) find that low- and high-skilled

[1] The only exception is Tomohara (2017a), who constructs two broad skill groups based on a wide range of occupational categories for Japan only.

migrants strongly boost bilateral trade while medium-skilled migration does not seem to matter. This could be explained by the mismatch between formal educational attainment and job skills, which is a common feature of the labor market in general and seems to be particularly pronounced for migrants (Aleksynska and Tritah, 2013; Chiswick and Miller, 2009b). The mismatch that occurs when a person has a level of formal education above that required for her job is referred to as over-education, and the opposite as under-education. Migrants are more likely than native-born workers to be either under- or over-educated with respect to the jobs that they hold. Saxenian (1999) provides casual evidence of this mismatch by showing that the superior educational attainment of Silicon Valley's Asian immigrants is only partially reflected in their occupational status.

Our analysis is a novel attempt to provide a theoretical rationale for the role played by migrants' occupations in influencing FDI, with empirical evidence in a multi-country gravity framework. Our empirical strategy relies on the evidence obtained by a handful of studies which advocate using migrants' job position rather than education as a suitable proxy for the migrants' effective job skill-sets and decision-making power (Aleksynska and Peri, 2014; Martín-Montaner et al., 2014). According to these studies, migrants' proximity to decision-making positions appears to have a more crucial influence on international trade than their formal knowledge or abilities: Occupations such as business directors or managers may play a particularly important role in facilitating trade connections. Such professionals have a direct role in channeling relevant information and knowledge of potential export markets and import opportunities, as well as in facilitating the understanding of differences in culture and business practices. As illustrated by Mundra (2014), an immigrant who is a homemaker or a student might not participate in professional networking or move in entrepreneurship circles, and will thus have a lower information effect on trade than an engineer or a CEO. Moreover, there will be a greater exchange of ideas across managerial and professional immigrant groups, which increases the potential for lowering transaction costs through access to more extensive information about foreign markets as well as through personal business contacts.

We shed new light on several mechanisms that remain under-explored by previous studies: the role played by migrants' job positions, the direction of migration and sectoral effects. First, the literature does not provide a conclusive picture of the effects of i→j or j→i migration on i→j FDI flows. On the one hand, a higher presence of i-born migrants in the host country of investment may attract new investment projects to that country (see Buch et al. 2006; Foad 2012; Gheasi et al. 2013). On the other hand, j-born migrants who live in the home country of investment may act as ambassadors for prospective foreign investors in their homeland (see Kugler and Rapoport 2007; Javorcik et al. 2011; Cuadros et al. 2016). To test the significance of both mechanisms, both types of migrants have been included in our estimations.

Second, our analysis provides a plausible interpretation for a confusing finding that the literature has largely swept under the rug. In Table 1, we have highlighted those studies reporting a negative effect of low-skilled-migrants**.** Our model reconciles theory with data by showing that what matters is the job skills composition of migrant stock. Foreign affiliates face higher high-skilled labor costs (e.g., searching, identification and communications costs) when management skills become relatively less abundant.

Third, the effects of migrants' job skills on FDI may also vary depending on the activity at which the investment is targeted. This could be explained by the fact that different types of FDI may require different types of skills according to their main activity (e.g., extraction industries, manufacturing or provision of services; see Checchi et al., 2007). Moreover, the determinants of foreign entry decisions may vary between services and manufacturing activities (Kolstad and Villanger, 2008). These arguments suggest that it is appropriate to account for the specific activity at which the FDI is targeted. To the best of our knowledge, within the migration-FDI literature, just a handful of studies have dealt with the sector composition of FDI. Kugler and Rapoport (2007) find a dynamic complementary between skilled migration and US outward FDI in services, and contemporaneous substitution between unskilled migration and US outward FDI in manufacturing. Javorcik et al. (2011) examine whether the positive relationship between migration and US FDI abroad that they obtain at the aggregate level is also present at the industry level. A key outcome of the model that we develop below is that the effect of migrant managers is more intense in high-skilled activities.

3 Theoretical framework

3.1 Setup

The basic setup is a world of J countries with the assumption of a Cobb-Douglas utility function for a representative consumer $U_j = X^{\mu}_{NTj} X^{1-\mu}_{Tj}$, for a two-sector economy with NT (non-traded) and T (traded) goods. The parameter μ is the share of total spending R_j in each industry, which consists of a continuum of differentiated products. The aggregate consumption in this sector is the sum of all goods produced. The term X_{Tj} is a standard CES aggregator across the continuum of products (l): $X_j = \left[\int x_j(l)^{\iota} dl\right]^{1/\iota}$, where $\sigma \equiv (1-\iota)^{-1} > 1$ is the elasticity of substitution between any two products. The maximization of the demand of the good l is $x_j(l) = \frac{p_j^{-\sigma} Y_j}{P_j^{1-\sigma}}$, where $Y_j \equiv (1-\mu)R_j$, p_j is the price of the good and P_j the price index in the traded sector $P_j = \left[\int_l {p_j}^{1-\sigma} dl\right]^{1/(1-\sigma)}$.

3.2 Production

Production is undertaken by price-taking firms in monopolistic competition. To produce the good l, a firm z uses three inputs: capital K, skilled inputs or services S (which are provided by high-skilled labor), and low-skilled inputs or services L (which are provided by low-skilled labor). The firm combines high-skilled labor (e.g., management or engineering) with capital and low-skilled labor in a second step. To model production, we use a Cobb-Douglas variant of a two-level CES production function in the spirit of Krusell et al. (2000):

$$x_{jz}(l) = S^s[K^k L^l]^{1-s}, \tag{1}$$

where the positive constants $s < 1$ and $k + l < 1$ measure the intensity with which the inputs are used in production and are constant at the sectoral level.

Upon entry, the firm discovers its total factor productivity $1/\alpha$, where α is the number of input units per input bundle used by the firm to produce one unit of output. We follow the standard assumption that the distribution of α across firms is continuous Pareto c.d.f. $G(\alpha)$ with $[\underline{\alpha}, \bar{\alpha}]$. The density of $G(\alpha)$ is denoted by $g(\alpha)$ and the distribution is the same across countries.

To produce a good, a domestic firm incurs a marginal cost of:

$$\omega_j^{Dom}(\alpha) \equiv \alpha(\bar{w}_j S + r_j K + w_j L), \tag{2}$$

where each unit of capital comes at a cost of $r_j > 1$, which reflects the capital, interest and search costs. The high-skilled and low-skilled labor costs (coordination costs and wages) are, respectively, $\bar{w}_j > w_j > 1$. This assumption is based on the fact that management skills are relatively less abundant than low-skilled skill sets.

The firm incurs a fixed cost of production f_j and sells its product at prices p_j.

Thus, the problem of the firm is:

$$\max_{K,S,L} \pi_{iz}^{Dom} = \max\{p_j S^s [K^k L^l]^{1-s} - \omega_j^{Dom}(\alpha) - f_j\}. \quad (3)$$

In equilibrium the market clears and the firm determines the optimal levels of capital investment and labor. Let us normalize the prices per unit of demand to $p_j = \frac{Y_j^{1/\sigma}}{P_j^{(1-\sigma)/\sigma}}$, so that the optimal equilibrium for capital is:

$$K_j^{Dom} = \left(\frac{Y_j^{1/\sigma}}{P_j^{(1-\sigma)/\sigma}} \frac{(k-sk)}{\alpha r_j^{1-\eta-sk+k} \left(\frac{k-sk}{s}\bar{w}_j\right)^s \left(\frac{k-sk}{l-sl}w_j\right)^{l-sl}} \right)^{\frac{1}{1-\eta}}, \quad (4)$$

where $\eta = s - sk + l - ls + k$. [2]

Equation (4) is in line with economic intuition, which would suggest that productive firms (with lower α) in markets with higher demand and lower factor costs tend to be larger in terms of capital.

The least productive firm determines the minimum capital required to enter the market, which is $K_j^{Dom}(\bar{\alpha})$. Firms that enter the market and discover that their productivity is such that the capital is lower than $K_j^{Dom}(\bar{\alpha})$ do not produce in that market.

3.2.1 Foreign entry

Now let a foreign firm from country i enter the market in country j with an affiliate that uses its headquarter's blueprints to produce product l with domestic capital and labor. The only difference between a domestic and a foreign firm is that management is needed to translate blueprints and coordinate with the headquarters.

[2] In the online Appendix, we show the solution to all equations of the model.

In this setup, the affiliate incurs a marginal cost of:

$$\omega_{ij}^{FDI}(\alpha) \equiv \alpha(\bar{w_{ij}}S + r_j K + w_j L) \tag{5}$$

where $\bar{w_{ij}}$ is the labor cost of high-skilled management to coordinate with the headquarters (coordination, searching and wages). We assume that this specific skill-set is relatively less abundant, meaning that $\bar{w_{ij}} > \bar{w}_j$. Intuitively, the affiliate requires managers with certain coordination abilities and thus face high search and attrition costs. Conversely, low-skilled labor is sourced locally from a pool of workers with similar characteristics.

Therefore the problem of the affiliate yields an optimal capital of:

$$K_{ijz}^{FDI} = \left(\frac{1}{\psi_{ij}}\right)^{\frac{s}{1-\eta}} K_{jz}^{Dom}. \tag{6}$$

where $\psi_{ij} = \bar{w_{ij}}/\bar{w}_j > 1$ is the ratio of high-skilled foreign managers to local management labor costs. Therefore, we can express the capital in terms of the minimum capital to enter the market as:

$$K_{ijz}^{FDI} = \left(\frac{1}{\psi_{ij}}\right)^{\frac{s}{1-\eta}} \left(\frac{\bar{\alpha}}{\alpha}\right)^{\frac{1}{1-\eta}} K_j^{Dom}(\bar{\alpha}), \tag{7}$$

Equation (7) imposes a productivity threshold of $\alpha^* = \frac{\bar{\alpha}}{\psi_{ij}^s}$. Therefore, in line with ample empirical evidence, for the same level of capital, foreign entry imposes a productivity markup. Our model offers a new insight: the higher productivity of foreign entrants holds only for skill-intensive sectors. In other sectors that rely exclusively on low-skilled labor and capital ($s \to 0$), foreign and domestic capital and productivity are equal (for example farming).

3.2.2 Multiple firms

The capital investment is defined as the sum of the capital invested from the most productive firm $\underline{\alpha}$ to the least productive foreign firm α^*.

$$\tilde{K}_{ij} = N_i \int_{\underline{\alpha}}^{\alpha^*} K_{jz}^{FDI} \frac{g(\alpha)}{G(\alpha^*)} d\alpha =$$
$$= N_i K_j^{Dom}(\bar{\alpha}) \left(\frac{1}{\psi_{ij}}\right)^{\frac{s}{1-\eta}} \int_{\underline{\alpha}}^{\alpha^*} \left(\frac{\bar{\alpha}}{\alpha}\right)^{\frac{1}{1-\eta}} \frac{g(\alpha)}{G(\alpha^*)} d\alpha, \quad (8)$$

where N_i is the total number of firms in country i.

To calculate the foreign capital invested by foreign firms, we follow the assumptions of Helpman et al. (2008), adapted for FDI in Cuadros et al. (2016), to obtain a log-linear and estimable equation from (8):

$$\ln FDI_{ij} \equiv \ln \tilde{K}_{ij} \quad = \quad n_i + k_j - \frac{s}{1-\eta} \ln \psi_{ij} + \omega_{ij}, \quad (9)$$

where $n_i = \ln N_i$ and $k_j = \ln K_j^{Dom}(\bar{\alpha})$ are home and host country fixed effects, respectively, and parameter ω controls firm selection as in Helpman et al. (2008). Equation 9 is effectively a gravity equation for foreign capital, where the total foreign capital investment is the result of home country fixed effects (the number of firms or the country's economic mass), a host country fixed effect (minimum capital requirements determined by the host's factor endowments and demand via prices), a bilateral transaction cost (related to high-skilled labor costs) and selection into an investment mechanism.

3.3 Migration

To obtain an empirical equation that allows us to estimate equation (9), we must appropriately parametrize ψ_{ij}. Affiliates need to hire skilled labor which is able to translate headquarters' blueprints. Consequently, the parameter ψ_{ij} captures labor cost differences and communication costs between the affiliate and headquarters. The assumption that $\psi_{ij} \geq 1$ comes from high-skilled labor cost differentials, which unfortunately are not directly observable to the econometrician. However, high-skilled labor mobility has an effect on labor cost differentials and is directly observable. Given a downward-sloping of labor demand curve, an increase in supply should be expected to lower labor costs. Recent studies suggest that in terms of labor effects, migrants particularly affect the labor costs (particularly wages) of previous migrants (Borjas, 2017; Ottaviano and Peri, 2012). Therefore, allowing for labor mobility between country pairs[3], an increase in the share of high-skilled i-born workers (with management skills) in country j is expected to reduce the labor costs of high-skilled managers $\overline{w}_{ij}$ as these high-level skills become more abundant.

Let us assume that the observed labor cost differential for managers increases with the distance to the headquarters and is inversely proportional to the observed stock of migrant managers, with some measurement error. The intuition here is that the affiliate faces lower communication and labor search costs when the supply of management skills (which help to intermediate between headquarters and affiliate) is higher. Then,

$$\psi_{ij} = d_{ij}^{\upsilon} e^{-\bar{m}_{ij} \cdot \epsilon_{ij}} \tag{10}$$

where $\upsilon > 0$ is the foreign distance-wage elasticity, $\bar{m}_{ij} > 0$ is the bilateral stock of migrants with management skills and ϵ is a stochastic error term. Let us represent the total bilateral stock as

$$m_{ij} = \bar{m}_{ij} + \underline{m}_{ij} = (1 + \zeta)\bar{m}_{ij}, \tag{11}$$

[3]Alternatively, the host country could impose a fee on foreign managers to train local workers (Stark and Byra, 2018)

where $\underline{m}_{ij}$ is the low-skilled migrant stock and $\zeta = \underline{m}_{ij}/\bar{m}_{ij}$ is low-skilled to high-skilled migrant ratio.

Therefore, an empirical equation to estimate is:

$$\ln FDI_{ij} = n_i + k_j - \frac{sv}{1-\eta}\ln d_{ij} + \frac{s}{(1-\eta)}\frac{m_{ij}}{(1+\zeta)} + \omega_{ij} + \epsilon_{ij}. \qquad (12)$$

The effects of skill shifting in the migration stock follow naturally from equation (12). For a fixed total migrant stock, an exogenous increase in the share of high-skilled migrants (i.e., lower ζ) increases bilateral FDI. Conversely, an increase in low-skilled immigrant share (i.e., higher ζ) reduces the volume of bilateral FDI.

It is interesting to note that parameter ψ_{ij} affects both the capital invested (intensive margin) and the productivity threshold (extensive margin). Therefore, we should expect that an increase in high-skilled migration reduces the productivity threshold α^*. Thus, the share of migrants with management skills, has a positive effect on both investment margins.

4 Data and Econometric Specification

A naïve gravity augmented empirical gravity equation of (9) would take the form:

$$lnFDI_{ijt} = \beta_1 gravity_{ijt} + \beta_2 gravity_{ij} + \beta_3 \ln manager_{ijt} + \gamma_{it} + \gamma_{jt} + u_{ijt} \quad (13)$$

where FDI_{ijt} is the aggregate capital expenditure on foreign projects from country i to country j in year t; $gravity_{ijt}$ and $gravity_{ij}$ is a standard set of time-varying and time-invariant gravity control variables, respectively; $manager_{ijt}$, represents the stock of people born in country i working in country j as managers. Lastly, γ refers to country-year fixed effects to control for multilateral resistance (time-varying third-country effects) and u is a stochastic error term. The FDI source country (i) matches the migrant's country of origin; and the FDI recipient country (j) is the migrant's host country.[4]

The baseline gravity equation (13) suffers from several biases. In the first place, omitted variable bias occurs since we do not control for other types of job skills included in the total migrant stock. Therefore, an appropriate empirical specification should simultaneously control for all types of migration. Inferences from regressions that introduce separately the two types of migrants are difficult to interpret. For example, one cannot be sure that a positive sign on low-skilled migration can be a confounding effect of increasing high-skilled migration.

The second set of potential biases are related to the gravity specification of (13). The log version of the gravity equation has a self-selection bias, which stems from the omission of zeros. Additionally, the estimation of FDI capital expenditure flows suffers a potential over-aggregation bias. We adopt different empirical strategies to hedge against these empirical issues. Silva and Tenreyro (2015) show that Helpman et al.'s (2008) two-stage estimation imposes overly strict homoscedasticity restrictions on the error term. As an alternative, the authors show that the simpler Pseudo-Poisson Maximum Likelihood (PPML) method yields similar results to the two-step procedure. To overcome this issue, we use a non-linear variant of the gravity equation in line with that proposed by Silva and Tenreyro (2006), which does not require a log-linearization. Therefore, we use the following non-linear specification for the

[4] In the online Appendix, we estimate equation (13) with the full set of time-invariant controls.

intensive margin[5]:

$$FDI_{ijt} = \exp\left(\begin{array}{c} \beta FTA_{ijt} + \beta BIT_{ijt} \\ \beta_2 \ln manager_{ijt} + \beta_3 \ln professional_{ijt} + \beta_4 \ln nonqual_{ijt} + \\ \gamma_{it} + \gamma_{jt} + \gamma_{ij} \end{array}\right) + u_{ijt} \tag{14}$$

where $manager_{ijt}$, $professional_{ijt}$, and $nonqual_{ijt}$ represent the stock of people born in *country i* working in country j as managers, professionals and non-qualified workers respectively[6], BIT is a dummy variable that takes the value of 1 if the country pair has a bilateral investment treaty in force, and FTA is a dummy variable that indicates whether both countries have a free trade agreement in force.

Equation (13) controls for potential estimation biases such as unobserved bilateral heterogeneity, multilateral resistance terms, zero trade flows or heteroscedastic residuals. The estimation strategy follows the recent proposal by Larch et al. (2017) which, through an iterative PPML algorithm, allows us to account for all the above issues and deals efficiently with high-dimensional fixed effects: country-pair, source-time and destination-time fixed effects.

As in similar studies, the migrant source data is taken from the DIOC-E database on migrants in OECD and non-OECD countries (Dumont and Widmaier, 2010), which constrains the analysis to 91 source countries and 24 host economies (the complete list is reported in the Online Appendix). The DIOC-E provides information about the percentage of migrants in occupations such as business directors or managers, who are more directly related to the creation of international linkages and investment opportunities abroad. The BIT and FTA agreements are sourced from

[5]The equation for the extensive margin follows the same specification, but substituting the left-hand-side variable for the number of firm-level projects.

[6]With this specification, we are controlling for the share of each skill group in line with our model.

UNCTAD and FDI data come from FDIMarkets.[7]

The migrant data refer to the years 2001 and 2004 and provide information about migrants' job positions. As in similar studies, we apply a three-year lag (2004 and 2007) to the FDI data to reduce the potential bias of reverse causality (Bratti et al., 2014; Peri and Requena-Silvente, 2010). We apply also several instrumental variable techniques to rule out potential endogeneity bias.

Certain aspects of the data on the stock of migrants should be noted. DIOC-E uses the standard 2-digit ISCO-88 classification for all but three countries (Argentina, Turkey and the United States). In order to keep the United States in the sample, categories from ISCO-88 and US were aggregated up to the three broad groups used in equation (14): non-qualified, non-managerial qualified and managers. It is worth emphasizing two issues regarding these categories. First, ISCO-88 categories are defined by the skills required for each job regardless of the way those skills were acquired. Second, the categories refer to the tasks associated with the job rather than the employer/employee status of the person carrying them out. More specifically, the three categories defined by aggregating the 2-digit ISCO-88 are described in Table (2).

[Table 2 about here.]

In Table 3 we list the host countries in the sample and some statistics about the distribution of migrants in the different job positions by countries of origin. The distribution of migrants across job positions is fairly even across countries, with approximately 12% of migrants working in managerial positions (on average), 30% as professionals and almost 60% in non-qualified jobs. These figures hold remarkably

[7] The data allow us to directly observe the extensive margin with firm-level data. Therefore, we do not need to estimate the two-step HMR equation since the selection mechanism ω_{ij} of our empirical equation is directly present in the extensive margin. Additionally, Silva and Tenreyro (2015) argue that the HMR two-step estimation method has certain limitations which the PPML estimator overcomes.

well not only for migration flows from the investing country towards the FDI recipient country but also for flows in the opposite direction.

[Table 3 about here.]

We estimate equation (14) for both the intensive (FDI flows) and the extensive margin (number of projects). The PPML estimator is a way of dealing with known gravity estimation issues such as the presence of zeros in the dependent variable and heteroscedasticity. The dataset is unbalanced with 70% zeros. Therefore, we follow Paniagua (2016) to construct efficient gravity datasets with many zeros.

A relevant question is whether migration can be treated as exogenous. Rose (2018) and Beverelli et al. (2018) argue that the inclusion of time-varying country fixed effects reduces the potential endogeneity for dyadic data. Following their arguments, the multilateral resistance terms eliminate the effect of any specific economic phenomena in a particular country, such an increase in the migration rate. The economic argument is that the gravity equation controls for both monadic (which we do not estimate) and dyadic migration.

Nonetheless, we take some precautions to mitigate a possible endogeneity bias. In the first place, our econometric specification measures FDI in flows and migration in lagged stocks. It is very unlikely that the 4-year lagged migration stock has an effect on future FDI flows. However, to rule out the concern of double causality in our estimates, we perform several additional tests based on an instrumental variable approach, which we detail with the results reported below.

Alongside endogeneity, lies the issue of identification or perhaps omitted variable bias, which remains in the error term. The inclusion of country-pair fixed effects should help with the correct identification of migrants in the equation. However, we try to corroborate the robustness of the results with an extensive set of robustness checks. In particular, we introduce $j \to i$ migrants to control for the information channel, as in Javorcik et al. (2011) and Cuadros et al. (2016). We also use an alternative specification measuring migrants in shares rather than in logs.[8] Additionally, we control for other sources of heterogeneity with a gravity quantile regression (Paniagua et al., 2015) and a sectoral analysis. Finally, we compare job position and educational attainment to determine the best measure to estimate the effects modeled in our theoretical framework.

Lastly, our micro-founded model assumes Pareto-distributed productivities to close the gap between the Melitz framework and the gravity equation. Since Chaney (2008), many related studies have taken a similar route, at the risk of a disconnection between theory and empirics. Furthermore, we do not have employee-employer matched data. Unfortunately, our dataset does not contain detailed information indicating whether migrants with managerial jobs are employed by multinationals. Acknowledging all these issues, we are accordingly cautious in interpreting the results of the empirical analysis presented below.

5 Results

The gravity estimates reported in Table 4 constitute our baseline results. The first four columns show the results for aggregate FDI flows (intensive margin) and the last four are those corresponding to the explanation of the extensive margin.

[Table 4 about here.]

We start by analyzing the determinants of the investment decision (extensive margin). Our estimation procedure forces us to drop traditional invariant variables

[8] The results for migrant shares are reported in the Online Appendix

included in gravity equations, with the exception of bilateral agreements, which displays heterogeneous effects.[9]

Let us focus on the effects of migrants occupying different job positions. In our first estimates, we consider only one job position in each equation, as displayed in columns (1) to (3) in the intensive margin and columns (5) to (7) in the extensive margin. All categories are found to be highly significant for both dependent variables. Besides, the highest impact comes from management skills, followed by professionals and low-skilled workers. This decreasing pattern can be seen in the estimates for both margins. This outcome is not entirely satisfying from our theoretical perspective, since we expected opposite impacts of migrants on FDI depending on their skills and job positions. Besides, as discussed in Section 4 and from an econometric perspective, these results do not control for job skill composition adequately since each individual estimate does not include the number of migrants in the rest of the job categories.[10] The inclusion of all three variables simultaneously in columns (4) and (8) could block the effect of the omitted categories. This specification reveals that migrants in non-qualified positions do not significantly affect FDI in either margin, whereas professionals become non-significant only in the intensive margin. To rule out confounding effects, we re-estimate our baseline model controlling for the aggregate migrant stock in the remaining positions as in equation (14). This specification amounts to an analysis of the impact of the share of each job category, as in Aleksynska and Peri (2014) and Javorcik et al. (2011). The results are displayed in Table 5 only for our variables of interest.

[Table 5 about here.]

[9] Paniagua et al. (2015) show that the unexpected effect of BIT on FDI is explained by firm-heterogeneity bias. To overcome this bias, the authors develop a quantile regression procedure.

[10] As the number of individuals from country i working in country j is distributed across all the job positions, they could all increase or decrease simultaneously in this specification.

Some interesting differences emerge in the impact of migrants depending on the job categories, as can be seen in Table 5. On the one hand, the effect of managers is always significant and positive, whereas in the case of professionals we do not find any significant influence. On the other hand, migrants in non-qualified jobs display a negative effect only in the extensive margin (column 6). These results are in line with our hypothesis regarding the key role of migrants with management skills, but also with our view of the impact of low-skilled migrants. The negative effect of non-qualified migrants on FDI is not new in the literature (as shown in Table 1), although explanations for this puzzling result offered by previous studies have been ad-hoc at best.[11] However, this negative impact a predicted outcome of our model. All else being equal, an increase in non-qualified migrants results in a decrease in the share of managers and professionals (captured by ζ in equation 12).

Viewed from another angle, increasing the share of non-qualified migrants increases the management costs ψ_{ij}. The intuition being that this cost stems from scarcity but also from difficulties in identifying migrants endowed with informational skills (managers and, to a lesser extent, professionals). It is precisely the shift in the skills composition that affects FDI.

Moving forward, our model studies the contribution of $i \rightarrow j$ migrant stock to the $i \rightarrow j$ FDI flows via high-skilled labor cost differentials. However, the model is agnostic as to the effect of the $j \rightarrow i$ migrant stock since we modeled production located in country j. Nevertheless, previous research (see Cuadros et al. (2016); Javorcik et al. (2011) among others) has highlighted the impact of the informational flows provided by $j \rightarrow i$ migrants on FDI flows. In our framework, this type of migrants represent an

[11]According to Flisi and Murat (2011), this negative relationship could be interpreted as a substitution effect between low-skilled migrants and FDI abroad. In a previous version of that work, the authors stated that this negative sign could be reflecting the preference of the firms from the migrants' countries of origin to invest in countries with a greater presence of skilled nationals and business networks. Gheasi et al. (2013) also report a negative influence of low-skilled migrants, albeit with no convincing explanation.

exogenous information channel, which we want to empirically control for in order to reduce omitted variable bias.

To take into account these effects, we introduce the stock of $j \to i$ migrants by means of the specification already used in Table 5. The new outcomes appear in Table 6. As expected, the new variable is significant in both margins and refines the mechanisms highlighted by the aforementioned research. Only the information provided by j-born migrant managers seems to influence both the decision to invest as well as the amount invested.

[Table 6 about here.]

The estimates for the job categories indicators are not qualitatively different from those displayed in Table 5, as they retain their sign and significance. However, in quantitative terms, the impact of all the indicators increases significantly. One possible interpretation, other than a country selection bias due to the reduced number of observations, might rest on a positive feedback process between different migrants.

Additionally, we can better understand the role played by both types of migrants in FDI. On the one hand, j→i migrants provide a signal about which locations to invest in. This signal is only relevant for migrant managers. On the other hand, in addition to possible information signals, the effect of i→j migrants encompasses both managers and professionals, who can reduce production labor costs, as predicted by our model.

5.1 Sources of FDI heterogeneity

Next, we tighten our specification by introducing two sources of heterogeneity in the dependent variable. Thus, we distinguish FDI (i) by the branch of activity (Table 7) and (ii) by the level of investment, which is likely to be highly correlated with firm size (Table 8).

With regard to the first distinction, we split our dependent variable into four possible activities at which the investment project might be targeted: Manufacturing, Sales, Construction and Services. A key element of our model is that the effect of the share of migrant managers would be more intense in sectors that are more dependent on high-skilled inputs ($s \gg 0$). The high level of aggregation makes it difficult to identify the high-skill intensive activities; however, the decomposition into four branches allows us to test our theoretical predictions and draw interesting conclusions from the outcomes presented in Table 7.

First, managers appear as the primary source of impact on FDI, confirming the need for migrants to be close to decision-making positions if they are to have any influence on FDI. Second, this influence shows different patterns across branches and allows us to clarify the effects of both types of migrants. On the one hand, the information provided by j→i migrants focuses on construction and manufacturing activities, where local knowledge is relevant to choose the best manufacturing locations and compete for construction contracts. On the other hand, the effect of i→j migrants is concentrated in sales (managers and professionals), and services (managers). These high-skill intensive activities benefit from imported talent to overcome the difficulties involved in relocating production to country j.

[Table 7 about here.]

To control for the second source of heterogeneity, we rely on the level of the investment, which is likely to be associated with the size of the investing firm. We employ quantile regressions, which are appropriate for the estimation of skewed data such as that on international trade (Baltagi and Egger, 2016; Machado et al., 2016) and FDI (Myburgh and Paniagua, 2016; Paniagua et al., 2015). We follow Baker's (2014) procedure to fit a censored quantile regression model, with investments considered separately depending on the amount invested (i.e., only accounting for the intensive margin) and the results conditional on the values of the migration indicator. The results are presented in Table 8.[12]

[Table 8 about here.]

As expected, managers have a higher impact on the lowest levels of FDI, populated by smaller firms. The positive effect of managers decreases with FDI quantiles, while the negative effect of low-skilled migrants increases (becomes more negative). This opposing trend is in line with our model where the negative effect of low-skilled migrants is due to the migrant job skills composition. Therefore, in those levels of FDI where management skills have a lower impact, the negative effect of low-skilled migrants emerges as a consequence of the relative composition of migrants' jobs skills.

5.2 Job position vs. educational attainment

We have previously discussed in Section 2 the problems associated with the use of educational attainment as a measure of migrants' skills. For the sake of comparison, however, we replicate our estimates shown in Tables 6 and 7, substituting our job position indicators with traditional indicators of educational attainment.[13]

However, this does not mean that we establish a one-to-one equivalence between these levels of education and our job categories. First, it is likely that most migrants would have secondary or higher educational levels (in fact, higher-educated migration has grown steadily in the last decade). Second, many of these higher-educated migrants might not be working in managerial or professional positions; on the contrary, a high proportion may be occupying non-qualified positions (Arslan et al., 2015; Widmaier and Dumont, 2011). Third, Hartog and Zorlu (2009) report that

[12] Due to convergence issues, we controlled for country-pair heterogeneity with the time-invariant controls detailed in the online Appendix

[13] In the online Appendix, we replicate all the empirical analysis with educational attainment and provide further evidence.

higher education does not provide the expected returns on a migrant's salary, thus reducing the educational incentives of prospective migrants.

Table 9 reports the educational results. In this specification, we observe evident differences with the results of Table 6. Here only highly-educated i→j migrants have a positive and significant impact on both margins, which is consistent with i→j migrant managers and professionals having a positive impact in Table 6. But the results regarding the information signal provided by j→i migrants are mixed. For the intensive margin, no educational level seems to be significant.[14] For the extensive margin, the effect of primary education cancels out that of secondary education. Recalling the results in Table 6, j→i migrant managers had a consistent positive effect. The economic interpretation of these results might suggest that only the information signal of i→j migrants with significant corporate responsibility emerges above the noise level.

Overall, these results align with those of Hartog and Zorlu (2009), who reported the low influence of educational level on migrants' salaries. Migrants seem to exert a more intense influence on FDI when their education allows them to work in decision-making occupations. Chiswick and Miller (2009a) posit that earnings appear to be more closely related to a worker's occupation than to the individual level of schooling. Therefore, when we assess migrants by their occupation rather than by education, we can be confident of correctly capturing the high-skilled labor cost ratio.

These results uncover a relevant message. Migrants' educational skills are undoubtedly important to foster FDI flows. However, within the stock of skilled migrants, those occupying a certain type of job positions facilitate FDI. This would support our hypothesis that the distribution across job categories is the best way to account for migrants' heterogeneity.

[14]However, this appears to be an artifact of collinearity, because when we aggregated them in the online Appendix, we observed a mild positive effect.

[Table 9 about here.]

5.3 Endogeneity

Several studies that deal with migrant endogeneity have used different instruments such as passport costs (Hatzigeorgiou, 2010), dual citizenship (Mundra, 2014) and ancestors (Burchardi et al., 2016). We use these instruments in a step-wise manner that allows us to differentiate between skilled (managers and professionals) and non-skilled migrants.

Current migration can be related back to historical migration patterns (Burchardi et al., 2016; Card, 2001; Peri and Requena-Silvente, 2010). However, historical migration distribution should have a weak relationship with present FDI flows. Therefore, we use as an instrument the proportion of the ancestors from 1500, defined as the share of the population in year 2000 in every host country (Putterman and Weil, 2010). We also add as an instrument a dummy variable which captures the possibility that the home country allows for dual citizenship, as in Mundra (2014). To differentiate between skill endowments, in addition to ancestors and dual citizenship, we instrument non-qualified workers with passport costs as a percentage of gross national income (Hatzigeorgiou, 2010). Passports might be a strong barrier for the low-income level migrants but not for managers and professionals.

[Table 10 about here.]

The results are shown in Table 10. The instrumental variable two-set least-squares (IV-2SLS) regression results do not deviate substantially from our previous standard regression results. The Hansen J statistic suggests that risk of over-identification is relatively low (except for professionals in the extensive margin). The signs and relative magnitudes of the estimated coefficients for the different occupations are in line with our expectations both in the extensive and extensive margins. Management skills have a positive and significant effect on FDI, which is bigger than the effect of professionals. Non-qualified migrants have a negative and significant effect on FDI, after controlling for other job skills.

For robustness, we used the poisson IV version, as it allows for multiplicative errors, which better fits dyadic data (Silva and Tenreyro, 2006). The results are reported in Table 11. The magnitude of the coefficients has been considerably reduced with respect to the 2SLS linear version and are in line with our previous estimates. Managers emerge as the most important job category in both margins, and non-qual retains the negative sign in the intensive margin. Professionals do not seem to have a significant effect on FDI, after controlling for endogeneity with this procedure.

[Table 11 about here.]

6 Concluding remarks

This paper disentangles some unexplored mechanisms behind the migration-FDI nexus. We provide theoretical and empirical arguments to highlight the relevance of job skills in an analysis of how migration impacts FDI flows. The model boils down to a key insight: migrants with jobs that entail decision-making foster FDI.

Our empirical findings show that migrant managers in particular, and to a lesser extent professionals, exert a positive and significant influence on both the extensive and the intensive margins of FDI. Moreover, the results reveal sectoral heterogeneity. Our analysis also illustrates that the effects are larger for the lower levels of FDI, populated by smaller investment projects, where management skills might be more useful.

The paper also tackles an issue that has been overlooked by the literature: the heterogeneous impact of different migration flows. Now we can better understand the role played by both types of migrants: the empirical exercise suggests that j→i migrants reduce information asymmetries and j→i have labor-related effects.

One novelty of our analysis is to provide a rationale for the puzzling negative effect of non-qualified migrants on FDI. This negative effect is only perceptible after controlling for the rest of the job skill-sets, suggesting that the marginal effect of non-qualified migration is explained by a change in the job skills composition. The robust structural gravity estimates reveal a consistent partial equilibrium effect of decision-making migrants on FDI. Policies aimed at fostering FDI might want to consider these insights, for example by promoting management training for migrants. Future studies could use the insights of this paper to assess the general equilibrium effects of such policies.

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Table 1: Literature review summary

STUDY	COUNTRY / PERIOD	MAIN RESULTS
Kugler and Rapoport (2007)	United States 1990 and 2000	Higher unskilled emigration in 1990 is associated with higher growth of total FDI inflows over the following decade. **Negative impact for migrants with secondary education in the manufacturing sector**
Docquier and Lodigiani (2010)	Cross section 114 countries. Panel data/ 83 countries	Strong network externalities mainly associated with the skilled diaspora
Ivlevs and De Melo (2010)	1990-2000 103 migration-sending countries	If exports are low skill intensive, emigration of high-skilled labour leads to positive FDI
Flisi and Murat (2011)	Immigrant networks for France, Germany, UK, Italy and Spain	Skilled immigrants increase bilateral FDI in UK, France and Germany. In Italy and Spain, FDI is influenced by their emigrant diaspora network. **Negative impact for unskilled migrants**: substitution effect between low-skilled immigration and investment abroad
Javorcik et al. (2011)	United States 1990 and 2000	Outward FDI (stock) positively related with the presence of migrants in US (stock). Stronger effect for the share of tertiary educated migrants
Leblang (2011)	26 OECD reporting countries and 120 destination countries 2000 and 2001	Migrant networks encourage cross-border investments (FDI and portfolio). The effect on FDI is substantially larger. Stronger for migrants with tertiary education
Foad (2012)	50 US states, 10 source countries 1990 and 2000 for immigration	Presence of immigrants leads to new FDI from immigrants' native countries. This effect is stronger for skilled migrants and might take a few years to occur
Gheasi et al. (2013)	United Kingdom 2001-2007	FDI abroad positively related with the presence of migrants. More educated migrants have a higher positive effect on FDI. **Negative impact of low-skilled migrants on FDI**
Tomohara (2017b)	Japan 1996-2011	FDI inflows become more dominant compared to imports when skilled immigration flows increase and less dominant when unskilled immigration flows increase
Tomohara (2017a)	Japan 1996-2011	**Contemporaneous negative relationship between low-skilled migration and FDI**

Table 2: 2-digit ISCO-8

variables	2-digit ISCO-8
manager	Legislators, senior officials and managers
professional	Professionals
	Technicians and associate professionals
	Skilled agricultural and fishery workers
	Craft and related trade workers
	Plant and machine operators and assemblers
nonqual	Clerks
	Elementary occupations

Table 3: Migrant shares in the sample

	Emigrants ($i \rightarrow j$)				Immigrants ($j \rightarrow i$)			
Country (i)	Total	Managers	Professionals	Non-qual	Total	Managers	Professionals	Non-qual
Australia	0.03	0.16	0.22	0.62	0.24	0.08	0.28	0.64
Austria	0.04	0.12	0.25	0.63	0.14	0.09	0.34	0.57
Belgium	0.04	0.14	0.22	0.63	0.10	0.20	0.22	0.57
Canada	0.05	0.14	0.33	0.52	0.21	0.10	0.24	0.66
Switzerland	0.07	0.14	0.25	0.60	0.25	0.06	0.51	0.43
Czech Rep	0.02	0.11	0.26	0.63	0.04	0.15	0.23	0.62
Denmark	0.03	0.16	0.27	0.58	0.06	0.01	0.61	0.38
Spain	0.02	0.14	0.30	0.55	0.07	0.10	0.39	0.50
Finland	0.06	0.07	0.31	0.62	0.02	0.02	0.43	0.55
France	0.03	0.13	0.27	0.59	0.09	0.14	0.22	0.64
UK	0.07	0.15	0.24	0.60	0.09	0.16	0.29	0.55
Greece	0.06	0.14	0.43	0.43	0.14	0.11	0.36	0.53
Hungary	0.04	0.11	0.29	0.60	0.03	0.14	0.22	0.65
Ireland	0.21	0.15	0.31	0.54	0.12	0.13	0.32	0.54
Italy	0.05	0.11	0.37	0.52	0.05	0.10	0.33	0.57
Luxembourg	0.09	0.13	0.25	0.63	0.43	0.10	0.28	0.62
Mexico	0.12	0.03	0.57	0.40	0.00	0.19	0.30	0.50
Netherlands	0.03	0.17	0.22	0.61	0.10	0.04	0.30	0.66
New Zealand	0.17	0.13	0.26	0.62	0.20	0.12	0.32	0.56
Poland	0.07	0.04	0.34	0.62	0.01	0.13	0.14	0.73
Portugal	0.15	0.10	0.33	0.57	0.09	0.12	0.29	0.60
Slovakia	0.08	0.08	0.27	0.65	0.03	0.13	0.25	0.62
Sweden	0.02	0.14	0.31	0.55	0.11	0.03	0.50	0.48
United States	0.01	0.16	0.17	0.67	0.14	0.09	0.42	0.50

Table 4: Baseline Results

	Intensive Margin				Extensive Margin			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
BIT_{ijt}	0.161	0.223	0.059	0.187	0.085	0.126	0.093	0.048
	(0.16)	(0.18)	(0.21)	(0.18)	(0.10)	(0.11)	(0.11)	(0.10)
FTA_{ijt}	0.340*	0.327*	0.397**	0.382**	0.290***	0.324***	0.337***	0.331***
	(0.18)	(0.17)	(0.19)	(0.19)	(0.06)	(0.06)	(0.06)	(0.06)
$\ln manager_{ijt}$	0.476***			0.684***	0.348***			0.635***
	(0.06)			(0.17)	(0.03)			(0.08)
$\ln professionals_{ijt}$		0.410***		-0.139		0.267***		0.238**
		(0.05)		(0.19)		(0.02)		(0.10)
$\ln nonqual_{ijt}$			0.346***	-0.049			0.243***	-0.033
			(0.05)	(0.13)			(0.02)	(0.06)
Observations	1660	1735	1691	1625	1660	1735	1691	1625
R^2	0.862	0.871	0.863	0.869	0.926	0.914	0.902	0.927

Notes: Robust standard errors in parentheses (PPML estimation in levels) clustered by country pair.
Home*year and source*year country fixed and country-pair effects included.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Results controlling for other jobs

	Intensive Margin			Extensive Margin		
	(1)	(2)	(3)	(4)	(5)	(6)
Managers	0.667***			0.587***		
	(0.17)			(0.08)		
Other jobs	-0.085			-0.112***		
	(0.07)			(0.03)		
Professionals		-0.145			-0.162	
		(0.21)			(0.10)	
Other jobs		0.290***			0.232***	
		(0.11)			(0.05)	
Non-qualified			-0.206			-0.147**
			(0.14)			(0.07)
Other jobs			0.340***			0.237***
			(0.09)			(0.04)
Observations	1625	1625	1625	1625	1625	1625
R^2	0.863	0.872	0.864	0.925	0.912	0.913

Notes: Robust standard errors in parentheses (PPML estimation in levels) clustered by country pair. Home*year and source*year country fixed and country-pair effects included.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Results controlling for other jobs and j→i migrants

	Intensive Margin (1)	Extensive Margin (2)
Managers i→j	1.057***	0.824***
	(0.19)	(0.11)
Professionals i→j	0.532**	0.436***
	(0.27)	(0.14)
Non-qualified i→j	-0.292*	-0.163*
	(0.17)	(0.10)
Managers j→i	0.961***	0.426***
	(0.28)	(0.12)
Professionals j→i	-0.472	-0.143
	(0.37)	(0.18)
Non-qualified j→i	-0.006	-0.027
	(0.23)	(0.12)
Observations	698	698
R^2	0.829	0.959

Notes: Robust standard errors in parentheses (PPML estimation in levels) clustered by country pair. Home*year and source*year country fixed and country-pair effects included.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Results controlling for other jobs and other migrants

	Manufacturing (1)	Sales (2)	Construction (3)	Services (4)
Managers i→j	0.464	1.292***	0.149	0.859**
	(0.31)	(0.41)	(0.42)	(0.38)
Professionals i→j	-0.656	1.421*	-0.039	-0.778
	(0.42)	(0.73)	(0.58)	(0.48)
Non-qualified i→j	0.134	0.456	0.119	0.085
	(0.34)	(0.48)	(0.34)	(0.33)
Managers j→i	0.880*	-0.172	0.800*	-0.042
	(0.52)	(0.49)	(0.47)	(0.51)
Professionals j→i	0.256	-0.481	-0.889	0.856
	(0.67)	(0.61)	(0.63)	(0.69)
Non-qualified j→i	-0.495	0.652*	0.478	-0.291
	(0.38)	(0.35)	(0.41)	(0.43)
Observations	585	543	354	530
R^2	0.834	0.874	0.584	0.582

Notes: Robust standard errors in parentheses (PPML estimation in levels) clustered by country pair. Home*year and source*year country fixed and country-pair effects included.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Quantile regression

	Intensive Margin			
	(1)	(2)	(3)	(4)
	Q(0.25)	Q(0.50)	Q(0.75)	Q(0.90)
Average project size (mUSD):	14	28	61	79
Managers	0.933***	0.818***	0.342***	0.363***
	(0.10)	(0.16)	(0.11)	(0.10)
Other jobs	-0.454***	-0.346***	-0.067	-0.141*
	(0.08)	(0.06)	(0.07)	(0.08)
Migrants j→i	0.677***	0.631***	0.409***	0.483***
	(0.11)	(0.07)	(0.06)	(0.09)
Professionals	0.544***	0.307***	0.544***	0.254*
	(0.11)	(0.08)	(0.08)	(0.13)
Other jobs	0.006	-0.184**	-0.121	0.029
	(0.13)	(0.07)	(0.08)	(0.08)
Migrants j→i	0.596***	0.343***	0.335***	0.485***
	(0.10)	(0.12)	(0.05)	(0.10)
Non-qual	-0.263***	-0.581***	-0.540***	-0.814***
	(0.08)	(0.07)	(0.07)	(0.07)
Other jobs	0.141**	0.430***	0.338***	0.566***
	(0.06)	(0.05)	(0.04)	(0.06)
Migrants j→i	0.621***	0.471***	0.528***	0.333***
	(0.09)	(0.08)	(0.07)	(0.10)
Observations	269	269	269	269

Notes: Robust standard errors in parentheses (Dep variable $\ln(FDI + 1)$).
Home*year and source*year country fixed effects included.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 9: Results controlling for other education levels and other migrants

	Intensive Margin (1)	Extensive Margin (2)
Higher edu i→j	0.583***	0.192*
	(0.21)	(0.11)
Secondary edu i→j	-0.168	0.057
	(0.21)	(0.12)
Primary edu i→j	-0.002	-0.088
	(0.11)	(0.07)
Higher edu j→i	0.190	-0.101
	(0.18)	(0.08)
Secondary edu j→i	0.011	0.331**
	(0.29)	(0.13)
Primary edu j→i	-0.212	-0.220***
	(0.16)	(0.08)
Observations	1118	1118
R^2	0.857	0.984

Notes: Robust standard errors in parentheses (PPML estimation in levels) clustered by country pair. Home*year and source*year country fixed and country-pair effects included.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 10: Endogeneity (2SLS)

	Intensive Margin			Extensive Margin		
	(1)	(2)	(3)	(4)	(5)	(6)
Managers	3.167***			1.237**		
	(1.02)			(0.49)		
Other jobs	-1.27***			-0.505**		
	(0.41)			(0.20)		
Professionals		1.29*			0.381	
		(0.74)			(0.226)	
Other jobs		-0.620*			-0.190	
		(0.36)			(0.123)	
Non-qualified			-2.699***			-0.883***
			(0.50)			(0.19)
Other jobs			1.466***			0.471***
			(0.27)			(0.10)
Observations	998	998	998	998	998	998
R^2	0.45	0.48	0.23	0.60	0.27	0.27
Hansen J statistic	5.30*	8.5*	5.38*	3.81*	6.82***	4.34

Notes: Robust standard errors in parentheses, clustered by country pair. Dependent variables+1 in logs
Instruments: Ancestors (j), Dual citizenship (i). For non-qual Passport cost (% GNI) is added.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 11: Endogeneity (IV-poisson)

	Intensive Margin			Extensive Margin		
	(1)	(2)	(3)	(4)	(5)	(6)
Managers	0.537*			0.571*		
	(0.30)			(0.32)		
Other jobs	-0.188			-0.175		
	(0.17)			(0.15)		
Professionals		-1.082			-1.123	
		(2.26)			(1.78)	
Other jobs		0.558			0.539	
		(0.97)			(0.78)	
Non-qualified			-1.216***			-0.554
			(0.38)			(0.90)
Other jobs			0.389*			0.329
			(0.27)			(0.49)
Observations	746	746	746	746	746	746
Hansen J statistic	3.74**	2.84*	13.73***	1.16	0.53	3.09

Notes: Robust standard errors in parentheses, clustered by country pair. Dependent in levels
Instruments: Ancestors (j), Dual citizenship (i). For non-qual Passport cost (% GNI) is added.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Online Appendix
Migration and FDI: The role of job skills

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Abstract

Using a multi-country gravity framework, this paper models and quantifies the relevance of migrants' job position in fostering Foreign Direct Investment (FDI). High-skilled migrants are defined as those individuals born in the investors' home/host country occupying managerial or professional positions in the host/home country of investment. Our estimates show that higher shares of migrants with management skills in a given country promote FDI into that country. In contrast, an increase in the share of migrants in non-qualified positions (regardless of their educational attainment) has a negative impact on FDI decisions. These findings highlight that the FDI-enhancing effect of migrants is related to a shift in their skill composition due to their occupation. We test our model on a new global panel data set of Greenfield bilateral investment with a wide variety of specifications, both at the extensive and intensive margins. Additionally, we provide new insights into the mechanisms by which migration influences FDI flows, with particular attention to the relevance of FDI level and activity.

Keywords: Skilled migration; Foreign Direct Investment; Job skills; Gravity equation; Extensive and Intensive Margins.
JEL Classification: F22, F23, F16

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1 Introduction

This technical appendix contains additional theoretical and empirical material that complements the results shown in the paper "Migration and FDI: The role of job skills". In Section 2, we present a detailed analysis of the solution of our model, which includes the full set of derivations. In Section 3, we provide additional data and empirical robustness analyses. Table A1 presents the list of countries used both in the main paper and in this Appendix.

[Table A.1 about here.]

2 Additional theoretical analyses

In the paper, we describe the main elements and assumptions of our theoretical model and report the main theoretical results. In this section, we explain in detail how those results have been derived.

2.1 Solution of the model for capital

We start by deriving the first-order conditions of the firm' problem:

$$\max_{K,S,L} \pi_{iz}^{Dom} = \max\{p_j S^s [K^k L^l]^{1-s} - \alpha(\bar{w}_j S + r_j K + w_j L) - f_j\}.$$

Which are:

$$\frac{\partial \pi_{iz}^{Dom}}{\partial S} = s p_j S^{s-1} [K^k L^l]^{1-s} = \alpha \bar{w}_j \tag{A.1}$$

$$\frac{\partial \pi_{iz}^{Dom}}{\partial K} = (k - sk) p_j S^s G^{k-sk-1} L^{l-sl} = \alpha r_j \tag{A.2}$$

$$\frac{\partial \pi_{iz}^{Dom}}{\partial L} = (l - kl) p_j S^s K^{k-sk} L^{l-sl-1} = \alpha w_j \tag{A.3}$$

From (A.2):

$$L^{l-sl} = \frac{r_j \alpha}{(k-sk)p_j} S^{-s} K^{-k+sk+1}, \tag{A.4}$$

now (A.4) in (A.1):

$$sp_j S^{s-1} K^{k-sk} \frac{r_j \alpha}{(k-sk)p_j} S^{-s} K^{-k+sk+1} = \alpha \bar{w}_j, \tag{A.5}$$

we obtain the relationship between K and S:

$$\frac{s}{k-sk} S^{-1} K = \frac{\bar{w}_j}{r_j} \rightarrow K = \frac{k-sk}{s} \frac{\bar{w}_j}{r_j} S. \tag{A.6}$$

From (A.3):

$$S^s = \frac{\alpha w_j}{(l-sl)p_j} K^{-k+sk} L^{-l+sl+1} \tag{A.7}$$

now (A.7) in (A.2):

$$(k-sk)p_j \frac{\alpha w_j}{(l-sl)p_j} K^{-k+sk} L^{-l+sl+1} K^{k-sk-1} L^{l-sl} = \alpha r_j \tag{A.8}$$

we obtain the relationship between K and L:

$$K^{-1} L = \frac{l-sl}{k-sk} \frac{r_j}{w_j} \rightarrow K = \frac{g-hg}{l-hl} \frac{w_j}{r_j} L. \tag{A.9}$$

Substituting (A.6) in (A.9) we obtain the relationship between S and L:

$$L = \frac{k-sk}{s} S \frac{\bar{w}_j}{r_j} \frac{l-sl}{k-sk} \frac{r_j}{w_j} = S \frac{l-sl}{s} \frac{\bar{w}_j}{w_j}. \tag{A.10}$$

Substituting (A.6) and (A.10) in (A.2):

$$(k-sk)p_j\left(\frac{s}{k-sk}K\frac{r_j}{\bar{w}_j}\right)^s K^{k-sk-1}\left(K\frac{l-sl}{k-sk}\frac{r_j}{w_j}\right)^{l-sl}=\alpha r_j\rightarrow$$

$$(k-sk)p_j\left(\frac{s}{k-sk}\frac{r_j}{\bar{w}_j}\right)^s K^{s+l-sl+k-sk-1}\left(\frac{l-sl}{k-sk}\frac{r_j}{w_j}\right)^{l-sl}=\alpha r_j. \tag{A.11}$$

Rearranging terms:

$$K^{s+l-sl+k-sk-1}\left(\frac{s}{k-sk}\frac{r_j}{\bar{w}_j}\right)^s\left(\frac{l-sl}{k-sk}\frac{r_j}{w_j}\right)^{l-sl}=\frac{\alpha r_j}{(k-sk)p_j}\rightarrow$$

$$K^{s+l-sl+k-sk-1}=\frac{\alpha r_j}{(k-sk)p_j}\left(\frac{s}{k-sk}\frac{r_j}{\bar{w}_j}\right)^{-s}\left(\frac{l-sl}{k-sk}\frac{r_j}{w_j}\right)^{sl-l}\rightarrow$$

$$K^{s+l-sl+k-sk-1}=\frac{\alpha r_j^{1-s-l+sl}}{(k-sk)p_j}\left(\frac{k-sk}{s}\bar{w}_j\right)^s\left(\frac{k-sk}{l-sl}w_j\right)^{l-sl} \tag{A.12}$$

And we obtain an expression for K:

$$K=\left(\frac{(k-sk)p_j}{\alpha r_j^{1-s-l+sl}\left(\frac{k-sk}{s}\bar{w}_j\right)^s\left(\frac{k-sk}{l-sl}w_j\right)^{l-sl}}\right)^{\frac{1}{-h+1-g+hg-l+lh}} \tag{A.13}$$

Now, naming $\eta=s-sk+l-ls+k<1$, we obtain the expression for K_j^{Dom} in the paper:

$$K_j^{Dom}=\left(\frac{(k-sk)p_j}{\alpha r_j^{1-\eta-sk+k}\left(\frac{k-sk}{s}\bar{w}_j\right)^s\left(\frac{k-sk}{l-sl}w_j\right)^{l-sl}}\right)^{\frac{1}{1-\eta}}.$$

2.2 Solution for labor

Similarly, we can obtain the optimal solution for skilled and unskilled labor:

$$S = \left(\frac{sp_j}{\alpha \bar{w}_j^{\,1-k+sk-l+ls} \left(\frac{s}{k-sk} r_j \right)^{sk-k} \left(\frac{s}{l-sl} w_j \right)^{ls-l}} \right)^{\frac{1}{1-\eta}} \tag{A.14}$$

$$L = \left(\frac{(l-sl)p_j}{\alpha w_j^{1-s-k+sk} \left(\frac{l-sl}{s} \bar{w}_j \right)^{s} \left(\frac{l-sl}{k-sk} r_j \right)^{k-sk}} \right)^{\frac{1}{1-\eta}} \tag{A.15}$$

3 Additional empirical analyses

We start our robustness checks by reporting the results that replace country-pair fixed effects with an array of constant country-pair variables. Table A2 describes the gravity controls and the source of each variable. Table A3 reports the descriptive statistics and correlations of the data.

[Table A.2 about here.]

[Table A.3 about here.]

The gravity estimates are reported in Table A4. The first four columns show the results for aggregate FDI flows (intensive margin) and the last four are those corresponding to the explanation of the extensive margin.

[Table A.4 about here.]

We start by analyzing the determinants of the investment decision (extensive margin). Our results are consistent with those obtained by previous studies estimating a gravity equation for FDI. The market size has the standard positive effect on the dependent variables, whereas geographical obstacles such as distance and one of the countries being landlocked display a standard negative impact (however, sharing a border is not relevant). On the cultural side, the investment decision is positively affected by the existence of a common language or past political links such as a former colonial relationship. Finally, the existence of bilateral agreements displays heterogeneous effects.[1] The outcomes for the intensive margin are quite similar to those for the extensive margin, although the impact of distance seems less clear in this case. Sharing a common language is not significant in any case.

Regarding the variables of interest, we observe few differences with the results reported in the paper. The most evident one is the negative effect of non-qualified jobs, which here is negative and significant when all categories are included (columns 4 and 8). However, in the results reported in Table 4 of the paper, we do observe a negative and significant effect on non-qual jobs on the extensive margin only.

In order to confirm the validity of the results of the paper, we try an alternative specification following Aleksynska and Peri (2014) and Javorcik et al. (2011). Thus, in the estimates displayed in Table A5, we introduce separately shares of managers, professionals and non-qualified migrants together with the total stock of migrants. This latter variable absorbs omitted variables that affect both FDI and total migration, enabling us to single out the direct effect of migrants in each job position on FDI.[2]

[Table A.5 about here.]

The total stock of migrants coming from the investing country is significant in all cases, as expected. More interestingly, the share of migrants in managerial positions displays a positive and significant impact, whereas the share of non-qualified migrants has a negative effect on the extensive margin, confirming the existence of

[1]Paniagua et al. (2015) state that the negative effect of BIT is explained by firm-heterogeneity bias. To overcome this bias, the authors develop a quantile regression procedure. Furthermore, this bias is corrected with the country-pair fixed effects.

[2]Additionally, this specification allows us to distinguish between Mundra's (2010) information and demand channels. Thus, the migrant share measures the information channel. The migrant stock controls for the demand channel, through which FDI can be attracted by the demand for goods and services from the migrants' country of origin created by the stock of migrants from that country.

the composition effect mentioned above.

3.1 Educational Attainment vs. Jobs Positions

Most previous studies have quantified migrants' capacities and skills through their educational attainment. Our robustness analysis here considers three categories of migrants' educational level: primary, secondary and higher education.

Several of the considerations regarding the education-occupation mismatch can be traced out in the outcomes presented in tables of this sub-section, where we replicate our results for job occupations displayed in the main paper. Thus, the positive and significant impact reported for higher-educated migrants in Table A6 is consistent with the impacts corresponding to managers and professionals, and in line with the assumption that most managers and professionals are highly-qualified. We find mixed evidence regarding the effect of migrants with a less advanced level of schooling: the impact of secondary-educated migrants is positive only on the intensive margin and non-significant on the extensive margin, whereas migrants with primary studies do not have any effect on either of them.

[Table A.6 about here.]

Table A7 presents the results for the quantile regression. These outcomes do not seem to improve our understanding of the link between our educational indicators and FDI. As we can see, the impact of higher educational levels is positive and significant for most of the investments, but we do not observe significant differences across quantiles, the only exception being the last quantile, where we obtain a much smaller impact. Migrants with secondary studies are significant only for the smallest investments, although the sign of the effect varies. This lack of consistent evidence could stem from the group of migrants with secondary studies being divided across job positions, with different impacts on our dependent variable. Primary studies are significant and negative, regardless of the size of the investment. The explanation for this is probably that the educational level has a more direct equivalence with a particular job position: non-qualified jobs. In fact, the pattern across investment sizes is the closest to those in Table 11 in the paper.

[Table A.7 about here.]

Table A8 also considers the activity at which the investment is targeted. Recall that managers in Table 9 had a consistent positive effect across all activities (except construction). Higher education pays off only for sales and its effect is only barely significant for construction. Secondary education is only positive and significant for manufacturing activities and primary education is non-significant, except in sales, where it is negative and significant.

[Table A.8 about here.]

In Table A9 we subdivide j→ i migrants by education level.We can confirm a positive and significant impact for higher-educated migrants, with mixed results at the activity level. Moreover, the evidence obtained for lower educational levels is mixed, at best. This lack of clear evidence regarding the relevance of the level of education can be interpreted as attesting to a mismatch between migrants' formal education and the job they hold, and minimal returns on migrant education.

[Table A.9 about here.]

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Table A1: List of Countries

Source countries (i):
Angola, Argentina, Armenia, Australia, Austria, Azerbaijan, Belgium, Bangladesh, Bulgaria, Bahrain, Belarus, Bermuda, Brazil, Canada, Switzerland, Chile, China, Colombia, Costa Rica, Cayman Islands, Cyprus, Czech Republic, Germany, Denmark, Dominican Republic, Algeria, Ecuador, Egypt, Spain, Estonia, Finland, France, UK, Greece, Hong Kong, Croatia, Hungary, Indonesia, India, Ireland, Iraq, Iceland, Israel, Italy, Jamaica, Jordan, Japan, Kazakhstan, South Korea, Kuwait, Lebanon, Sri Lanka, Lithuania, Luxembourg, Latvia, Morocco, Mexico, Macedonia, Malta, Malaysia, Nigeria, Netherlands, Norway, New Zealand, Pakistan, Panama, Peru, Philippines, Papua New Guinea, Poland, Portugal, Qatar, Russia, Saudi Arabia, Singapore, Slovakia, Slovenia, Sweden, Togo, Thailand, Trinidad & Tobago, Tunisia, Turkey, Taiwan, Ukraine, Uruguay, United Arab Emirates, United States, Venezuela, Vietnam, South Africa.
Host countries (j):
Portugal, Australia, Canada, Switzerland, France, UK, Ireland, Italy, New Zealand, United States, Mexico, Czech Republic, Denmark, Spain, Hungary, Luxembourg, Poland, Sweden, Finland, Greece, Slovakia, Austria, Belgium, Netherlands.

Table A2: Variable description and sources

Variable	Description	Source
FDI_{ijt}	Intensive margin: Aggregate bilateral greenfield investments	FDIMarkets
N_{ijt}	Extensive margin: Number of investment projects (firm-level)	
$\ln(Y_{it} * Y_{jt})$	Logarithm of the gross domestic products of home and host countries respectively	World Bank
D_{ij}	Distance in kilometers between country capitals	
$border_{ij}$	Takes the value 1 when countries share a common border, and 0 otherwise	CEPII
$lang_{ij}$	Takes the value 1 if both countries share the same official language	
$colony_{ij}$	Takes the value 1 if the two countries have ever had a colonial link, and 0 otherwise	
$locked_{ij}$	Number of landlocked countries in the pair (0,1,2)	
FTA_{ijt}	Is a dummy that indicates whether both countries have a free trade agreement in force	UNCTAD
BIT_{ijt}	Is a dummy that takes the value of 1 if the country pair has a bilateral investment treaty in force	
$manager_{ijt}$	Stock of manager migrants	
$professionals_{ijt}$	Stock of professional migrants	OECD
$nonqual_{ijt}$	Stock of non-qualified migrants	
$migra_{ijt}$	Total migration defined as $migra_{ijt} = manager_{ijt} + professionals_{ijt} + nonqual_{ijt}$	

Table A3: Descriptive statistics and correlations

	mean	sd	FDI_{ij}	Nij	$\ln(Y_i \cdot Y_j)$	$\ln(D_{ij})$	$border_{ij}$	$lang_{ij}$	$colony_{ij}$	$locked_{ij}$	BIT_{ij}	FTA_{ij}	$manager_{ij}$	$professionals_{ij}$
FDI_{ij}	115.35	84.99	1											
Nij	1.40	1.14	0.388***	1										
$\ln(Y_i \cdot Y_j)$	27.31	1.40	0.162***	0.368***	1									
$\ln(D_{ij})$	8.33	1.00	-0.002	-0.027	0.281***	1								
$border_{ij}$	0.06	0.24	0.076**	0.146***	-0.036	-0.473***	1							
$lang_{ij}$	0.16	0.36	0.039	0.120***	0.053	0.053	0.180***	1						
$colony_{ij}$	0.05	0.21	0.049	0.155***	0.064*	0.015	0.117***	0.357***	1					
$locked_{ij}$	0.26	0.47	-0.037	-0.029	-0.025	-0.065*	0.060*	0.039	0.010	1				
BIT_{ij}	0.37	0.48	-0.075**	-0.091**	-0.167***	-0.093***	-0.029	-0.147***	0.081**	0.058	1			
FTA_{ij}	0.24	0.42	-0.028	-0.030	-0.309***	-0.739***	0.252***	-0.0821**	-0.064*	0.036	0.024	1		
$manager_{ij}$	5.35	2.50	0.142***	0.270***	0.572***	0.050	0.215***	0.363***	0.280***	0.013	-0.182***	-0.116***	1	
$professionals_{ij}$	6.81	2.70	0.126***	0.241***	0.528***	0.006	0.242***	0.347***	0.277***	0.019	-0.191***	-0.110***	0.954***	1
$nonqual_{ij}$	6.11	2.78	0.112***	0.195***	0.510***	0.050	0.214***	0.304***	0.261***	0.022	-0.185***	-0.156***	0.918***	0.962***

Note: $^{*}\ p < 0.10$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$

Table A4: Results (CYFE)

	Intensive Margin				Extensive Margin			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\ln(Y_{it} * Y_{jt})$	0.717***	0.797***	0.814***	0.693***	0.793***	0.835***	0.860***	0.762***
	(0.17)	(0.14)	(0.15)	(0.17)	(0.13)	(0.11)	(0.12)	(0.10)
$\ln D_{ij}$	-0.391*	-0.320	-0.358	-0.371	-0.381***	-0.396***	-0.354**	-0.298**
	(0.23)	(0.21)	(0.23)	(0.27)	(0.13)	(0.13)	(0.14)	(0.14)
$border_{ij}$	0.050	0.060	0.154	0.108	-0.039	-0.138	0.045	0.067
	(0.32)	(0.33)	(0.35)	(0.33)	(0.23)	(0.22)	(0.26)	(0.20)
$lang_{ij}$	0.003	0.058	0.187	-0.075	0.138	0.183	0.370*	0.072
	(0.26)	(0.25)	(0.27)	(0.28)	(0.21)	(0.21)	(0.22)	(0.20)
$colony_{ij}$	1.007***	1.079***	1.084***	0.930***	0.793***	0.800***	0.875***	0.695***
	(0.27)	(0.28)	(0.29)	(0.28)	(0.26)	(0.26)	(0.30)	(0.19)
$smcntry_{ij}$	0.339	0.642	0.671	0.404	0.735	0.929	1.080*	0.765
	(0.71)	(0.74)	(0.74)	(0.74)	(0.60)	(0.63)	(0.56)	(0.62)
$locked_{ij}$	-0.580***	-0.605***	-0.558***	-0.539**	-0.442***	-0.434***	-0.417***	-0.428***
	(0.20)	(0.21)	(0.22)	(0.21)	(0.12)	(0.12)	(0.12)	(0.11)
BIT_{ijt}	-0.797***	-0.909***	-0.901***	-0.684***	-0.752***	-0.774***	-0.698***	-0.635***
	(0.23)	(0.22)	(0.23)	(0.23)	(0.15)	(0.15)	(0.15)	(0.14)
FTA_{ijt}	0.273	0.447	0.391	0.260	0.051	0.037	0.110	0.064
	(0.61)	(0.52)	(0.57)	(0.69)	(0.33)	(0.32)	(0.31)	(0.35)
$\ln manager_{ij}$	0.245***			0.446*	0.173***			0.393**
	(0.07)			(0.23)	(0.07)			(0.16)
$\ln professionals_{ijt}$		0.180***		0.140		0.162***		0.398**
		(0.06)		(0.24)		(0.06)		(0.17)
$\ln nonqual_{ijt}$			0.139**	-0.285*			0.082	-0.539***
			(0.06)	(0.15)			(0.07)	(0.11)
Observations	1021	1066	1041	998	1021	1066	1041	998
R^2	0.620	0.602	0.613	0.639	0.562	0.563	0.589	0.714

Notes: Robust standard errors in parentheses (PPML estimation in levels). Home*year and source*year country fixed effects.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A5: Occupation shares

	Intensive Margin			Extensive Margin		
	(1)	(2)	(3)	(4)	(5)	(6)
Managers share	0.713***			0.635***		
	(0.17)			(0.09)		
Professionals share		-0.443			-0.299	
		(0.37)			(0.19)	
Non-qualified share			-0.205			-0.143*
			(0.18)			(0.08)
Total migrant stock	0.489***	0.393***	0.406***	0.363***	0.290***	0.288***
	(0.06)	(0.05)	(0.06)	(0.03)	(0.03)	(0.03)
Observations	1636	1650	1639	1636	1650	1639
R^2	0.863	0.872	0.864	0.925	0.912	0.913

Notes: Robust standard errors in parentheses (PPML estimation in levels) clustered by country pair. Home*year and source*year country fixed and country-pair effects included.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A6: Educational levels

	Intensive Margin			Extensive Margin		
	(1)	(2)	(3)	(4)	(5)	(6)
Higher edu	0.919***			0.482***		
	(0.30)			(0.14)		
Other levels	-0.016			-0.014		
	(0.10)			(0.06)		
Secondary edu		0.714**			0.251	
		(0.34)			(0.19)	
Other levels		0.034			0.060	
		(0.18)			(0.11)	
Primary edu			-0.277			-0.127
			(0.19)			(0.10)
Other levels			0.556***			0.276***
			(0.15)			(0.07)
Migrants j→i	0.079**	0.118***	0.074**	-0.016	-0.027	-0.015
	(0.03)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)
Observations	467	467	467	467	467	467
R^2	0.895	0.879	0.893	0.942	0.935	0.941

Notes: Robust standard errors in parentheses (PPML estimation in levels) clustered by country pair. Home*year and source*year country fixed and country-pair effects included.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A7: Quantile regression (education)

	Intensive Margin			
	(1)	(2)	(3)	(4)
	Q(0.25)	Q(0.50)	Q(0.75)	Q(0.90)
Average project size (mUSD):	14	28	61	79
Higher edu	0.929***	1.105***	1.159***	0.317**
	(0.04)	(0.07)	(0.07)	(0.13)
Other levels	-0.402***	-0.385***	-0.390***	-0.003
	(0.05)	(0.06)	(0.07)	(0.10)
Migrants j→i	0.517***	0.703***	0.540***	0.478***
	(0.07)	(0.10)	(0.07)	(0.09)
Secondary edu	-0.227***	0.188**	-0.206	-0.103
	(0.09)	(0.09)	(0.14)	(0.08)
Other levels	0.124**	-0.008	0.158***	0.181**
	(0.06)	(0.08)	(0.05)	(0.08)
Migrants j→i	0.494***	0.430***	0.460***	0.377***
	(0.10)	(0.09)	(0.05)	(0.11)
Primary edu	-0.106*	-0.334***	-0.542***	-0.573***
	(0.06)	(0.06)	(0.10)	(0.07)
Other levels	0.138	0.341***	0.436***	0.494***
	(0.08)	(0.03)	(0.07)	(0.06)
Migrants j→i	0.494***	0.442***	0.388***	0.351***
	(0.10)	(0.04)	(0.05)	(0.05)
Observations	269	269	269	269

Notes: Robust standard errors in parentheses (Dep variable $\ln(FDI + 1)$).

Home*year and source*year country fixed effects.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A8: FDI by activity (education)

	Manufacturing			Sales			Construction			Services		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Higher edu	0.666			0.898***			1.027*			0.336		
	(0.42)			(0.24)			(0.57)			(0.35)		
Other levels	-0.014			-0.274**			-0.141			-0.110		
	(0.21)			(0.11)			(0.21)			(0.12)		
Secondary edu		1.382**			0.152			0.280			0.101	
		(0.62)			(0.51)			(0.91)			(0.49)	
Other levels		-0.367			0.008			0.099			-0.051	
		(0.32)			(0.24)			(0.51)			(0.25)	
Primary edu			-0.365			-0.475**			-0.514			-0.210
			(0.32)			(0.19)			(0.50)			(0.19)
Other levels			0.507**			0.384***			0.583*			0.155
			(0.21)			(0.12)			(0.14)			(0.17)
Migrants j→i	-0.007	-0.079	-0.013	0.028	0.002	0.033	0.049	0.013	0.041	0.557***	0.575***	0.650***
	(0.06)	(0.05)	(0.07)	(0.04)	(0.05)	(0.04)	(0.07)	(0.07)	(0.07)	(0.16)	(0.18)	(0.16)
Observations	300	300	300	349	349	349	115	115	115	0.078	0.081	0.080
R^2	0.925	0.924	0.917	0.912	0.893	0.910	0.569	0.573	0.566	(0.06)	(0.06)	(0.06)

Notes: Robust standard errors in parentheses (PPML estimation in levels) clustered by country pair.

Home*year and source*year country fixed and country-pair effects included.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A9: Sectoral results controlling for education levels

	Manufacturing	Sales	Construction	Services
	(1)	(2)	(3)	(4)
Higher edu i→j	0.066	0.579**	-0.266	-0.014
	(0.27)	(0.24)	(0.32)	(0.18)
Secondary edu i→j	0.475	-0.251	0.316	0.303
	(0.30)	(0.26)	(0.42)	(0.25)
Primary edu i→j	-0.360**	0.081	0.180	-0.221
	(0.18)	(0.14)	(0.21)	(0.14)
Higher edu j→i	0.879*	-0.168	0.798*	-0.143
	(0.51)	(0.48)	(0.46)	(0.52)
Secondary edu j→i	0.840**	-0.230	0.202	-0.419
	(0.34)	(0.28)	(0.47)	(0.34)
Primary edu j→i	-0.329	0.061	0.509	0.626**
	(0.25)	(0.20)	(0.32)	(0.27)
Observations	877	937	426	909
R^2	0.846	0.982	0.708	0.948

Notes: Robust standard errors in parentheses (PPML estimation in levels) clustered by country pair. Home*year and source*year country fixed and country-pair effects included.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$