Moving ideas across borders: Foreign inventors, patents and FDI*

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Abstract

This paper investigates the mechanisms through which migrant inventors enhance multinational firms' innovation performance in their host country and ultimately foster Foreign Direct Investment (FDI) towards the migrant's country of origin. The paper develops a multi-country-sector model of international production with heterogeneous firms where foreign inventors' unique knowledge background contributes to an increase in R&D promoting a firm's internationalisation. To test the model's main predictions, we constructed a novel panel country-sector dataset including FDI, patents, and migrant inventors. A two-stage structural gravity estimation procedure is applied with patents to measure innovation and migrant inventors as a valid instrument. The results show that migrants inventors have sizable effects in the extensive and intensive margins of Greenfield FDI.

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1 Introduction

Multinational Enterprises (MNEs) account for a large proportion of world's research and development (R&D) activity. R&D enhances the firm's productivity and changes its competitive position relative to other firms (Doraszelski and Jaumandreu, 2013). Despite the importance of MNEs in R&D activities globally, some mechanisms through which globalization affects their innovation performance remain underexplored. This paper constitutes a contribution in this direction by exploring the link between foreign inventors, innovation, and Foreign Direct Investment (FDI).

The paper's main idea is that migrants working on R&D, or foreign inventors, improve the firms' innovation performance in foreign markets through their unique background knowledge, facilitating the adaptation of the firms' products to the investment destination market. Firms make an effort to accommodate consumer tastes in different parts of the world, generating the need to make substantial changes to the products to adapt them to local needs and practices. The customization of products increases potential firm revenues in the foreign market, increasing the benefits of establishing a facility abroad and the investments undertaken in that facility.

Anecdotal evidence illustrates the role of migrants in product customization. On Nov. 8th 2018, Ford Motor filed a patent application for an odor-removal process that eliminates the new car smell. The American multinational employed Chinese researchers with exceptionally sensitive noses to customize their cars for Chinese customers who, unlike Western consumers, dislike the smell of new cars (Truong, 2018).

The academic literature also provides some evidence of the role of foreign migrants on innovation and FDI. Useche et al. (2019) recently explored the role of migrant inventors in cross-border M&A undertaken by R&D active firms. According to these authors, parent companies who employ migrant inventors from a given country exhibit a higher probability of acquiring a domestic firm. This relationship operates by increasing information about the subsidiary's characteristics. Previously, Foley and Kerr (2013) studied the relationship between ethnic innovation and US multinational firms' activity abroad. These authors find that an increase in the share of a firm's innovation performed by inventors of a particular ethnicity is associated with increases in the share of that firm's affiliate activity related to that ethnicity.

The paper contributes to expanding this literature in some exciting ways. The paper constitutes a novel attempt to study the relationship between migration, innovation, and FDI in a multi-country-sector framework from both a theoretical and an empirical perspective.

The paper starts by building a multi-country-sector model of trade with heterogeneous firms in which firms can serve the foreign market either by exporting or by conducting FDI. We embed firm innovation in the Helpman et al.'s (2004) framework, particularly endogenous innovation that increases the product's perceived quality in the destination market as in Feenstra and Romalis (2014) and in the spirit of early endogenous growth models of product quality improvement as in Aghion and Howitt (1992). Our model derives an explicit gravity equation that accounts for the extensive margin of FDI (the expected investment of a domestic firm in establishing a new subsidiary abroad) and the intensive margin of FDI (the parent company's investment in a subsidiary already established in the foreign destination market).

Foreign inventors play a role in the firm's innovation productivity by adapting the product to local preferences and increasing FDI towards that particular market.

Guided by our theory suggesting that foreign investors might be an appropriate instrument to estimate the effect of endogenous innovation on FDI, we employ a two-stage instrumental-variable 2S-IV estimation strategy embedded in structural gravity. In the spirit of Anderson and Yotov (2012) and Fally (2015), we introduce numerous fixed effects to control for multilateral resistance terms and potential unobserved heterogeneity as standard in the gravity literature since Anderson and Van Wincoop (2003).

The paper uses a novel dataset that merges three underlying databases. Firstly, the dependent variable (greenfield FDI) is sourced from The Financial Times Ltd. cross-border investment monitor (FDIMarkets, 2017) and provides firm-level bilateral FDI flows for 2003-2012. Secondly, we merged this dataset with patent data at the firm level provided by PATSTAT. Finally, Miguelez and Fink (2013) provide bilateral flows of foreign inventors (those who have filed a patent in their host country) at the sectoral level.

The empirical results align with our model, suggesting that innovation has a sizable effect on FDI in both margins, measured in levels and shares. We show how the effect of patents on FDI is biased downward if we do not consider foreign inventors as an instrument, revealing that migrant inventors have augmented the effect of innovation on FDI. We find some sectoral heterogeneity in our results and perform several checks to ensure that our results are robust and that our instrument is valid.

The rest of the paper is organized as follows. Section 2 presents the model. Section 3 describes the data and empirical strategy. Section 4 reports the main empirical results, and section 5 concludes.

2 The model

2.1 Setup

Consider a world with J small-open economies. In each of these countries, $K+1$ final goods are produced, denoted with subscript k. Consumers derive utility from the consumption of these goods. The following Cobb-Douglas utility function describes preferences across these goods:

$$U_j = \prod_{k=0}^{K} C_{kj}^{\mu_k}, \quad \sum_{k=0}^{k} \mu_k = 1,$$

where μ_k represents the importance of good k in the consumer's expenditure and is assumed to be common across countries. The good 0 is a homogeneous good while the rest of the goods are differentiated goods. More precisely, good $k \neq 0$, is composed of a continuum of varieties $\omega \epsilon \Omega_k$, **and the preferences across different varieties are represented through the standard CES utility function,**

$$C_{kj} = \left[\int_{\omega \in \Omega_k} \left((q_{kj}(\omega))^{\phi_k} c_{kj}(\omega) \right)^{\frac{\sigma_k - 1}{\sigma_k}} d\omega \right]^{\frac{\sigma_k}{\sigma_k - 1}}, \ \sigma_k > 1, \ 0 \leq \phi_k < 1,$$

where $c_{kj}(\omega)$ denotes the consumption of variety ω, in sector k in country j and $q_{kj}(\omega) > 0$ denotes the perceived quality of variety ω in sector k and country j.

$\sigma_k > 1$ controls for the elasticity of substitution across different varieties and ϕ_k measures the importance of quality in the utility of consumers. Note that when $\phi_k = 0$, quality does not matter in the consumer's utility and we will be in the case of the traditional CES utility function used in the gravity literature (see, Anderson and Van Wincoop, 2003 and Chaney, 2008, among others).

The homogeneous good is produced in perfect competition using labor and a constant returns to scale technology. Let denote $\varphi_{0i} = \varepsilon_i$, the productivity of country i in the homogeneous good. The assumption of perfect competition together with linear technology will imply that in equilibrium a country's wage will be equal to the marginal productivity in this sector(i.e. $w_i = \varepsilon_i$). Producing each of the differentiated final goods, instead, requires both capital and labor. Firms in each sector produce using a Cobb-Douglas technology:

$$x_k(\omega) = \varphi \left(\frac{K_k(\omega)}{\gamma} \right)^{\gamma} \left(\frac{L_k(\omega)}{1-\gamma} \right)^{1-\gamma},$$

where φ, denotes the firms' TFP and, as it is common in the literature on firm heterogeneity, it is assumed that it is obtained at the moment of firms' entry, as described below, and it is constant over time. $x_k(\omega)$ is the total quantity produced of variety ω, and $K_k(\omega)$ and $L_k(\omega)$ are respectively the capital and labor used in the production of variety ω. γ represents the importance of physical capital in the production of each variety. For simplicity, it is assumed that capital is perfectly mobile across countries, and consequently, the firm can freely source capital from any country at

the cost r.

Each firm, when entering, draws their productivity from a common productivity distribution which follows a Pareto functional form. More precisely, we have that

$$\Pr(\varphi \leq \varphi_0) = 1 - (\varphi_0)^{-\kappa}, \ \varphi_0 \geqslant 1, \ \kappa > \sigma - 1.$$

To serve the domestic market, the firm faces a fixed operational cost of f_{ii} units of capital. The firm can serve any foreign market $j \neq i$ either by exporting, in which case the firm faces a fixed operational cost of f_{ij} units of capital and a variable iceberg trade cost τ_{ij}. Instead, the firm can build a plant at the destination market, becoming a multinational company. In this case, the firm will not incur in an iceberg transportation cost, but it will incur a fixed cost of f_{Ij} units of capital.

Firms can also invest in the consumer's perceived quality in each destination market. For simplicity, let us assume that for the case of multinational companies, the improvements in the quality of the products are always made in the headquarters.[1] More precisely, the perceived quality of each product depends on the number of ideas the firm creates to get the product close to their customer's needs. The mapping of ideas onto quality is described by the following functional form:

$$q_{kj}(\omega)^{\sigma_k - 1} = z_{kj}(\omega),$$

where $z_{kj}(\omega)$, represents the number of specific ideas applied to the variety ω in destination j. Ideas are produced using labor. The production of ideas is given by the following functional form:

$$z_{kj}(\omega) = \frac{\theta_{ij} L_{kij}}{\varphi^{\sigma_k - 1}},$$

where L_{kij}, represents the number of country i researchers targeting market j and θ_{ij}, represents the productivity of $R\&D$ workers in country i making ideas applicable to the destination country j. Note that, for simplicity, we consider that ideas are destination specific.[2] This technology implies that the cost of producing a specific number of ideas $z_{kj}(\omega)$ is given by:

$$C(z_{kj}(\omega)) = \varepsilon_i \left(\frac{\varphi^{\sigma_k - 1}}{\theta_{ij}} \right) z_{kj}(\omega),$$

where, $w_i = \varepsilon_i$ denotes the wage in the country of origin i.

Note that the R&D technology is linear in labor, the unique production factor. The number of researchers needed to produce an idea depends negatively on θ_{ij}, which represents the researchers' productivity. Following a large literature on innovation,[3] we assume that researchers' productivity increases with the exchange of ideas that emerge when they network between them (brainstorm). The variable $\theta_{ij} > 1$ represents the increase in productivity that comes through such interaction, and it is considered by firms as an externality common to all firms.[4] This externality is country pair specific, and it will depend on the cultural distance between the country of origin of the R&D workers i and the destination country j. For example, we assume that when firms adapt their product to become international, Spanish researchers will be more successful in creating a variety that targets the Portuguese or the Italian markets because they have a better knowledge of their native culture than in creating a variety that targets the Chinese market. Although this seems a strong assumption, recently Koning et al. (2019), using US biomedical inventions, found that patents in which there are women inventors are significantly more likely to focus on female conditions and diseases. Such evidence suggests that the nature of the inventor may shape the type of invention they are developing.

Finally, we assume that the number of researchers needed to produce ideas increases with the complexity of the product, considering that the complexity is proxied by the firm's productivity. This resembles earlier semi-endogenous growth models, whereas the economy was moving to the technology frontier, the cost of doing R&D increases. This assumption implies that the investment in quality does not depend on the firm's productivity, with all firms investing in the same degree of quality. Relaxing this assumption in this model, in which a firm's investment in quality depends on the firm's productivity, does not generate further interesting qualitative results.[5]

When migration is allowed between countries, instead, the production of ideas is given by the following functional form

$$z_{kij}(\omega) = \frac{\tilde{\theta}_{ij} \sum_{m=1}^{J} L_{ij}^{m}}{\varphi^{\sigma_k - 1}},$$

where L_{ij}^{m} represents the workers from country m working in country i to develop ideas targeting country m. The knowledge externality in this economy is given by:

$$\tilde{\theta}_{ij} = \sum_{m=1}^{J} \beta_{ij}^{m} \theta_{ij}^{m}, \tag{1}$$

where $\beta_{ij}^{m} = \frac{L_{ij}^{m}}{L_{ij}}$ represents the share of the total labor force in country i that comes from country m which is employed in R&D.[6] Several assumptions are introduced here in order to allow for migration in the model without unnecessarily complicate it. First, foreign workers are considered to be ex-ante identical in terms of productivity compared to native workers. However, we assume that, when working in the lab, the presence of migrants in the $R\&D$ sector will increase the knowledge externality that is specific to the markets for which the migrants have a cultural affinity. This is reflected in equation 2.1 where the variable $\tilde{\theta}_{ij}$ is a weighted share of the individual θ_{ij} where the different weights reflects the composition of the R&D labor force in that sector in terms of nationality. Our main argument is that migrants offer specific knowledge regarding tastes and cultural features that allow the native firms to better adapt the product to the migrants' country of origin and those with a similar culture. However, this specific knowledge comes through the interaction between native and migrant researchers within the economy.

Following a long tradition in international trade and industrial organization, the timing of the events from a firm's perspective is as follows. First, the firm decides their strategy for each market (in the case of the domestic market whether to stay or exit and in the case of each of the foreign markets, whether to serve the market and whether doing it by exporting, building a plant, or producing there). Then the firm decides how much to invest in quality upgrading for each market, and finally it chooses how much to charge and how much to produce in each market. In the next subsections, we present the two gravity equations and the main propositions of our theoretical model. A detailed analysis of the model is then provided in the appendix.

2.2 The gravity equation for FDI

Consistent with the traditional definition for FDI, we measure FDI as the investment in capital made by a firm in a foreign's country facility. This can come from two sources: The investment made by the parent company in a subsidiary already established in the destination market (the intensive margin) and the investment made to establish a new subsidiary in the destination market (the extensive margin). Conditional on having established a plant there, we can obtain the value of a firm's investment in foreign assets in equilibrium, which is given by the following expression

$$rK_{kIj}(\varphi) = \left\{ \begin{array}{ll} \lambda''_{kj} \left(Y_j\right)^{\frac{\sigma_k - 1}{\kappa}} \bar{\eta}_{kj}^{\frac{1}{\phi_k - 1}} \left(\frac{\tilde{\theta}_{ij}}{\varepsilon_i}\right)^{\frac{\phi_k}{1-\phi_k}} \varphi^{\sigma_k - 1} & \text{if } \varphi \geqslant \varphi^*_{kIj} \\ 0 & \text{otherwise} \end{array} \right\}, \tag{2}$$

with $\lambda''_{kj} = \gamma\left(\sigma_k - 1\right)\left(\frac{\varepsilon_i}{\varepsilon_j}\right)^{\frac{(1-\gamma)(\sigma_k-1)}{1-\phi_k}} \phi_k^{\frac{\phi_k}{1-\phi_k}} \lambda'_{kj}$.[7] The first term of the equation above can be also expressed as $\lambda'''_{kj}\left(Y_j\right)^{\frac{(\sigma_k-1)(1-\phi_k)}{\kappa}} \left(q_{kIj}\right)^{(\sigma_k-1)\phi_k} \eta_{kj}^{-1} \varphi^{\sigma_k-1}$ with $\lambda'''_{kj} = \gamma\left(\sigma_k - 1\right) \lambda'^{1-\phi_k}_{kj}$.

Aggregating across firms within the same industry, the gravity equation for the intensive margin at the sectoral level is given by:

$N_i \int_{\varphi^*_{kIj}}^{\infty} rK_j(\varphi) g(\varphi) d\varphi =$

$$\lambda^{iv}_{kij} Y_i Y_j \bar{\eta}_{kj}^{\frac{\kappa}{(\phi_k-1)(\sigma_k-1)}} \left(\frac{\tilde{\theta}_{ij}}{\varepsilon_i}\right)^{\frac{\phi_k \kappa}{(1-\phi_k)(\sigma-1)}} \left(\left(\frac{\varepsilon_i}{\varepsilon_j}\right)^{\frac{(1-\gamma)(\sigma_k-1)}{1-\phi_k}} - (\tau_{ij})^{\frac{1-\sigma_k}{1-\phi_k}}\right)^{\frac{\kappa-(\sigma_k-1)}{\sigma_k-1}},$$

where $\lambda^{iv}_{kij} = \lambda''_{kj} \left(\lambda'_{kj} \phi_{kj}^{\frac{\phi_{kj}}{1-\phi_{kj}}} (1-\phi_{kj})\right)^{\frac{\kappa-(\sigma_k-1)}{\sigma_k-1}} \frac{\kappa}{\kappa-(\sigma_k-1)} \left(r(f_{Ij} - f_{ij})\right)^{\frac{\sigma_k-\kappa-1}{\sigma_k-1}}$.

Note that the expression represents a gravity equation on the intensive margin of FDI, in which the FDI volume at the industry level is proportional to the size of both the country of origin and the destination market. Interestingly, this volume is also inversely proportional to the cultural distance. This second relationship comes from our innovative element: The investment in perceived quality that the parent company does to increase the sales in the destination market depends negatively on the cultural distance between both countries, the destination country and the country of origin.

Similarly, we can obtain a gravity equation for the extensive margin of FDI. The expected volume of investment in a new establishment abroad of a firm with productivity φ is given by:

$$r f_{Ij} \Pr(\varphi \geqslant \varphi^*_{kIj}) = r f_{Ij} (\varphi^*_{kIj})^{-\kappa}.$$

Aggregating across firms within the same sector we obtain the gravity equation for the expected investment in new establishments (i.e., extensive margin) which is given by

$$N_i r f_{Ij} (\varphi^*_{kIj})^{-\kappa} = Y_i Y_j \bar{\eta}_{kj}^{\frac{\kappa}{(\phi_k - 1)(\sigma_k - 1)}} \left(\frac{\tilde{\theta}_{ij}}{\varepsilon_i} \right)^{\frac{\phi_k \kappa}{(1-\phi_k)(\sigma_k - 1)}} \lambda^v_{kij}, \tag{3}$$

where λ^v_{kij}, includes variables common across origins, destinations and origins and destinations.[8]

Similarly to the conclusions obtained for the intensive margin case, the expected investment of creating new establishments in a particular industry increases with the size of both the origin and destination market and decreases with the cultural distance between both countries. As in the intensive margin, there is a negative relationship between cultural distance and the investment in new establishments abroad, which comes through the effect that this distance exerts on research productivity. In both cases, this relationship is shaped by the parameter ϕ_k, which measures the importance of quality in the industry. When quality does not matter much in consumer's utility, firms are reluctant to invest in quality, and therefore, the cultural distance will not affect the probability of the firm investing in FDI.

Finally the expression for the gravity equation at the sectoral level is the sum of both the extensive and the intensive margin ones. These expressions are given by:

$$FDI_{kij} = Y_i Y_j \bar{\eta}_{kj}^{\frac{\kappa}{(\phi_k - 1)(\sigma_k - 1)}} \left(\frac{\tilde{\theta}_{ij}}{\varepsilon_i} \right)^{\frac{\phi_k \kappa}{(1-\phi_k)(\sigma_k - 1)}} \lambda^{vi}_{kij}, \tag{4}$$

where $\lambda^{vi}_{kij} = \left(\left(\frac{\varepsilon_i}{\varepsilon_j} \right)^{\frac{(1-\gamma)(\sigma_k - 1)}{1-\phi_k}} - (\tau_{ij})^{\frac{1-\sigma_k}{1-\phi_k}} \right)^{\frac{\kappa - (\sigma_k - 1)}{\sigma_k - 1}} (r(f_{Iij} - f_{ij}))^{\frac{\sigma_k - 1 - \kappa}{\sigma_k - 1}} \lambda^{iv}_{kij} + \lambda^v_{kij}.$

This equation can also be expressed as

$$FDI_{kij} = \lambda_{kij}^{vii} Y_i \left(Y_j\right)^{\frac{(\sigma_k-1)(1-\phi_k)}{\kappa}} \bar{\eta}_{kj}^{-1} \left(\left(q_{kIj}\right)^{(\sigma-1)\phi}\right)^{\frac{\kappa}{\sigma_k-1}},$$

where the expression for $\left(q_{kIj}\right)^{(\sigma-1)} = \left(\frac{\phi\tilde{\theta}_{ij}}{\varepsilon_i}\right)^{\frac{1}{1-\phi}} \left(B_j\right)^{\frac{1}{1-\phi}} = \left(\frac{\phi\tilde{\theta_{ij}}}{\varepsilon_i}\right)^{\frac{1}{1-\phi}} \lambda'_{kj} \left(Y_j\right)^{\frac{(\sigma_k-1)}{\kappa}} \left(\bar{\eta}_{kj}\right)^{\frac{1}{\phi_k-1}}$.

Note that in a world in which migration is allowed, the productivity in the R&D sector depends on their cultural distance between the home country and the target market but also on the cultural distance between the countries from which the researchers are coming and the target market We assume that $\theta_{ij}^l = \bar{\theta}_{ij}$ if $l = j$ and $\theta_{ij}^l < \bar{\theta}_{ij}$ for every $l \neq j$, that is, the higher the proportion of migrants from the destination market the higher is going to be the increase in productivity. More generally, we assume that $\theta_{ij}^l = \theta(d_{lj})$, with $\theta'(d_{lj}) < 0$ and d_{lj} representing the cultural distance between the country of origin of the workers l and the destination market j.

The latter allows us to establish the following proposition:

Proposition. $\frac{\partial \ln FDI_{kij}}{\partial \ln L_{ij}^j} > 0$ *(i.e., an increase in the number of R&D workers coming from a specific country j into country i increases FDI from country i into country j).*

Corollary. $\frac{\partial^2 \ln FDI_{kij}}{\partial \ln L_{ij}^j \partial \phi_k} > 0$ *The increase in FDI from country i into a specific country j due to an increase in R&D workers coming from country j into country i is increasing in ϕ_k.*

Proof. See Appendix □

Therefore, in our model, the entry of migrants to work in the R&D sector increases the investment in quality made by firms in the host country, boosting their internationalization strategy and increasing the volume of FDI. More precisely, the relationship between migrants who work in the $R\&D$ sector, innovation, and FDI is described by the following equations:

$$FDI_{kij} = \lambda_{kij}^{vii} Y_i \left(Y_j\right)^{\frac{(\sigma_k - 1)(1-\phi_k)}{\kappa}} \bar{\eta}_{kj}^{-1} \left(\left(q_{kIj}\right)^{(\sigma_k - 1)\phi_k}\right)^{\frac{\kappa}{\sigma_k - 1}} \tag{5a}$$

$$\left(q_{kIj}\right)^{(\sigma-1)} = \left(\frac{\phi_k \tilde{\theta}_{ij}}{\varepsilon_i}\right)^{\frac{1}{1-\phi}} \lambda'_{kj} \left(Y_j\right)^{\frac{(\sigma_k - 1)}{\kappa}} \left(\bar{\eta}_{kj}\right)^{\frac{1}{\phi_k - 1}} . \tag{5b}$$

3 Data and empirics

3.1 Empirical model

The model offers several testable empirical implications. The theoretical results suggest that FDI increases in country-pair-sector specific investment in quality, fueled by migrants in the R&D sector. These migrants have a particular skill-set; they possess technical skills and cultural traits that allow them to increase the lab's productivity by tailoring technical specifications for a particular destination.

Our data does not allow us to observe a bilateral stock of patents directly. Given that firms tend to patent in multiple destinations even if their innovation is focused in a particular market[9], we assumed that patents are non-rival in terms of destination, with a small twist. Not all firms within a sector invested in the same country every year. We use this sporadic property of FDI to construct the patent variable by allowing firms to use patents only in the destinations that they invested during a particular year. In particular, we created the a country-pair-sector patent variable aggregating the patents of firms in the sector only when they invested:

$$\text{Patent}_{ki\tilde{j}t} = \sum_{z=1}^{z=z_k} T_{zijt} \times \text{Patent}_{zit}, \tag{6}$$

where Patent are the patents filed by a firm z in sector k, z_k is the number of firms in sector k, and T is a variable that takes the value of 1 if the firm z invested in country j in year t and 0 otherwise. This way, the patent variable has origin-destination-sector specific variation and it will be not absorbed the fixed effects.[10]

There are two caveats with the definition of Patent. Firstly, there could be measurement error as patents would overstate the notion of innovation used in this paper, especially for those firms that generate a large number of patents and invest in many small countries. Secondly, there could be reverse causality as the variable $Patent_{ki\tilde{j}t}$ it is related to FDI and clearly endogenous. This assumption falls in line with our model, which suggested that innovation was an endogenous process within the firm.

We overcome the first two limitations with a two-stage instrumental variable (2S-IV) estimation strategy. The idea generation process that allows firms to invest in quality described in our model and capture in equation 6 is endogenous. **According to our model, it** depends on migrant inventors, who can increase the lab's productivity. Migrant inventors contribute to building team-specific capital and have a persuasive influence on their collaborators' innovation production (Jaravel et al., 2018). Further, migrant and natives have different knowledge pools and their combinations are especially fruitful for innovation (Bernstein et al., 2019).

In our model, other channels by which these inventors might affect FDI (e.g., increasing the firm's overall productivity, reducing information asymmetries) are shut down. This assumption is supported by the evidence provided by Cuadros et al. (2019), who show that the influence of migrants on FDI is linked to their job position rather than their education. The authors show that migrant managers have the largest direct effect on FDI.

Additionally, several studies outline the importance of indirect channels, by which migration influences variables affecting FDI, rather than FDI itself. For example, by increasing Total Factor Productivity (TFP) in the host country. However, the mechanism through which this channel operates differs substantially from the one considered in our paper, as these papers focused on the static rather than the dynamic impact of migrants on TFP.[11] Previous work also emphasizes the importance of diversity in creativity skills as a relevant reason behind the migrants' productivity increase (Alesina et al., 2016; Docquier et al., 2018; Lazear, 1999; Kemeny and Cooke, 2017). According to these studies, a birthplace diverse team of workers augments the variety of skills, ideas, and capabilities, which allows the firm to increase its efficiency (Ortega and Peri, 2014). Kerr (2008) found that a large ethnic research community in the US improves technology diffusion to foreign countries of the same ethnicity. This study is complementary to those as it highlights a new mechanism through which the increase in R&D productivity that migrants bring operates, which is based on their cultural and idiosyncratic knowledge about their own country and those with a cultural affinity.

According to Choudhury and Kim (2019), previous literature has overlooked that migrant inventors differ from local inventors as they play an important role in codifying knowledge from their home countries and transferring it to their host country. There is a shred of growing evidence supporting that migrants play a key role in US innovation. Aghion et al. (2019) have recently concluded that migrants produce more patents than natives in the US (see also Bernstein et al., 2019). However, little is known about the role that this type of migrant is playing outside the US (Nathan, 2014). Therefore, R&D migrant inventors should have a negligible direct influence on FDI as they are not employed as managers. Therefore, we adopt a 2S-IV procedure instrumenting patents with migrant inventors as the IV exclusion restriction should be met.

The empirical translation of (2) considers the endogenous generation of ideas through migrants in (1) would lead to a 2S-IV structural gravity estimation procedure. Taking the natural logarithm of expressions (5a) and (5b), we obtain the following expressions.

$$\ln \mathrm{PatStock}_{ki\tilde{j}t} = \beta_2 \ln \mathrm{MigraInvStock}_{kjit} + \lambda_{it} + \lambda_{jt} + \lambda_{ij} + \lambda_k + e_{kijt} \quad \text{(7a)}$$

$$\ln FDI_{kijt} = \beta_1 \ln \mathrm{Pat\hat{S}tock}_{ki\tilde{j}t} + \lambda_{it} + \lambda_{jt} + \lambda_{ij} + \lambda_k + e_{kijt} \quad \text{(7b)}$$

where FDI is the foreign capital investment between source country i, destination country j in sector k and year t. **PatStock is the total stock of patents in**

sector $\boldsymbol{k}$, originated in country $\boldsymbol{i}$ that available for adaptive innovation production in country $\boldsymbol{j}$ in year $\boldsymbol{t}$. [12] **MigraInvStock** are the stock of j-born individuals that filed a patent in country i and sector k at year t. [13]

All results control for time-varying multilateral resistance terms by adding the interaction of home and host dummies (λ) with year. The estimates include a full set of country-pair fixed effects to control for unobservable heterogeneity at the country pair and sectoral levels. This specification increases the identification of the effects, but reduces the type of control variables, which have to be time-varying at the country pair level to prevent co-linearity with the fixed effects. To estimate the extensive margin, we use the same specification but with the number of FDI projects as the dependent variable.

The model guides us directly to the workhorse empirical tool in international economics, the gravity equation, which has been extensively used to estimate international trade flows, FDI, migration, tourism, and energy. The popularity of the gravity approach rests on a solid theoretical ground and a robust econometric technique. The gravity approach fits dyadic data flows well. However, the empirical literature has identified several potential sources of bias. The econometric specification and efficient computational algorithms have made feasible to hedge against most known biases like unobserved bilateral heterogeneity, multilateral resistance terms, zeros in the dependent variable and heteroscedastic residuals.[14] To control for these issues, we use a Pseudo-Poisson Maximum Likelihood (PPML) estimator as proposed by Santos Silva and Tenreyro (2006). In particular we use the estimation procedure developed by Correia et al. (2019), which performs high-dimensional non-linear PPML estimation and implements 2S-IV in its OLS version:

$$FDI_{kijt} = \exp\begin{pmatrix}\beta_1 \ln \mathrm{Pat}\hat{\mathrm{S}}\mathrm{tock}_{ki\tilde{j}t} + \\ \lambda_{it} + \lambda_{jt} + \lambda_{ij} + \lambda_{kt}\end{pmatrix} + e_{ijkt}. \tag{8}$$

In this model, the influence of multilateral resistance terms can be controlled adequately in PPML by home country-sector fixed effects and home country and host country fixed effects. On the endogeneity front, we adopted a cautious approach by specifying the left-hand side variables in flows and right-hand side in stocks, which should mitigate endogeneity in contrast to a specification with flows on both sides of the equation. Further, recent research claims that the large amount of control variables in structural gravity reduces the threat of endogeneity on dyadic variables (Beverelli et al., 2018; Rose, 2018). However, we cannot be entirely sure that this specification is not affected by such endogeneity. To have consistent estimates, we check instrument validity, both for weak instrument bias and the exclusion restriction.

3.2 Data Sources

Testing the theoretical model's main predictions poses data challenges to gather country-pair-sector data on FDI, R&D activities (i.e., investment in quality), and migration. We use firm-level data on greenfield investments at the intensive margin (investment in established subsidiaries) and the extensive margin (investment in new subsidiaries). Then, we matched this data with their patenting activity as an outcome measure of their investment in perceived quality. Finally, we collapsed and matched the FDI and patent data with sectoral data on migrant inventors, foreign individuals who filed a patent and serve as our proxy for migration in the R&D sector.

As commented above, our dataset merges data from three sources. The dependent variable, greenfield investment operations, is sourced from The Financial Times Ltd. cross-border investment monitor (FDIMarkets, 2017). These data are relatively standard in empirical studies of FDI (see, for instance, Myburgh and Paniagua 2016; Costa-Campi et al. 2018). It has the advantage that the data are available at the firm level. We merged this dataset with patent **application** data at the firm level provided by PATSTAT. Our sample contains yearly data for 1450 firms from 34 OECD countries with investment in 145 host countries in 19 sectors during 2003-2012. When merging the patent data, we correct for truncation.

Ideally, we would like to identify foreign-born R&D workers in each firm. Unfortunately, this data is not available, and therefore, the best identification strategy possible is at the country-pair-sector level.

To get as close as possible to our theory, we use a novel dataset created by Miguelez and Fink (2013). This dataset identifies migrant inventors in OECD countries since 1978 at the sector level (in terms of foreign residents who patented an invention in a specific country) by exploiting a legal requirement for all patents filed under the Patent Cooperation Treaty (PCT) of disclosing the nationality of all applicants. Besides, up to 2011, all patents which include the US as a destination target (which, according to Miguelez and Fink (2013), were more than 80% of the international patents) were obliged to include all inventors as applicants. The Miguelez and Fink (2013) data allow us to identify foreign R&D workers in three broad categories: Mechanical Engineers, Electrical Engineers, and Chemists. This limits the sectoral breadth of the analysis since we have to map the original firm sectors into the migrant sector data. Practically, this means that we drop 8 sectors and match the sector and migrant types in Table 1.

[Table 1 about here.]

Lastly, since our dataset is aggregated from firm-level data, we have to reconstruct the dataset to include zeros in the dependent variable. We extended the procedure proposed by Paniagua (2016) and added zeros only when there was a previous non-zero observation in the quartet country-pair-sector-year. Table 2 shows the descriptive statistics.

[Table 2 about here.]

3.2.1 Data visualization

We provide additional data description with three motivating visualizations. Firstly, bilateral FDI and patents are significantly correlated. Each dot in Figure 1 represents a country-pair in a particular year of our sample that goes from 2003 to 2012. Figure 1a shows the aggregate investment between country pairs and the patent activity of MNEs at the source country. The correlation is positive and significant as in 1b, where we repeat the exercise with foreign affiliates. The scatter cloud has a clear growing trend, which increases towards the upper quantiles.

[Figure 1 about here.]

Secondly, sectors with high patenting activity also have higher volumes of FDI. In Figure 2 we have ordered the sectors in terms of their average patenting activity. We have then used this "patenting order" to represent FDI activity. The leading patenting sectors (Software & IT services, Automotive OEM, Communications and Industrial Machinery) in Figure 2a rank above the average in terms of yearly FDI projects in Figure 2b. The data represented in Figure 2 also reveals sectoral heterogeneity in terms of patents and FDI. Patents are highly concentrated in the Software & IT sector, while FDI activity seems to be more evenly distributed.

[Figure 2 about here.]

Thirdly, multinational's patents and migrant inventors are correlated as shown in Figure 3. We should expect this positive relationship for a valid instrument.

[Figure 3 about here.]

4 Empirical Results

We start by presenting in the next set of tables the results of the empirical exercise. Table 3 reports the baseline results of regressing FDI against the patent stock at the country of origin (without instruments). The empirical results are in line with our theoretical results. Columns 1 and 2 report the results of the patent stock's effect on the intensive (total FDI flows) and extensive (number of FDI affiliates) margins with OLS. The marginal effect of patents is positive and significant, with a larger effect at the intensive margin. Part of the effect of patents on bilateral flows is attributable to the creation of new investment partners (extensive margin effect) and larger investments with existing partners (intensive margin).

[Table 3 about here.]

However, as discussed earlier, the OLS estimator has known issues that might bias the estimates. Therefore, we turn to a structural gravity PPML estimation in column 3 for the intensive margin and column 4 for the extensive margin. This specification is compatible with zeros and therefore, the number of observations and the R^2 increases. We observe similar results in terms of magnitude and pattern compared to the OLS results in the intensive margin: Increasing the number of patents by 1% increases the volume of FDI by 0.17% (OLS) and by 0.14% (PPML) on average. However, in the extensive margin, where even the count nature of the dependent variable would advise a Poisson count model, we observe that OLS's coefficient (0.094) is significantly lower than PPML's (0.146).

In our theory, we considered a particular type of investment in innovation, which is destination-country specific. To test whether our empirical results are consistent with this hypothesis, we consider as dependent variables the shares rather than the levels of FDI either at the intensive and the extensive margin. On the one hand, the intensive margin share is the volume of investment made by country i into country j in existing subsidiaries in that sector over the total volume of investment in existing subsidiaries in that sector made by that country abroad (i.e. including all destinations). On the other hand the extensive margin share is the number of new subsidiaries in country i into country j, in that sector over the total number of subsidiaries in that sector. A significant effect on shares would confirm our theoretical assumption that innovation is destination-specific as an increase in our instrumented measure of patents exerts a relatively larger increase in FDI towards the country where those migrants are coming from. Conversely, if innovation was affecting all countries generally (as for example a cost-reduction innovation) the effect of patents on FDI will be the same across all countries and the shares will not be affected. [15]

Columns 5 and 6 report our results when we use the shares rather than the levels. In column 5 we used the investment share rather the share of the invested capital volume, and in column 6 the share of the total the number of projects share. In both cases the intensive and the extensive margins coefficients are positive and significant. More precisely, we find that increasing by 1% the number of patents increases the share of the volume of FDI invested in existent subsidiaries by 0.136 percentage points and increases the share of expected investment in new plants by a similar amount, 0.139 percentage points.

The baseline evidence presented in Table 3 supports the basic implications of the model. However, as discussed in the model, the patents are endogenous, and therefore the estimates might be biased. The model proposes that migrants increase the lab's productivity and consequently, we use migrant inventors as an instrument as discussed in the empirical section. The results of regressing patents against migrant inventors in (7a) and then FDI against the instrumented patents in (7b) are reported in Table 4. The stock of migrant inventors is positively and significantly associated with patents in the first step (column 1). Additionally, the Cragg-Donald Wald F test's values and the Anderson LM statistic allow us to reject the null hypotheses of weak instrument and under-identification.

[Table 4 about here.]

Comparing the baseline results (without instrumenting) in Table 3 and the 2S-IV results in Table 4, it is clear that the instrumented patents' effect in the latter table is larger. Therefore, the effect of patents is downward-biased if we do not take action against endogeneity. The only exception is the estimated coefficient in the extensive margin with OLS, which shows similar results. Again, due to the limitations of OLS, we focus on what follows on PPML.

We observe larger results in terms of magnitude in the intensive margin: Increasing the number of patents by 1% increases the volume of FDI by 0.3% (2S-IV column 4) and by 0.14% (baseline column 3) on average. Also, on the extensive margin: Increasing the number of patents by 1% increases the volume of FDI by 0.37% (2S-IV column 5) and by 0.15% (baseline column 4) on average. The effect on FDI shares is similar: 0.273 vs. 0.136 in the intensive margin and 0.273 vs. 0.139 in the extensive margin.

The inflation in the coefficient estimates is the indirect effect of migrant inventors, which we attributed to a better performance in country-sector specific innovation. We can compute the marginal effects of the stock of migrant inventors on FDI through its effects on patents. Column 1 reports the first stage results, which regresses the stock of patents on the stock of migrant inventors with a marginal effect of 0.574. Therefore, increasing the stock of migrant inventors by 1% should increase the intensive and extensive FDI margins by 0.17% and 0.21% respectively.[16] Theses magnitudes correspond roughly to the difference in the coefficient estimates in tables 3 and 4.

To put our results in context, we compare them with similar studies. With the same set of controls, Brunel and Zylkin (2019) report a marginal effect of 0.404 of patent stock on trade. Our results lie in between their higher and lowest estimates for trade. Regarding the impact of migrant inventors, however, it is lower than the effect of other types of migrants. For example, using a similar FDI dataset and econometric specification, Cuadros et al. (2019) report marginal effects of 1.1 for migrant managers, of 0.53 for professionals, and of 0.6 for high educated migrants, regardless of occupation.

Standard models of FDI and migration suggest that migrants at the host reduce transaction costs and informational asymmetries. Therefore, our baseline results may suffer from omitted variable bias. To contest this, we introduce the flow of migrant inventors from the source to the destination (in a particular sector) in Table 5.[17]

Focusing directly on our preferred PPML results in the last 4 columns of Table 5, we observe that the effect of migrant inventors at the host is positive and significant, but only on the intensive margin. The value of the coefficients are lower than those reported by the literature for other types of migrants. The estimated coefficient of these migrants in the intensive share is comparable in size to the effect that we computed for the migrants at the host through patents (0.17). However, the impact of the host's migrant stock is not significant on the extensive margin. This means that the effect of migrant inventors is mostly amplified by its innovator and patenting role rather than by cost reduction when it comes to creating new investment partners.

[Table 5 about here.]

Our empirical test of the model concludes in Table 6 with a sectoral decomposition of the variables to investigate additional sources of heterogeneity. It is readily seen that the effect is only significant for electrical engineering (we report the second stage for brevity). Recall that the parameter ϕ shapes this relationship between R&D and FDI in the model. In sectors where quality does not matter for the consumers ($\phi = 0$), firms do not invest in quality. Further, recall that electrical engineering was composed of Communications, Electronic Components, Software & IT, Consumer Electronics, and Semiconductors. These activities rely significantly on the quality and, more specifically, on adapting the quality to their final customers' tastes, language, and culture worldwide.

[Table 6 about here.]

5 Conclusions

This paper examines a new channel through which globalization may affect MNEs, namely migration-fueled innovation. We build a theoretical model where sector-country innovation is endogenous and foreign inventors enhance heterogeneous firms' innovation strategy in the extensive and intensive margin.

Structural gravity estimates on a novel FDI-patent-migration dataset at the country-pair-sector level reveal significant and sizable effects when instrumenting patents with migrant inventors on FDI at both margins (the extensive and the intensive) measured in levels and shares. Robustness checks confirm the results and validate the instrument.

This paper contributes in different dimensions to the existing literature on the effects of migration on innovation and FDI. The study refines the existing literature results providing worldwide evidence. Besides, we identify the indirect effects of migrant inventors rather than ethnic innovators, which, not only includes naturalized migrants but also inventors who belong to the second generation of migrants.

The outcomes obtained in this paper may help design and evaluate migration policies in association with innovation policies, e.g., efforts to attract talent. This question seems to be particularly important in the current situation of increased economic protectionism. Talent allocation is a relevant lever for economic growth (Hsieh et al., 2019). Migration flows associated with innovation might prove useful to innovation and capital investment.

Online Appendix

A Theoretical Appendix

A.1 Solution of the model

Solving for the utility maximization problem that households face, we have that each household dedicates a fixed proportion of their income to spend on each of the composite goods,

$$C_{kj} = \mu_k R_j,$$

where R_j denotes total income in country j and the demand for each variety, $c_{kj}(\omega)$, is given by

$$c_{kj}(\omega) = (q_{kj}(\omega))^{(\sigma_k - 1)\phi_k} \frac{\mu_k R_j}{P_{kj}} \left(\frac{p_{kj}(\omega)}{P_{kj}} \right)^{-\sigma_k}, \tag{9}$$

where p_{kj} is the price charged for the variety ω in sector k and country j and P_{kj} is the CES adjusted-quality aggregate price index associated with C_{kj}, $P_{kj} = \left[\int_{\omega \in \Omega_k} \left(p_{kj}(\omega) / (q_{kj}(\omega))^{\phi_k} \right)^{1-\sigma_k} d\omega \right]^{1/(1-\sigma_k)}$.

Since the firm is using a constant returns to scale technology to produce, the cost function is linear in the output produced by the firm. More precisely the expression is given by:

$$C(x_{kij}, w_i, r) = (w_i)^{1-\gamma} r^{\gamma} \frac{x_{kij}(\omega)}{\varphi}$$

The firm's problem

Firms choose prices and the investment in quality by maximizing profits. To avoid excessive notation, let us drop ω and the subscript k. The last one, k, will be re-introduced when the gravity equation is derived to better inform the empirical strategy.

The model is solved by backward induction. To solve for the firm's optimal price and quantity we use the expression for the cost function found above. It is important to note that the cost function and the revenue function are separable across destinations and this allows us to solve for the optimal quality choice separately for each destination. Solving the standard firm's maximization problem we have $p_{ij} = \frac{\sigma}{\sigma-1} \frac{\varepsilon_i^{1-\gamma} r^{\gamma} \tau_{ij}}{\varphi}$. Substituting in the demand function and rearranging terms we obtain the firm's variable profit for each destination for a given quality level is as follows:

$$\pi_{oij}(\varphi) = p_{ij}x_{ij} - C(x_{ij,}\varphi) - rf_{ij} = B_{ij}q_j^{(\sigma-1)\phi}\varphi^{\sigma-1} - rf_{ij},$$

where $B = (\tau_{ij})^{(1-\sigma)\xi}\left(\frac{(\sigma-1)}{\sigma\varepsilon_i^{(1-\gamma)\xi}\varepsilon_j^{(1-\gamma)(1-\xi)}r^{\gamma}}\right)^{\sigma-1}\frac{\mu R_j}{\sigma P_j^{1-\sigma}}$ is constant from the point of view of the firm. Note that ξ takes the value of 1 when the firm is an exporter and 0 when the firm serves market j through an affiliate. Now we turn to the firm's quality decision for a variety that it is produced in country i but sold in country j. Firms' solve the following maximization problem:

$$\max Bq_{ij}^{(\sigma-1)\phi}\varphi^{\sigma-1} - \varepsilon_i\frac{\varphi^{\sigma-1}}{\theta_{ij}}z_{ij} - rf_{ij}$$

$$\text{s.t.}\quad {q_{ij}}^{\sigma-1} = z_{ij},$$

where z_{ij} denotes the investment in quality by a variety that is produced in country i but sold in country j. This gives us the optimal quality decision:

$$z_{ij} = {q_{ij}}^{\sigma-1} = \left(\frac{\phi B\theta_{ij}}{\varepsilon_i}\right)^{\frac{1}{1-\phi}}. \tag{10}$$

The firm's operating profits of an exporting firm, for a given optimal investment in quality, becomes

$$\begin{aligned}\pi'_{oij}(\varphi) &= (\tau_{ij})^{1-\sigma}B_{ij}q_j^{(\sigma-1)\phi}\varphi^{\sigma-1} - \frac{\varepsilon_i}{\theta_{ij}}z_{ij}\varphi^{\sigma-1} - rf_{ij} = \\ &\left((\tau_{ij})^{1-\sigma}B_{ij}\right)^{\frac{1}{1-\phi}}\phi^{\frac{\phi}{1-\phi}}(1-\phi)\left(\frac{\theta_{ij}}{\varepsilon_i}\right)^{\frac{\phi}{1-\phi}}\varphi^{\sigma-1} - rf_{ij}.\end{aligned} \tag{11}$$

where $B_{ij} = \left(\frac{(\sigma-1)}{\sigma\varepsilon_i^{(1-\gamma)}r^{\gamma}}\right)^{\sigma-1}\frac{\mu R_j}{\sigma P_j^{1-\sigma}}$. If the firm decides to invest in FDI, in country j the operating profits in country j will be given by:

$$(B_j)^{\frac{1}{1-\phi}}\,\phi^{\frac{\phi}{1-\phi}}(1-\phi)\left(\frac{\theta_{ij}}{\varepsilon_i}\right)^{\frac{\phi}{1-\phi}}\varphi^{\sigma-1} - r_j f_{Ij},$$

where it can be noted that $B_j = \left(\frac{\varepsilon_i}{\varepsilon_j}\right)^{(1-\gamma)(\sigma-1)} B_{ij}$. The latter implies that the benefits of undertaking FDI are given by

$$\left(\left(\frac{\varepsilon_i}{\varepsilon_j}\right)^{\frac{(1-\gamma)(\sigma-1)}{1-\phi}} - (\tau_{ij})^{\frac{1-\sigma}{1-\phi}}\right)(B_{ij})^{\frac{1}{1-\phi}}\,\phi^{\frac{\phi}{1-\phi}}(1-\phi)\left(\frac{\theta_{ij}}{\varepsilon_i}\right)^{\frac{\phi}{1-\phi}}\varphi^{\sigma-1} \geqslant r(f_{Ij}-f_{ij}). \quad (12)$$

Note that there are several interesting results derived from the expressions above. First, the investment in quality is always larger for the case of FDI compared to exporting.[18] This results from the fact that, ceteris paribus, a firm sells more units in the destination market if it serves it through FDI rather than exports. The latter increases the investment in quality. Second, common to the horizontal models of trade and FDI, the proportion of firms doing FDI within an industry increases with the extent of the market B_{ij} and decreases the larger the difference in fixed costs are (i.e., the extent to which firms benefit from concentration). Third, novel to the literature on trade and FDI, there is an inverse relationship between cultural distance and horizontal FDI. More culturally distant countries imply a higher cost of adapting the product to local tastes. This implies that firms will invest less in adapting the product to those destinations. The latter implies that the firm's sales will be low in these destinations, decreasing the firm's profitability of serving the foreign market.[19]

Note that common to all Melitz (2003) models, the variable profits of serving any market, is proportional to a measure of firms' productivity $\varphi^{\sigma-1}$. Moreover, the operating profits of undertaking FDI as opposed to exporting (i.e., left hand side of condition (12) are also increasing in the productivity of the firm). This implies that there exists a productivity threshold level φ_{Ij} such that the firm will undertake FDI if and only if $\varphi \geqslant \varphi_{Ij}$. The condition defining this productivity threshold comes from the previous expression evaluated as an equality, that is:

$$\left(\left(\frac{\varepsilon_i}{\varepsilon_j}\right)^{\frac{(1-\gamma)(\sigma-1)}{1-\phi}} - (\tau_{ij})^{\frac{1-\sigma}{1-\phi}}\right)(B_{ij})^{\frac{1}{1-\phi}}\,\phi^{\frac{\phi}{1-\phi}}(1-\phi)\left(\frac{\theta_{ij}}{\varepsilon_i}\right)^{\frac{\phi}{1-\phi}}\varphi_{I_j}^{\sigma-1} = r(f_{Ij}-f_{ij}). \quad (13)$$

A threshold level of productivity φ^*_{ij} can be established such that firms with productivity $\varphi_{Ij} \geqslant \varphi \geqslant \varphi^*_{ij}$ would find it profitable to serve the market j through exporting. This productivity threshold is given by the following condition:

$$\left((\tau_{ij})^{1-\sigma} B_{ij}\right)^{\frac{1}{1-\phi}}\phi^{\frac{\phi}{1-\phi}}(1-\phi)\left(\frac{\theta_{ij}}{\varepsilon_i}\right)^{\frac{\phi}{1-\phi}}\left(\varphi^*_{ij}\right)^{\sigma-1} = rf_{ij}. \quad (14)$$

Note that under certain conditions the following holds: $\varphi^*_{ij} > \varphi^*_{ii}$, where φ^*_{ii} is the survival productivity threshold (i.e., domestic firms serving market i). If these conditions hold, the economy will exhibit selection into the export market.

A.2 Derivation of the gravity equations (extensive and intensive margins)

A.2.1 Derivation of the gravity equation at the intensive margin (firm and aggregate level)

The firm-level gravity equation for the intensive margin of FDI is given by the amount of capital that the affiliate is obtaining from the parent company, this is given by:

$$rK_{kIj}(\varphi) = \left\{ \begin{array}{ll} r\gamma \left(\frac{\varepsilon_j}{r}\right)^{1-\gamma} \frac{x_{kIj}(\varphi)}{\varphi} & \text{if } \varphi \geqslant \varphi_{Ij} \\ 0 & \text{otherwise} \end{array} \right\} \tag{15}$$

where the last condition comes from obtaining $K_{kIj}(\varphi)$ from equation **??**. [20] Note that using the expression for the local firm's optimal price in country j we have:

$$rK_{kIj}(\varphi) = \gamma \left(\frac{\sigma_k - 1}{\sigma_k}\right) p_{kIj}(\varphi) x_{kIj}(\varphi) = \gamma \left(\sigma_k - 1\right) B_{kj} q_{kIj}^{(\sigma_k-1)\phi_k} \varphi^{\sigma_k - 1} \tag{16}$$

where both B_{kj} and q_{kIj} are endogenous. Substituting the optimal expression for q_{kIj}, using **??** and rearranging terms we obtain

$$\gamma \left(\sigma_k - 1\right) \phi_k^{\frac{\phi_k}{1-\phi_k}} \lambda'_{kj} \left(Y_j\right)^{\frac{(\sigma_k-1)}{\kappa}} \bar{\eta}_{kj}^{\frac{1}{\phi_k - 1}} \left(\frac{\theta_{ij}}{\varepsilon_i}\right)^{\frac{\phi_k}{1-\phi_k}} \varphi^{\sigma_k - 1}$$

and note that we can express this equation as:

$$rK_{kIj}(\varphi) = \lambda_{kj}^{''}\left(Y_j\right)^{\frac{\sigma_k-1}{\kappa}}\bar{\eta}_{kj}^{\frac{1}{\phi_k-1}}\left(\frac{\theta_{ij}}{\varepsilon_i}\right)^{\frac{\phi_k}{1-\phi_k}}\varphi^{\sigma_k-1}$$

where $\lambda_{kj}^{''} = \gamma\left(\sigma_k-1\right)\phi_k^{\frac{\phi_k}{1-\phi_k}}\lambda_{kj}^{\prime}$, represents a constant that in the empirical exercise can be captured by destination and origin country fixed effects. Note that using 16 and rearranging terms, this gravity equation can be also expressed as:

$$rK_{kIj}(\varphi) = \lambda_{kj}^{'''}\left(Y_j\right)^{\frac{(\sigma_k-1)(1-\phi_k)}{\kappa}}\left(q_{kIj}\left(\varphi\right)\right)^{(\sigma_k-1)\phi_k}\eta_{kj}^{-1}\varphi^{\sigma_k-1}$$

where $\lambda_{kj}^{'''} = \gamma\left(\sigma_k-1\right)\left(\lambda_{kj}^{\prime}\right)^{1-\phi_k}$ and where the investment in quality is an endogenous variable. This version of the gravity equation is useful for our estimation procedure.

A.2.2 Derivation of the gravity equation at the intensive margin (aggregate level)

To obtain the gravity equation at the sectoral level, FDI needs to be aggregated across firms within the same sector. That is,

$$\int_{\varphi_{Ij}}^{\infty} N_i rK_j(\varphi)dG(\varphi) = N_i\int_{\varphi_{Ij}}^{\infty}\lambda_{kj}^{''}\left(Y_j\right)^{\frac{\sigma_k-1}{\kappa}}\bar{\eta}_{kj}^{\frac{1}{\phi_k-1}}\left(\frac{\theta_{ij}}{\varepsilon_i}\right)^{\frac{\phi_k}{1-\phi_k}}\varphi^{\sigma_k-1}g(\varphi)d\varphi$$

Solving for the integral and rearranging terms we find

$\int_{\varphi_{Ij}}^{\infty} N_i rK_j(\varphi)dG(\varphi) = N_i\lambda_{kj}^{''}\left(Y_j\right)^{\frac{\sigma_k-1}{\kappa}}\bar{\eta}_{kj}^{\frac{1}{\phi_k-1}}\left(\frac{\theta_{ij}}{\varepsilon_i}\right)^{\frac{\phi_k}{1-\phi_k}}\frac{\kappa}{\kappa-(\sigma_k-1)}\varphi_{Ij}^{\sigma_k-\kappa-1}$

Substituting the value for φ_{Ij} and rearranging terms we find

$$N_i \lambda''_{kij} Y_j \bar{\eta}_{kj}^{\frac{1}{\phi_k - 1} \frac{\kappa}{\sigma_k - 1}} \left(\frac{\theta_{ij}}{\varepsilon_i}\right)^{\frac{\phi_k}{1-\phi_k} \frac{\kappa}{\sigma_k - 1}} \frac{\kappa}{\kappa - (\sigma_k - 1)}$$

$$\left(\frac{r(f_{Ij} - f_{ij})}{\left(\left(\frac{\varepsilon_i}{\varepsilon_j}\right)^{\frac{(1-\gamma)(\sigma_k-1)}{1-\phi_k}} - (\tau_{ij})^{\frac{1-\sigma_k}{1-\phi_k}}\right)}\right)^{\frac{\sigma_k - \kappa - 1}{\sigma_k - 1}} \left(\lambda'_k \phi_k^{\frac{\phi_k}{1-\phi_k}} (1 - \phi_k)\right)^{\frac{\kappa - (\sigma_k - 1)}{\sigma_k - 1}}$$

Since $N_i = \frac{Y_i}{1+\pi}$, then we have

$$FDI^I_{kij} = \lambda^{iv}_{kij} Y_i Y_j \bar{\eta}_{kj}^{\frac{1}{\phi_k - 1} \frac{\kappa}{\sigma_k - 1}} \left(\frac{\theta_{ij}}{\varepsilon_i}\right)^{\frac{\phi_k}{1-\phi_k} \frac{\kappa}{\sigma_k - 1}} \left(\left(\frac{\varepsilon_i}{\varepsilon_j}\right)^{\frac{(1-\gamma)(\sigma_k-1)}{1-\phi_k}} - (\tau_{ij})^{\frac{1-\sigma_k}{1-\phi_k}}\right)^{\frac{\kappa - \sigma_k - 1}{\sigma_k - 1}}$$

where $\lambda^{iv}_{kij} = \lambda''_{kij} \left(\lambda'_{kj} \phi_{kj}^{\frac{\phi_{kj}}{1-\phi_{kj}}} (1 - \phi_{kj})\right)^{\frac{\kappa - (\sigma_k - 1)}{\sigma_k - 1}} \frac{\kappa}{\kappa - (\sigma_k - 1)} \left(r(f_{Ij} - f_{ij})\right)^{\frac{\sigma_k - \kappa - 1}{\sigma_k - 1}} \frac{1}{1+\pi}$

We can rewrite this equation as

$$FDI^I_{kij} = \lambda^{viii}_{kij} Y_i Y_j^{\frac{(\sigma_k - 1)(1-\phi_k)}{\kappa}} \bar{\eta}_{kj}^{-1} \left((q_{kIj})^{\sigma_k - 1}\right)^{\frac{\phi\kappa}{\sigma - 1}} \left(\left(\frac{\varepsilon_i}{\varepsilon_j}\right)^{\frac{(1-\gamma)(\sigma_k-1)}{1-\phi_k}} - (\tau_{ij})^{\frac{1-\sigma_k}{1-\phi_k}}\right)^{\frac{\kappa - \sigma_k - 1}{\sigma_k - 1}}$$

where $\lambda^{viii}_{kij} = \frac{\kappa}{\kappa - (\sigma_k - 1)} \left(r(f_{Ij} - f_{ij})\right)^{\frac{\sigma_k - \kappa - 1}{\sigma_k - 1}} \left(\left(\frac{\varepsilon_i}{\varepsilon_j}\right)^{\frac{(1-\gamma)(\sigma_k-1)}{1-\phi_k}}\right)^{\frac{\kappa - \sigma_k - 1}{\sigma_k - 1} \frac{\phi_k}{1-\phi_k}}$

Note that the equation of FDI that focuses on investment in existing projects (what we have called in this paper the intensive margin) can be also expressed as a function of innovation and the rest of the variables of the gravity. This will be useful in the estimation procedure.

A.2.3 Derivation of the gravity equation at the extensive margin (aggregate level)

The gravity equation for the extensive margin of FDI is given by:

$$N_i r f_{Ij} (\varphi_{kIj})^{-\kappa} = N_i \left[\begin{array}{c} \left(\left(\frac{\varepsilon_i}{\varepsilon_j}\right)^{\frac{(1-\gamma)(\sigma_k-1)}{1-\phi_k}} - (\tau_{ij})^{\frac{1-\sigma_k}{1-\phi_k}}\right) (B_{kij})^{\frac{1}{1-\phi_k}} \phi_k^{\frac{\phi_k}{1-\phi_k}} (1 - \phi_k) \left(\frac{\theta_{ij}}{\varepsilon_i}\right)^{\frac{\phi_k}{1-\phi_k}} \varphi_{kI_j}^{\sigma_k - \kappa - 1} + \\ \left((\tau_{ij})^{1-\sigma_k} B_{kij}\right)^{\frac{1}{1-\phi_k}} \phi_k^{\frac{\phi_k}{1-\phi_k}} (1 - \phi_k) \left(\frac{\theta_{ij}}{\varepsilon_i}\right)^{\frac{\phi_k}{1-\phi_k}} \left(\varphi^*_{kij}\right)^{\sigma_k - 1} \varphi_{kI_j}^{-\kappa} \end{array}\right]$$

where the previous expression comes from substituting the expression for rf_{Ij} from condition 13 and rf_{ij} from condition 14. Using the same conditions for obtaining an expression for φ_{Ij} and φ^*_{ij} and rearranging terms we find that

$$N_i r f_{Ij}(\varphi_{kIj})^{-\kappa} = N_i\left(B_{kij}\right)^{\frac{1}{1-\phi_k}} \phi_k^{\frac{\phi_k}{1-\phi_k}}(1-\phi_k)\left(\frac{\theta_{ij}}{\varepsilon_i}\right)^{\frac{\phi_k}{1-\phi_k}} \cdot$$
$$\cdot\left[\left(\left(\frac{\varepsilon_i}{\varepsilon_j}\right)^{\frac{(1-\gamma)(\sigma_k-1)}{1-\phi_k}} - (\tau_{ij})^{\frac{1-\sigma_k}{1-\phi_k}}\right)\Psi'' + (\tau_{ij})^{\frac{1-\sigma_k}{1-\phi_k}}\,\Psi'''\right]\left(\varphi^*_{kij}\right)^{\sigma_k-\kappa-1}$$

where $\Psi'' = \left(\left(\frac{\varepsilon_i}{\varepsilon_j}\right)^{\frac{(1-\gamma)(\sigma_k-1)}{1-\phi_k}} - (\tau_{ij})^{\frac{1-\sigma_k}{1-\phi_k}}\right)^{\frac{\kappa-\sigma_k-1}{\sigma_k-1}}\left((\tau_{ij})^{\frac{1-\sigma_k}{1-\phi_k}}\frac{r(f_{Ij}-f_{ij})}{rf_{ij}}\right)^{\frac{\sigma_k-\kappa-1}{\sigma_k-1}}$

and $\Psi''' = \left(\frac{(\tau_{ij})^{\frac{1-\sigma_k}{1-\phi_k}}}{\left(\left(\frac{\varepsilon_i}{\varepsilon_j}\right)^{\frac{(1-\gamma)(\sigma_k-1)}{1-\phi_k}} - (\tau_{ij})^{\frac{1-\sigma_k}{1-\phi_k}}\right)}\frac{r(f_{Ij}-f_{ij})}{rf_{ij}}\right)^{-\frac{\kappa}{\sigma_k-1}}$

Substituting the expression for $\left(\varphi^*_{kij}\right)^{\sigma_k-\kappa-1}$ and rearranging terms we find that:
$N_i\left((B_{ij})^{\frac{1}{1-\phi_k}}\phi_k^{\frac{\phi_k}{1-\phi_k}}(1-\phi_k)\left(\frac{\theta_{ij}}{\varepsilon_i}\right)^{\frac{\phi_k}{1-\phi_k}}\right)^{\frac{\kappa}{(\sigma_k-1)}}$
$\left(\left(\frac{\varepsilon_i}{\varepsilon_j}\right)^{\frac{(1-\gamma)(\sigma_k-1)}{1-\phi_k}} - (\tau_{ij})^{\frac{1-\sigma_k}{1-\phi_k}}\right)^{\frac{\kappa}{\sigma_k-1}}\left(r(f_{Ij}-f_{ij})\right)^{\frac{-\kappa}{\sigma_k-1}} rf_{ij}$

Substituting the expression for N_i and rearranging terms, we can express this equation as

$$N_i r f_{Ij}(\varphi_{Ij})^{-\kappa} = \lambda^v_{kij}Y_i\left((Y_j)^{\frac{(\sigma_k-1)}{\kappa}}\bar{\eta}_{kj}^{\frac{1}{\phi_k-1}}\left(\frac{\theta_{ij}}{\varepsilon_i}\right)^{\frac{\phi_k}{1-\phi_k}}\right)^{\frac{\kappa}{\sigma_k-1}} = \lambda^v_{kij}Y_iY_j\bar{\eta}_{kj}^{\frac{\kappa}{(\phi_k-1)(\sigma_k-1)}}\left(\frac{\theta_{ij}}{\varepsilon_i}\right)^{\frac{\phi\kappa}{(1-\phi_k)(\sigma_k-1)}} \tag{17}$$

where

$$\lambda^{v}_{kij} = (\lambda'_k)^{\frac{\kappa}{\sigma_k-1}} \left(\phi_k^{\frac{\phi_k}{1-\phi_k}}(1-\phi_k)\right)^{\frac{\kappa}{\sigma_k-1}} \left(\left(\frac{\varepsilon_i}{\varepsilon_j}\right)^{\frac{(1-\gamma)(\sigma_k-1)}{1-\phi_k}} - (\tau_{ij})^{\frac{1-\sigma_k}{1-\phi_k}}\right)^{\frac{\kappa}{\sigma_k-1}} (r(f_{Ij}-f_{ij}))^{\frac{-\kappa}{\sigma_k-1}} rf_{ij}\frac{1}{(1+\pi)}.$$

A.2.4 Proof of proposition 1

In this section we provide the proof of proposition 1. Taking logs and differentiating equation (4) with respect to L^j_{ij} we find that

$$\frac{\partial \ln FDI_{kij}}{\partial \ln L^j_{ij}} = \frac{\phi_k \kappa}{(1-\phi_k)(\sigma_k - 1)} \frac{\partial \ln(\tilde{\theta}_{ij})}{\partial \ln L^j_{ij}} > 0,$$

where now the productivity of researchers in the R&D lab generating ideas towards the destination market j is given by $\tilde{\theta}_{ij}$ rather than θ_{ij} (the case without migration).

Differentiating equation (1) with respect to $\ln L^j_{ij}$ we find

$$\frac{\partial \ln(\tilde{\theta}_{ij})}{\partial \ln L^j_{ij}} = \frac{\partial \ln(\tilde{\theta}_{ij})}{\frac{\partial L^j_{ij}}{L^j_{ij}}} = \frac{L^j_{ij}}{\sum\limits_{m=1}^{n}\beta^m_{ij}\theta^m_{ij}} \frac{\partial \sum\limits_{m=1}^{n}\beta^m_{ij}\theta^m_{ij}}{\partial L^l_{ij}} = \frac{L^j_{ij}}{\sum\limits_{m=1}^{n}\beta^m_{ij}\theta^m_{ij}} \left(\frac{\theta^j_{ij}L_{ij} - \sum\limits_{m=1}^{n}L^m_{ij}\theta^m_{ij}}{(L_{ij})^2}\right)$$

$$= \left(\frac{\beta^j_{ij}\sum\limits_{m=1}^{n}\left(\theta^j_{ij}-\theta^m_{ij}\right)L^m_{ij}}{\sum\limits_{m=1}^{n}L^m_{ij}\theta^m_{ij}}\right) > 0, \text{ since } \theta^j_{ij} > \theta^m_{ij}\ \forall m \neq j. \text{ Note that } L_{ij} = \sum_{m=1}^{n} L^m_{ij}.$$

Note as well that $\frac{\partial \ln FDI_{kij}}{\partial \ln L^j_{ij}\partial\phi_k} = \frac{\kappa}{(1-\phi_k)(\sigma_k-1)}\frac{\partial \ln(\tilde{\theta}_{ij})}{\partial \ln L^j_{ij}} > 0.$

B Empirical Appendix: Robustness

This section contains several robustness checks which aim to reinforce the empirical analysis presented in the main manuscript. The dataset is rich in country and sectoral variation, which allows us to to include different combinations of fixed effects. Table 7 allows the country-pair and sector characteristics to be time-variant. The results obtained align with the previous both in terms of magnitude, sign, and statistical significance.

[Table 7 about here.]

The analysis continues by using a different instrument, continues then, by checking the exclusion restriction and ends by specifying the variables in flows instead of stocks. We have also weighted the patents by family size, i.e., the flow of new patents in any given year, as suggested by De Rassenfosse (2013) to control for the value of patents. We obtained similar results, which we do not report for brevity.[21]

Instead of using migrant inventors, we instrument patents with the stock of foreign population by nationality and the stock of foreign labor by nationality sourced from the DIOC-E dataset from the OECD. We do so to ascertain more evidence that the effect proposed by the theoretical model was correctly identified by the inventor nature of migrants. We would expect non significant results when we use non-migrant inventors to capture the endogenous idea generation process.

The results are reported in Table 8. Firstly, the IV post-estimation statistics reveal that the instrument choice is rather weak in both cases. Further, there is no significant relationship between the stock of migrants or labor migrants and patents in the first step. Consequently, it is not surprising that the second stage results do not reveal any significant relationship between patents and FDI.

[Table 8 about here.]

Our second test is to validate the exclusion restriction, which will not be fulfilled if there existed alternative channels through which migrant inventors affect FDI. The estimates of the marginal effect of migrant inventor stocks on FDI presented in Table 9 suggests orthogonality between the instrument and the dependent variable.

[Table 9 about here.]

The marginal effect of our instrument (the stock of migrant inventors at firm's country of origin) is not significant in the intensive margin (in levels and and shares) and in the share of the extensive margin. We do find, however a significant and positive effect of the instrument in the extensive margin (column 3). This effect, however, disappears when we introduce an interaction between patents and migrant inventors. In column 4, the stock of patents is still positive and significant, but the migrant stock is not significant. Therefore, the effect of migrant inventors is absorbed by the interaction. This means that migrant inventors have only a positive effect on the extensive margin, conditional on patents. When the volume of patents is very small or zero, migrant inventors have no effect. This evidence suggests that the exclusion restriction is valid since migrant inventors do not directly affect the dependent variable. The results of column 3 can be attributable to omitted variable bias (i.e., the interaction).

We continue with an external validity test with an out of sample estimation. The 2S-IV standard procedure uses only the subset of migrant inventors to predict patents in the second stage when there are observations for both variables. This limits our sample since we have more observations in the migration variable than in the patent variable. Thus, in Table 10 we estimate on larger sample by predicting all possible patents for all sector-country-pairs. This expands considerably the observations to nearly 27,000. The estimates of the predicted patents are all positive and significant.

The magnitude of the effect is a bit lower than in our standard 2S-IV results in Table 4, but in any case higher than the baseline results obtained without instrumenting patents in Table 3.

[Table 10 about here.]

Our robustness exercise ends by presenting some sensitivity analysis. Our stock variables are constructed with initial values that might not represent the stocks if prior distributions of migrants or patents were structurally different. Our concern about this matter is however not very high since the technological cycles of companies in the sectors considered here are generally lower than the time span used to construct our stock data. **Additionally, adaptive innovation may be performed more before the investment than in the year of the investment and our definition of stock variable might not be capturing this fact. Therefore, we lag the variables one period.**

Regardless, we present in Table 11 the results of estimating the variables of interest as lagged flows rather than as stocks. The significance and sign of the estimates is basically unchanged, albeit with higher values of the estimated coefficients.

[Table 11 about here.]

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Table 1: Migrant type and firm sector matching

Migrant type	Firm Sector
Mechanical engineers	Industrial Machinery Automotive Components Automotive OEM Business Machinery
Electrical engineers	Communications Electronic Components Software & IT Consumer Electronics Semiconductors
Chemists	Chemicals Plastics Pharmaceuticals

Table 2: Descriptive statistics and correlation matrix

	mean	sd	max	min	FDI (intesive)	FDI (extensive)	Patents
FDI (intesive)	13.61	143.19	21159.6	0	1		
FDI (extensive)	0.364	2.58	217	0	0.613***	1	
Patents	22.07	599.69	114625	0	0.310***	0.415***	1
Migrant inventors	2.08	45.72	4620	0	0.246***	0.405***	0.254***

Notes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Yearly flows by country-pair-sector. FDI (intesive) in million USD.

Table 3: Baseline results

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Variable →	Int. Margin	Ext. Margin	Int. Margin	Ext. Margin	Int. Quota	Ext. Quota
$\ln \text{PatStock}_{k i \tilde{j} t}$	0.163***	0.094***	0.140***	0.146***	0.140***	0.139***
	(0.01)	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)
Observations	4455	4455	5967	5967	5967	5967
R^2	0.597	0.754	0.734	0.694	0.175	0.134
Home*Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Host*Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Country-pair FE	Yes	Yes	Yes	Yes	Yes	Yes
Sector*Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses, clustered by country pair

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

Table 4: 2S-IV gravity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	First stage (OLS)	Second stage (OLS)		Second stage (PPML)			
Dep. Variable →	$\ln \text{PatStock}_{ki\tilde{j}t}$	Int. Margin	Ext. Margin	Int. Margin	Ext. Margin	Int. Quota	Ext. Quota
$\ln \text{MigraInvStock}_{kjit}$	0.572***						
	(0.04)						
$\ln \text{Pat}\hat{\text{S}}\text{tock}_{ki\tilde{j}t}$		0.245***	0.088**	0.311***	0.370***	0.289***	0.307***
		(0.09)	(0.04)	(0.10)	(0.05)	(0.10)	(0.05)
Observations	6153	4455	4455	5967	5967	5967	5967
R^2	0.769	0.028	0.065	0.723	0.681	0.177	0.131
Home*Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Host*Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-pair FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector*Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cragg-Donald Wald F	92.915						
Anderson LM statistic	116.540***						

Robust standard errors in parentheses, clustered by country pair

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

Table 5: Results including inventors at the host.

	(1)	(2)	(3)	(4)	(5)	(6)
	Second stage (OLS)			Second stage (PPML)		
Dep. Variable→	Int. Margin	Ext. Margin	Int. Margin	Ext. Margin	Int. Quota	Ext. Quota
$\ln \text{Pat}\hat{\text{S}}\text{tock}_{ki\tilde{j}t}$	0.202^{**}	0.081^{**}	0.219^{**}	0.356^{***}	0.209^{**}	0.298^{***}
	(0.09)	(0.04)	(0.10)	(0.05)	(0.10)	(0.06)
$\ln \text{MigraInv}_{kijt}$	0.144^{***}	0.023	0.220^{***}	0.028	0.206^{***}	0.017
	(0.04)	(0.02)	(0.04)	(0.02)	(0.04)	(0.02)
Observations	4455	4455	5967	5967	5967	5967
R^2	0.039	0.065	0.728	0.681	0.178	0.131
Home*Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Host*Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Country-pair FE	Yes	Yes	Yes	Yes	Yes	Yes
Sector*Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses, clustered by country pair

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

Table 6: Sectoral results

	(1)	(2)	(3)	(4)	(5)	(6)
	Chemistry		Electrical engineering		Mechanical engineering	
$\ln \text{Pat}\hat{\text{S}}\text{tock}_{ki\tilde{j}t}$	-0.013	-0.417	1.681*	0.568*	-0.330	-0.521
	(1.56)	(0.55)	(0.99)	(0.32)	(1.15)	(0.49)
$\ln \text{MigraInv}_{kijt}$	0.068	0.013	-0.153	0.088**	0.026	0.023
	(0.13)	(0.04)	(0.13)	(0.04)	(0.14)	(0.06)
Observations	1353	1353	1858	1858	947	947
Home*Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Host*Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Country-pair FE	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses, clustered by country pair

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

Table 7: Robustness: Fixed-effects

	(1)	(2)	(3)	(4)
	Second stage (PPML)			
Dep. Variable $\rightarrow$	Int. Margin	Ext. Margin	Int. Quota	Ext. Quota
$\ln \widehat{\text{PatStock}}_{ki\tilde{j}t}$	0.317***	0.362***	0.295***	0.307***
	(0.09)	(0.05)	(0.09)	(0.04)
Observations	3995	3995	3995	3995
R^2	0.754	0.685	0.167	0.116
Home FE	Yes	Yes	Yes	Yes
Host FE	Yes	Yes	Yes	Yes
Country-pair*Year FE	Yes	Yes	Yes	Yes
Sector FE*Year FE	Yes	Yes	Yes	Yes

Robust standard errors in parentheses, clustered by country pair

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

Table 8: Robustness: Non-migrant inventors(2SLS)

	(1)		(2)	(3)	(4)	(5)
	First stage		Second stage (Migrants)		Second stage (Labor Migrants)	
Dep Variable:	$\ln \text{PatStock}_{i\tilde{j}t}$		Intensive Margin	Extensive Margin	Intensive Margin	Extensive Margin
$\ln \text{Migrants}_{jit}$	-0.003					
	(0.06)					
$\ln \text{LaborMigrants}_{jit}$		-0.028				
		(0.15)				
$\ln \text{Pat}\hat{\text{S}}\text{tock}_{i\tilde{j}t}$			0.982	-16.880	-5.993	-3.097
			(26.22)	(252.57)	(33.66)	(17.03)
Observations	8,242	1,326	8,242	8242	1,326	1326
R^2	0.98	0.98	0.620	-0.22	0.73	0.11
Home*Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Host*Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Country-pair FE	Yes	Yes	Yes	Yes	Yes	Yes
Cragg-Donald Wald F:	0.034	0.005				
Anderson LM statistic:	0.067	0.007				

Robust standard errors in parentheses, clustered by country pair

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

Table 9: Instrument validity

	(1)	(2)	(3)	(4)		(5)	(6)
	Intensive Margin		Extensive Margin			Int. Quota	Ext. Quot
$\ln \text{MigraInvStock}_{kjit}$	0.110*	0.022	0.117***	0.026	0.035	0.033	0.032
	(0.06)	(0.06)	(0.03)	(0.03)	(0.06)	(0.03)	(0.03)
$\ln \text{PatStock}_{ki\tilde{j}t}$	0.135***	0.053**	0.140***	0.081***	0.059***	0.071***	0.076***
	(0.02)	(0.02)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)
$\ln \text{PatStock}_{ki\tilde{j}t} \times \ln \text{MigraInvStock}_{kjit}$		0.025***		0.017***	0.025***	0.019***	0.017***
		(0.00)		(0.00)	(0.00)	(0.00)	(0.00)
Observations	5967	5967	5967	5967		5967	5967
R^2	0.734	0.746	0.694	0.701	0.182	0.136	0.135
Home*Year FE	Yes	Yes	Yes	Yes		Yes	Yes
Host*Year FE	Yes	Yes	Yes	Yes		Yes	Yes
Country-pair FE	Yes	Yes	Yes	Yes		Yes	Yes
Sector*Year FE	Yes	Yes	Yes	Yes		Yes	Yes

Robust standard errors in parentheses, clustered by country pair

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

Table 10: External validity: out of sample estimates

	(1)	(2)	(3)	(4)
		Second stage (PPML)		
Dep. Variable →	Int. Margin	Ext. Margin	Int. Quota	Ext. Quota
$\ln \text{Pat}\hat{\text{S}}\text{tock}_{ki\tilde{j}t}$	0.217**	0.257***	0.192**	0.231***
	(0.09)	(0.03)	(0.08)	(0.03)
Observations	26977	26977	26977	26977
R^2	0.730	0.689	0.241	0.189
Home*Year FE	Yes	Yes	Yes	Yes
Host*Year FE	Yes	Yes	Yes	Yes
Country-pair FE	Yes	Yes	Yes	Yes
Sector*Year FE	Yes	Yes	Yes	Yes

Robust standard errors in parentheses, clustered by country pair

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

Table 11: Robustness: Variables in flows

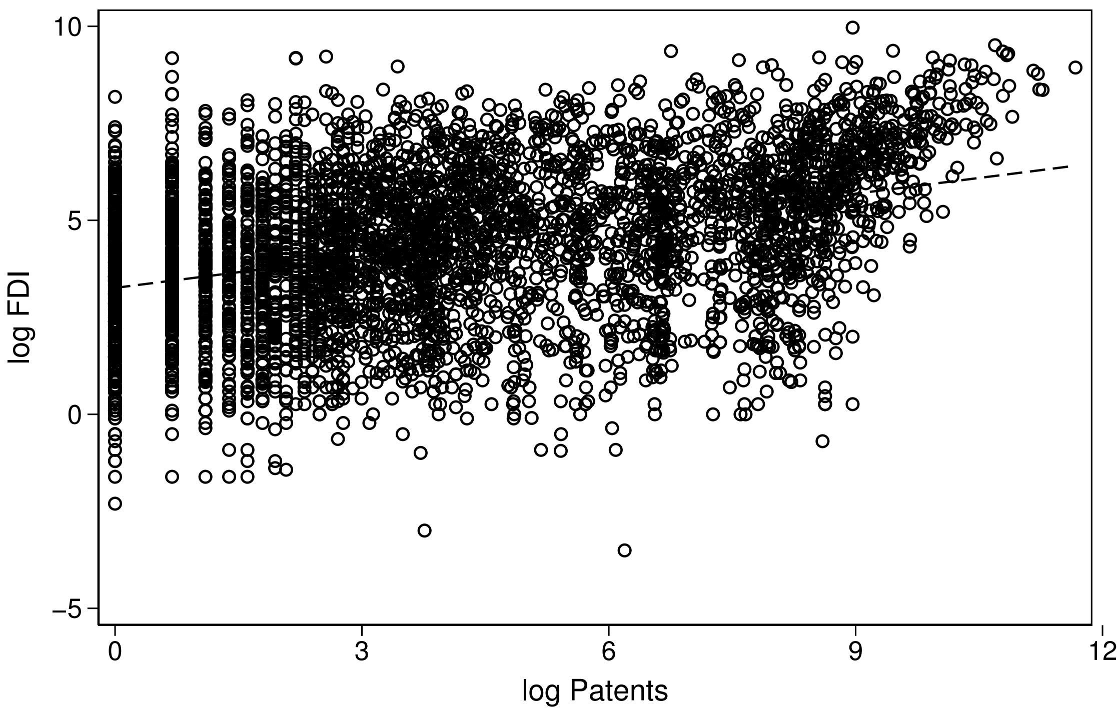
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	First stage (OLS)	Second stage (OLS)		Second stage (PPML)			
Dep. Variable →	$\ln \text{PatStock}_{ki\tilde{j}t}$	Int. Margin	Ext. Margin	Int. Margin	Ext. Margin	Int. Quota	Ext. Quota
$\ln \text{MigraInv}_{kjit-1}$	0.580***						
	(0.09)						
$\ln \hat{\text{Pat}}_{ki\tilde{j}t-1}$		0.395***	0.252***	0.235***	0.067**	0.224***	0.460 ***
		(0.10)	(0.05)	(0.05)	(0.03)	(0.05)	(0.03)
$\ln \text{MigraInv}_{kijt}$		0.159**	0.060	0.460***	0.436***	0.413***	0.380***
		(0.07)	(0.04)	(0.10)	(0.06)	(0.10)	(0.06)
Observations	2209	1889	1889	2152	2152	2152	2152
R^2	0.584	0.252	0.341	0.736	0.688	0.142	0.104
Home*Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Host*Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-pair FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector*Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cragg-Donald Wald F	92.915						
Anderson LM statistic	116.540***						

Robust standard errors in parentheses, clustered by country pair

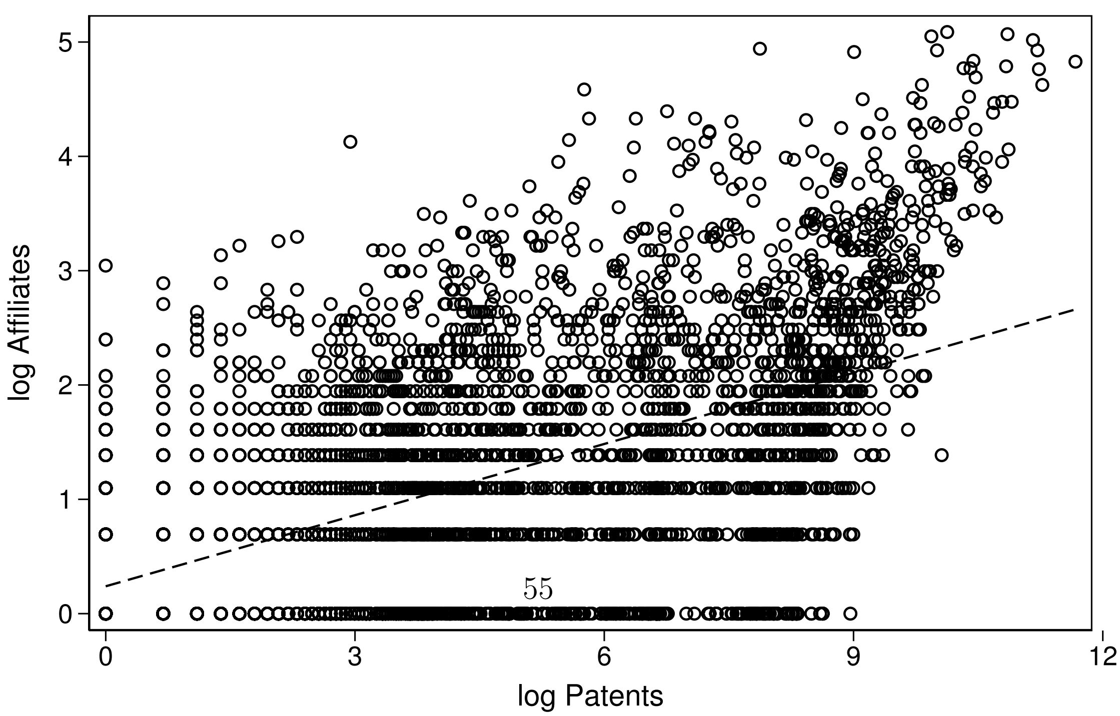
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure 1: Patents vs FDI: country pair correlation

(a) Intensive margin



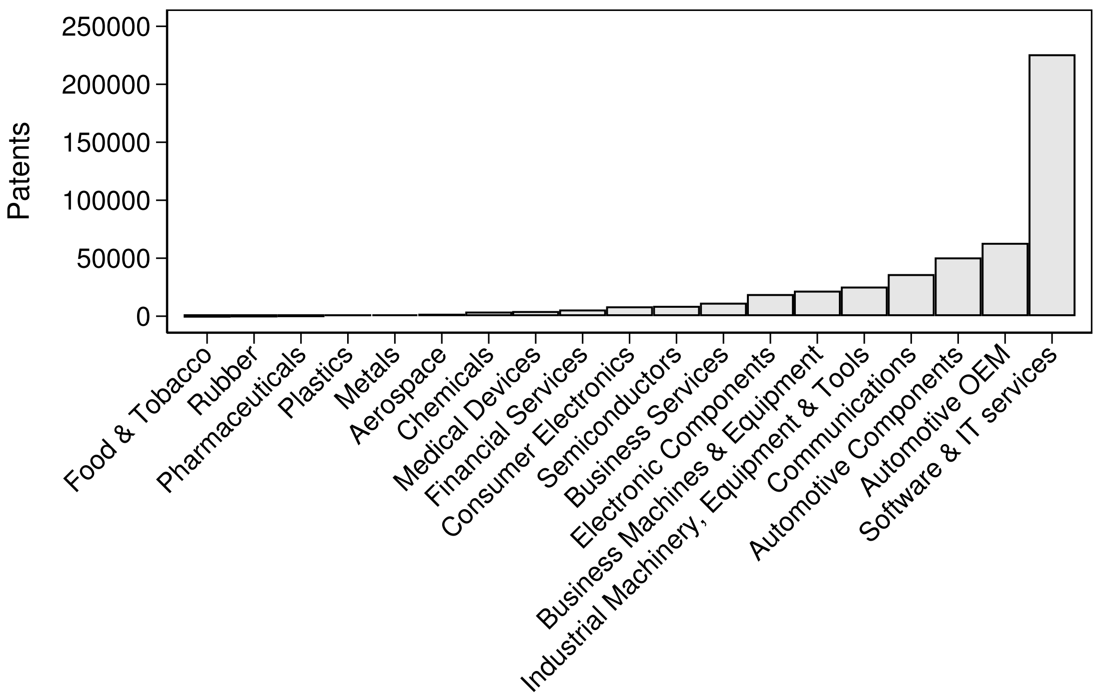
(b) Extensive margin



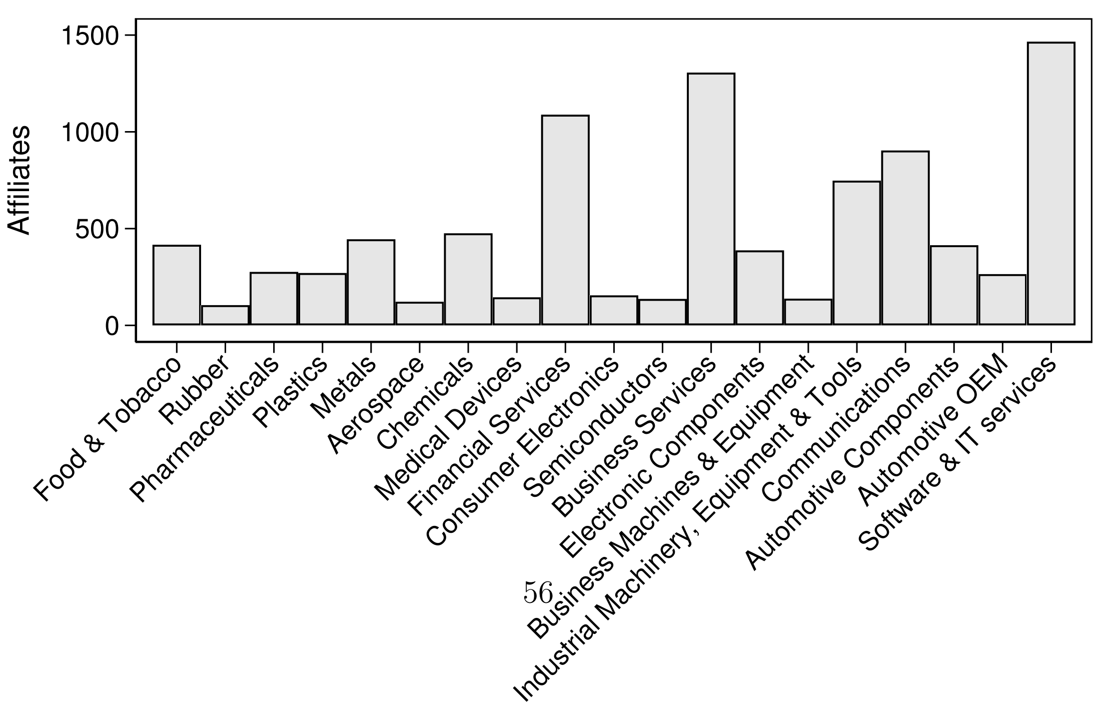
Notes: Greenfield FDI data comes from FDIMarkets and Patent data from Patstat

Figure 2: Patents and FDI: trends

(a) Patent per sector (yearly average)



(b) New affiliates per sector (yearly average)



Notes: Greenfield FDI data comes from FDIMarkets and Patent data from Patstat. Averages per sector and year, 2003-2012

Figure 3: Migrant inventors and FDI

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