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Moving ideas across borders: Foreign inventors, patents and FDI

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Abstract

This paper explores the link between innovation, migration and Foreign Direct Investment (FDI) empirically within a theoretically consistent framework. It analyses how migrant inventors enhance multinational firms' adaptive innovation performance and ultimately foster FDI towards the migrant's country of origin. Foreign migrant inventors (migrants who filed a patent in their host country) possess a unique mix of technical knowledge and cultural background that contribute to adapting Research and Development (R&D) activities for foreign markets. Therefore, FDI increases in country-pair-sectors with specific endogenous investment in quality, which depends on the migrants in the R&D sector. We constructed a novel panel country-sector data set including FDI, patents and migrant inventors and applied a two-stage structural gravity estimation procedure using migrant inventors as a valid instrument for patents. The results show sizable effects on the extensive and intensive margins of greenfield FDI.

KEYWORDS

foreign direct investment, gravity, migrant inventors, patents

1 | INTRODUCTION

Multinational Enterprises (MNEs) account for a large proportion of the world's research and development (R&D) activity. R&D enhances a firm's productivity and changes its competitive position relative to other firms (Doraszelski & Jaumandreu, 2013). Despite the importance of MNEs in R&D activities globally, some mechanisms through which globalisation affects these firms' 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 main idea behind this paper is that migrants working on R&D, or foreign inventors, improve firms' innovation performance in foreign markets through their unique cultural background and technical knowledge, facilitating the adaptation of the firms' products to the destination market. Firms make an effort to accommodate consumer tastes in different parts of the world, generating the need to make substantial changes in the products to adapt them to local tastes and practices. The customisation of products increases potential firm revenues in the foreign market and the benefits of establishing a facility abroad and the investments undertaken in that facility.

Anecdotal evidence illustrates the role of migrants in product customisation. On 8 November 2018, Ford Motor filed a patent application for an odour-removal process that eliminates the new car smell. The American multinational employed Chinese researchers with exceptionally sensitive noses to customise 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 through the increase in 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 the ethnicity in question.

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

The theoretical framework rests on 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.[1] We embed firm innovation in the Helpman et al. (2004) framework, particularly endogenous innovation, which increases the product's perceived quality in the destination market, as shown in Feenstra and Romalis (2014) and in the spirit of early endogenous growth models of product quality improvement, as shown by Aghion and Howitt (1992). We incorporate into the gravity equation endogenous investment in innovation for destination-specific quality upgrading. 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. Therefore, foreign inventors might be an appropriate instrument to estimate the effect of endogenous innovation on FDI. We thus employ a two-stage instrumental-variable 2S-IV estimation strategy embedded in a structural gravity model. In the spirit of Yotov et al. (2016) and Fally (2015), we introduce numerous

[1]The working paper version in Cuadros, Paniagua, and Navas (2019) contains a full formal model. In the Theoretical Appendix, we summarise the modelling that leads to the empirical equations.

fixed effects to control for multilateral resistance terms and potential unobserved heterogeneity, as has been the standard practice in the gravity literature since Anderson and Van Wincoop (2003). We estimate the extensive margin of FDI (the number of new subsidiaries abroad) and the intensive margin of FDI (the parent company's capital investment established subsidiaries).

The paper uses a novel data set that merges three underlying databases. First, 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 during 2003 to 2012. Second, we merged this data set 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 theoretical predictions, suggesting that innovation has a sizable effect on FDI in the extensive and intensive margins, measured in levels and shares. We show how the impact 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 organised as follows. Section 2 presents the theoretical framework. Section 3 describes the data and empirical strategy. Section 4 reports the main empirical results, and Section 5 concludes.

2 | THEORETICAL FRAMEWORK

This section describes the basic building blocks and the intuition of the theoretical framework, developed in Cuadros, Paniagua, and Navas (2019), which rests on a model of horizontal FDI with heterogeneous firms in the spirit of Helpman et al. (2004) and Chaney (2008).[2] In our set-up, consumers not only display love of variety but also derive utility from the perceived variety's quality, which is country-specific. Each firm produces a single variety in a monopolistic competition environment using labour and capital as inputs in fixed proportions. To enter the industry, firms need to pay a fixed cost of entry that could be associated with product creation. There is, however, uncertainty about the firm's Total Factor Productivity (TFP). Nevertheless, firms know that their productivity is a draw from a continuous productivity distribution, which is common across firms (Melitz, 2003). Once the firm enters, it decides to stay and produce, bearing a fixed cost of production of f_{ii} units of capital, or exit the market of country i. The firm can also decide to serve the foreign market of country j. There are two modes of serving the foreign market: exporting or doing FDI. As in Helpman et al. (2004), on the one hand, the exporting firms bear a fixed cost f_{ij} units of capital, and a variable iceberg trade cost, $_{ij}$. On the other hand, the most productive firms serve the foreign market through FDI by investing in a foreign subsidiary, bearing a fixed cost f_{Ij} units of capital.

We depart from the benchmark set-up in two important dimensions. First, we let firms endogenously decide their variety's perceived quality in each destination market by investing in innovation. Second, we incorporate migration to exogenously improve the innovation process that leads to the variety's perceived quality. We let firms hire specialised foreign workers to generate new ideas to increase the quality of the varieties sold in the foreign market. For simplicity, we assume that the firm's investment in quality is destination-specific. This simplifying assumption

[2]For a complete derivation of the theoretical model, see Cuadros, Paniagua, and Navas (2019),

allows us to maintain separability in profits across different destination markets, which is helpful when deriving the empirical gravity equation.

Therefore, each variety's perceived quality in each destination market is determined by the firm's investment in quality, which is a function of the number of workers devoted to that task. The productivity of the research laboratory results from the interaction between all researchers, which is common to all firms in the industry-destination pair. Following a large literature on innovation, we assume that researcher's productivity increases with a positive externality, like the exchange of ideas that emerge in a brainstorm.[3] We further assume that this externality is industry and country pair specific and that it depends on the cultural distance between the country of origin of the R&D workers i and the destination country j. For example, Spanish ex-pat researchers in a German automotive laboratory will be more successful in improving the perceived quality of German cars sold in the Spanish market than in the Chinese market. We find empirical evidence supporting this assumption in Koning et al. (2020), who, using US biomedical inventions, recently found that patents in which women inventors are involved are significantly more likely to focus on female conditions and diseases. Such evidence suggests that the characteristics of the inventor may shape the type of invention they are developing.

This modelling framework delivers sharp theoretical results regarding the role of innovation and migration in FDI. A closed economy that opens itself to migrant inventors improves the quality of the products that target the migrant's country of origin and those culturally closely related by boosting R&D productivity. The increase in product quality raises potential foreign sales. In line with Helpman et al. (2004), the increase in foreign sales will induce a larger proportion of firms to become multinationals and an increase in the volume of FDI of those firms that already have a subsidiary in the destination market.

In Cuadros, Navas and Paniagua (2019) we show formally that an increase in migrant inventors from a specific country j in country i, boosts the volume of FDI from country i to country j. The mechanism rests on the ability of these migrants to raise the firm's innovation productivity related to quality upgrading. This increases the firm's investment in the quality of the goods sold in country j and the firm's potential sales to that country. Therefore, these firms have more incentives to open new facilities or increase their investment in existing facilities.

Therefore, the increase in FDI (measured by the investment in capital made by a firm in a foreign country's facility) may come from two sources. On the one hand, the investment made by the parent company in a subsidiary is already established in the destination market (the intensive margin). On the other hand, the investment made to establish a new subsidiary in the destination market (the extensive margin).

Following the insights of Chaney (2008), we obtain two gravity equations that capture the endogenous process of investment in innovation as a function of migrant inventors, suggesting a two-step estimation procedure. First, we obtain an expression representing a gravity equation for the intensive margin of FDI. The FDI volume at the industry level is proportional to the economic size of both the country of origin and the destination market sizes represented by their GDPs. Interestingly, this volume is also inversely proportional to the cultural distance between the researchers in the R&D laboratory and the target country in terms of quality improvement.

[3]Nerkar and Paruchuri (2005) empirically show the importance of forming networks between researchers within a firm and their characteristics to enhance firms' R&D capabilities. This is shown to increase the number of patents. One way of measuring these potential knowledge flows is by looking at the effects of labour mobility. Using employer-employee data for Denmark, Kaiser et al. (2015) find positive spillovers on patenting through the mobility of R&D workers across firms. Besides, there is abundant evidence of the existence of positive knowledge spillovers related to labour mobility within a geographical area (Almeida and Kogut (1999), among others).

This second relationship comes from the novel element in our research: the investment in perceived quality that the parent company makes to increase the sales in the destination market, which depends negatively on the cultural distance between the two countries, the destination country and the country of origin as described above.

Second, we obtain a gravity equation for the extensive margin of FDI. The expected investment volume in 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 the two countries. As with the intensive margin, there is a negative relationship between cultural distance and the investment in new establishments abroad, which works through the effect that this distance exerts on the R&D laboratory's research productivity. In both cases, this relationship is shaped by a preference parameter that measures the importance of quality in the industry. When quality does not matter much in the consumer's utility, firms are reluctant to invest in quality; therefore, the cultural distance will not affect the firm's probability of investing in FDI.

We obtain gravity equations where bilateral FDI is a function of the investment in quality, which is determined by the volume of migrants:

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

$$\left(q_{kIj}\right)^{(\sigma_k - 1)} = \left(\frac{\phi_k \tilde{\theta}_{ij}}{\varepsilon_i} \right)^{\frac{1}{1-\phi_k}} \lambda_{kj}' \left(Y_j\right)^{\frac{(\sigma_k - 1)}{\kappa}} \left(\overline{\eta}_{kj}\right)^{\frac{1}{\phi_k - 1}}, \tag{1b}$$

where λ_{kj}', λ_{kij}^{vii} include all variables common across countries of origin, destination countries and elements that vary across both country of origin and destination country; Y_i,Y_j are the origin and destination country's market size, respectively; $\sigma_k > 1$ controls for the elasticity of substitution across different varieties; ϕ_k measures the importance of quality in the utility of consumers; ε_i is the productivity of country i in a homogeneous good; $\overline{\eta}_{kj}$ is the multilateral resistance term[4]; and q_{kIj} is the firm's investment in perceived quality. This investment in perceived quality depends, among other elements, on the variable θ_{ij}, that captures the firm's productivity in the research laboratory. This productivity is a weighted average of the productivity of the inventors coming from a particular country of origin 'm', living in country "i" and targeting country "j".[5]

Note that while this gravity equation corresponds to the total FDI volume, in the estimation procedure we consider both the extensive and the intensive margin of FDI.[6] Interestingly, the equations relative to the two margins will differ only in the constant with the elasticities of FDI to each country's market size and the investment in quality be the same across both margins.

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[4] $$\left[\overline{\eta}_{kj} = \left(\sum_{i=1}^{N} \left(\frac{Y_i}{Y}\right) \left(\frac{\phi_k \theta_{ij}}{\varepsilon_i}\right)^{\frac{\kappa\phi_k}{(\sigma-1)(1-\phi_k)}} \left(\varepsilon_i^{1-\gamma} r^{\gamma} \tau_{ij}\right)^{\frac{-\kappa}{1-\phi_k}} \left(rf_{ij}\right)^{\frac{\sigma_k - \kappa - 1}{\sigma_k - 1}} \Psi_{kij}' \right)^{\frac{(\sigma_k - 1)(1-\phi_k)}{\kappa}} \right]$$

[5] $\tilde{\theta}_{ij} = \sum_{m=1}^{J} \beta_{ij}^{m} \theta_{ij}^{m}$, where $\beta_{ij}^{m} = \frac{L_{ij}^{m}}{L_{ij}}$, θ_{ij}^{m} is the productivity of researchers from country m in country i targeting quality in country j, and L_{ij}^{m} denotes the number of researchers from country m living in country i and targeting country j.

[6] The derivation of the intensive and extensive margin equations is shown in Cuadros et al. (2019)

3 | DATA AND EMPIRICS

3.1 | Empirical model

Our theoretical framework offers several testable empirical implications and hints towards a theoretically consistent estimation. The theoretical framework delivers a gravity equation where FDI increases in country-pair-sectors with specific endogenous investment in quality, which depends on the migrants in the R&D sector. Therefore, the empirical roadmap combines the elements of a structural gravity equation in a two-step IV approach where migrant inventors instrument innovation. These migrants have a particular skill-set; they possess technical skills and cultural traits that allow them to increase the laboratory's productivity by tailoring technical specifications to a specific destination.

Since specific country-pair-sector innovation is not available, we rely on an indirect measure that combines firm-level patenting data with spatial variation in the investment data. Given that firms tend to patent in multiple destinations even if their innovation is focussed on a particular market,[7] we assume that patents are non-rival in terms of destination, with a slight 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 in which they invested in a particular year. In particular, we created the country-pair-sector patent variable aggregating the patents of firms in the sector only when they invested:

$$\text{Patent}_{k\tilde{ij}t} = \sum_{z=1}^{z=z_k} T_{zijt} \times \text{Patent}_{\text{zit}}, \tag{2}$$

where Patent are the patents filed by a firm z in sector k at time t, 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 an origin–destination-sector specific variation and it will not be absorbed by the fixed effects in the gravity equation.

Two caveats apply to the definition of the variable Patent in Equation (2). First, there could be measurement error as patents would overstate the notion of innovation used in this paper, especially for those firms that generate many patents and invest in many small countries. Second, there could be reverse causality as the variable $Patent_{k\tilde{ij}t}$ is related to FDI and endogenous. This assumption aligns with our theoretical framework, 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 is endogenous as it depends on migrant inventors, who can increase the laboratory's productivity. Migrant inventors contribute to building team-specific capital and have a persuasive influence on their collaborators' innovation production (Jaravel et al., 2018). Furthermore, migrants and natives have different knowledge pools, and the combination thereof is especially fruitful for innovation (Bernstein et al., 2019).

[7]Miguelez and Fink (2013) report that in 2010, 54% of the total international patent applications follow the PCT route, which allows claiming inventions in multiple jurisdictions over a short period of time. This implies that most firms, when patenting internationally tend to look for protection in various jurisdictions simultaneously since there could be uncertainty on the potential value of this innovation in several international markets.

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, Martín-Montaner, and Paniagua (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 TFP in the host country. However, the mechanism through which this channel operates differs substantially from the one considered in our paper, the papers mentioned earlier focussed on the static rather than the dynamic impact of migrants on TFP.[8] Previous work also emphasises the importance of diversity in creativity skills as a relevant reason behind the migrants' productivity increase (Alesina et al., 2016; Docquier et al., 2020; Kemeny & Cooke, 2017; Lazear, 1999). 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 & Peri, 2014). Kerr (2008) found that a large ethnic research community in the United States 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 brought about by migrants 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 the fact 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 countries. There is a shred of growing evidence that migrants play a key role in US innovation. Aghion et al. (2019) recently concluded that migrants produce more patents than natives in the United States (see also Bernstein et al., 2019). However, little is known about this type of migrant's role outside the United States (Nathan, 2014). Therefore, migrant inventors should have a negligible direct influence on FDI as they are not employed as managers. Consequently, we adopt a 2S-IV procedure instrumenting patents with migrant inventors that should meet the exclusion restriction.

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

$$\ln FDI_{kijt} = \beta_1 \ln \widehat{\mathrm{PatStock}}_{ki\tilde{j}t} + \lambda_{it} + \lambda_{jt} + \lambda_{ij} + \lambda_k + e_{kijt} \tag{3a}$$

$$\ln \mathrm{PatStock}_{ki\tilde{j}t} = \beta_2 \ln \mathrm{MigraInvStock}_{kjit} + \lambda_{it} + \lambda_{jt} + \lambda_{ij} + \lambda_k + e_{kijt} \tag{3b}$$

[8]An important exception is Ortega and Peri (2014), who found that a substantial volume of the differences in TFP across countries could be accounted for migration. In this paper, among other mechanisms, they analyse the impact of migration on TFP through its effect on the production of patents per inhabitant, finding this contribution to be positive and significant. The evidence presented in that paper accords with our theoretical argument and can be seen as complementary. Instead, we analyse a different mechanism through which migrants affect FDI (destination-country specific innovation), finding empirical support for this type of innovation concept.

where FDI is the foreign capital investment from source country i in destination country j in sector k and year t. Patstock is the sum of our variable $Patent_{ki\tilde{j}t}$ for every year up to the year in which the firm has invested, so that when the firm invests in FDI, the firm can use all the stock of patents available for the firm at time t. Therefore, PatStock is the total stock of patents in sector k, developed in country i that proxy for the adaptive innovation production in country j in year t, as defined by Equation (2).[9] MigraInvStock is yearly aggregate sum of j-born individuals that filed a patent in country i and sector k in year t.[10]

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 complete 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. Still, it entails restricting the control variables, which have to be time-varying at the country pair level to prevent collinearity 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 theoretical framework, developed in Cuadros (2019), 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 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 it feasible to hedge against most known biases such as unobserved bilateral heterogeneity, multilateral resistance terms, zeros in the dependent variable and heteroscedastic residuals.[11] 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. (2020), which performs high-dimensional non-linear PPML estimation and implements 2S-IV in its OLS version:

$$FDI_{kijt} = \exp\begin{pmatrix} \beta_1 \ln \widehat{\text{PatStock}}_{ki\tilde{j}t} + \\ \lambda_{it} + \lambda_{jt} + \lambda_{ij} + \lambda_{kt} \end{pmatrix} + e_{ijkt}. \quad (4)$$

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 the right-hand side in stocks, which should mitigate endogeneity, in contrast to a specification with flows on both sides of the equation. Furthermore, recent

[9] We use the stock of patents because adaptive innovation may be performed more before the investment than in the year of the investment. PatStock aggregates the variable Patent. We have not added any depreciation rate to the stocks of patents under the assumption that the value of ideas does not depreciate over the period. We have performed, however, some tests with several depreciation rates (between 1% and 6% according to the production function estimates of Hall, 2005), and the empirical results remain unchanged.

[10] The data on migration inventors are reported in positive flows, and we have assumed a 1% yearly depreciation rate in the migrant inventors to characterise the stock of migrants accurately.

[11] See, for example, Yotov et al. (2016) for an thorough introduction to the gravity models, the empirical challenges, and how to address them.

research claims that the large amount of control variables in structural gravity models reduces the threat of endogeneity in dyadic variables (Beverelli et al., 2018; Rose, 2021). However, we cannot be entirely sure that such endogeneity does not affect this specification. To have consistent estimates, we check instrument validity, both for weak instrument bias and the exclusion restriction.

3.2 | Data sources

Gathering country-pair-sector data on FDI, R&D activities (i.e. investment in quality) and migration is a challenge. We collected 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 that serve as our proxy for migration in the R&D sector.

Our data set 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 & Paniagua, 2016; Costa-Campi et al., 2018). This source offers the advantage that the data are available at the firm level. We merged this data set with patent application data at the firm level provided by PATSTAT. Our sample contains yearly data for 1450 firms from 34 OECD countries with investments in 145 host countries in 19 sectors during the period 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 information is not available, so 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 data set created by Miguelez and Fink (2013). This data set 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). The applicants must disclose their current living address because they are required to be nationals or residents of the country from which the application is filed for the patent application to be considered. Since all applicants must also provide their nationality as an application requirement, migrant inventors can be identified as foreign inventors whose home address is in the application country. Besides, up to 2011, all patents which include the United States as a destination target (which, according to Miguelez and Fink's (2013), accounted for more than 80% of international patents) were obliged to include all inventors as applicants. Miguelez and Fink's (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 onto the migrant sector data. In practical terms, this means that we drop 8 sectors and match the sector and migrant types in Table 1.

Lastly, since our data set is aggregated from firm-level data, we have to reconstruct the data set 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 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	114,625	0	0.310***	0.415***	1
Migrant inventors	2.08	45.72	4620	0	0.246***	0.405***	0.254***

Notes: Yearly flows by country-pair-sector. FDI (intesive) in million USD.
*$p<.05$, **$p<.01$, ***$p<.001$.

3.2.1 | Data visualisation

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

Second, 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 reveal 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.

Third, multinationals' patents and migrant inventors are correlated as shown in Figure 3. The first steps towards showing the validity of the instrument are looking deeper into this positive correlation and then validating the exclusion restriction.

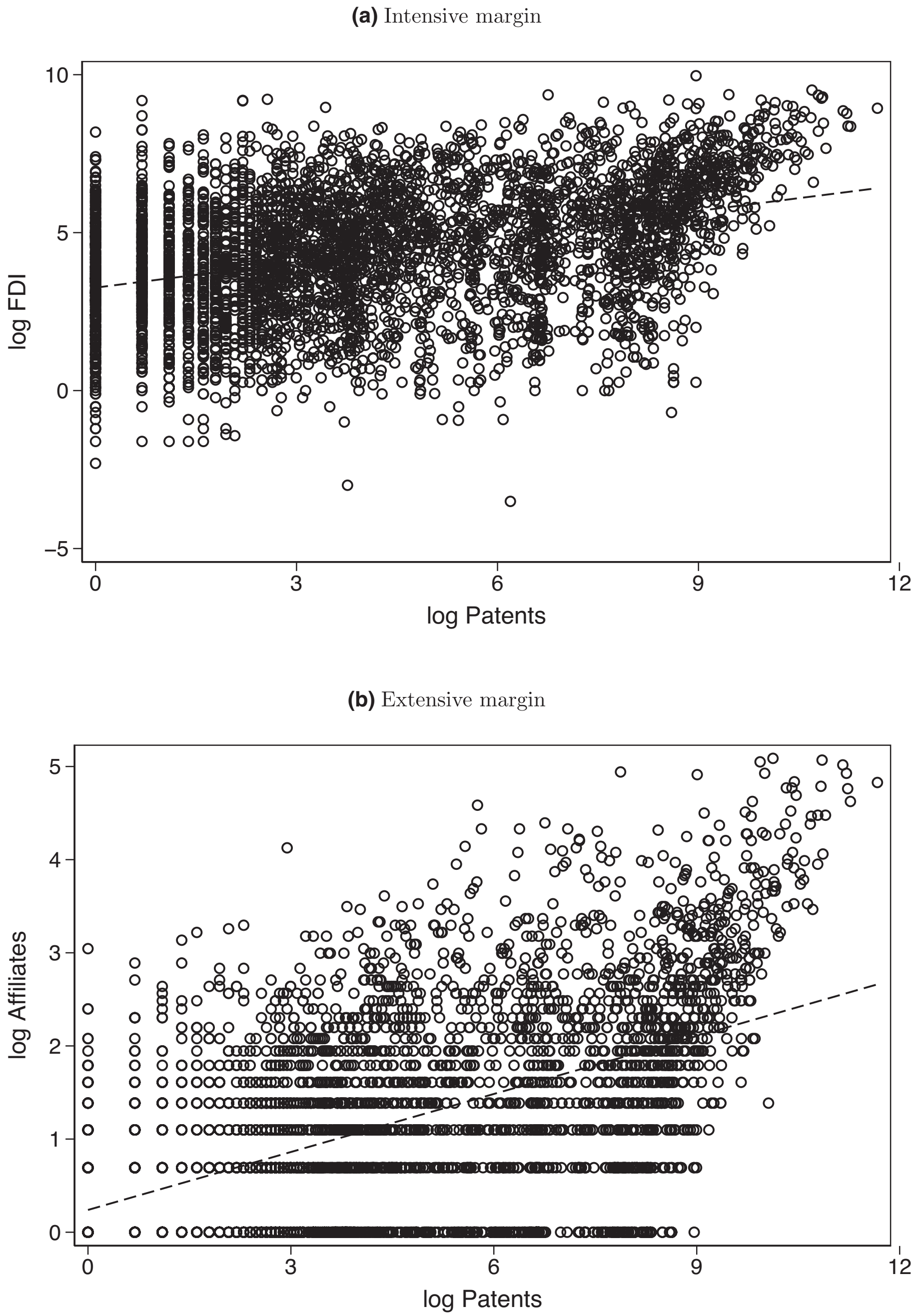

FIGURE 1 Patents vs FDI: Country pair correlation. (a) Intensive margin. (b) Extensive margin. Notes: Greenfield FDI data comes from FDIMarkets and patent data from Patstat

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 in the country of origin (without instruments). The empirical results are in line with our theoretical results. Columns 1 and 2

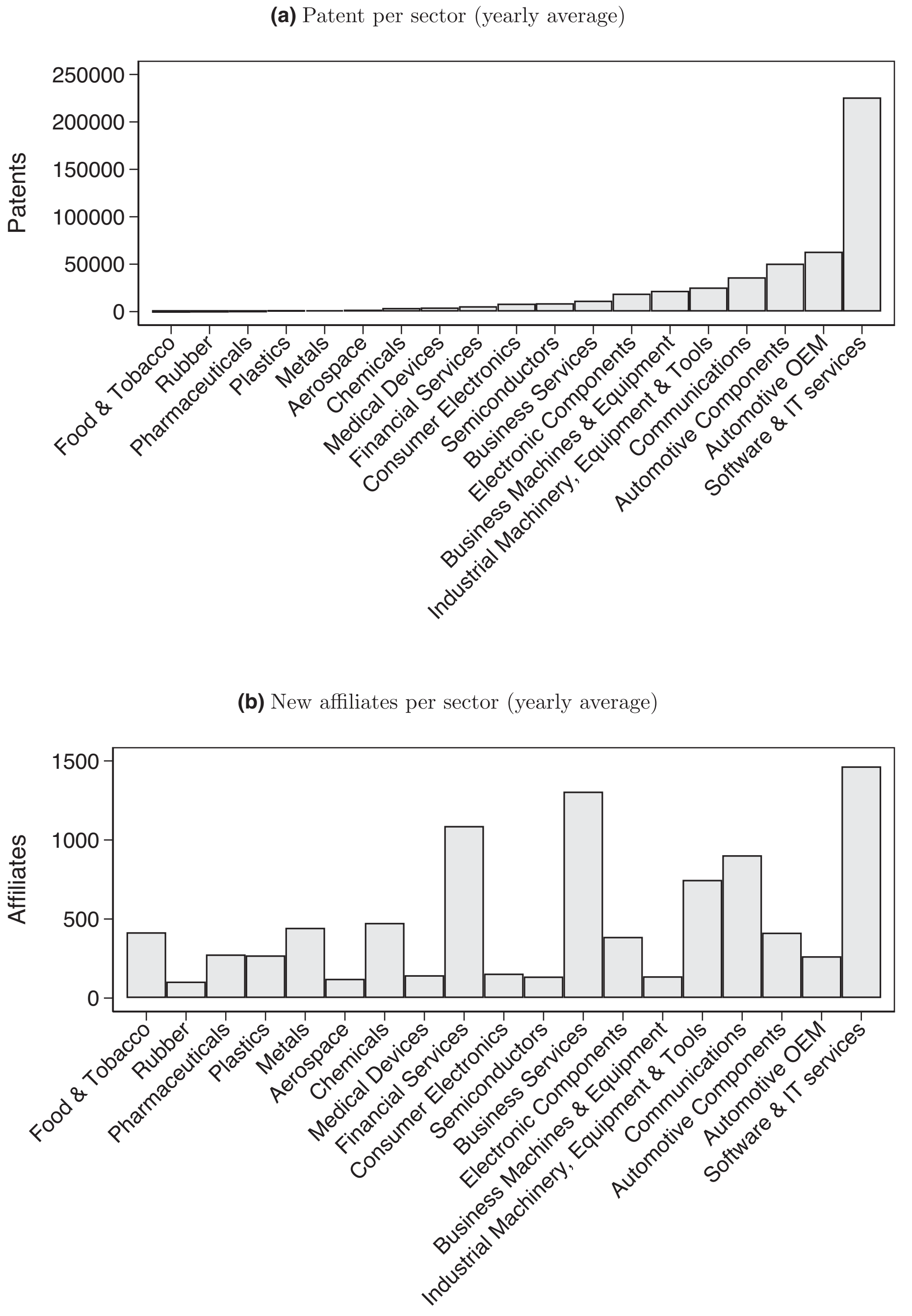

FIGURE 2 Patents and FDI: Trends. (a) Patent per sector (yearly average). (b) New affiliates per sector (yearly average). Notes: Greenfield FDI data comes from FDIMarkets and patent data from Patstat. Averages per sector and year, 2003–2012

report the results of the patent stock's effect on the intensive (total FDI flows) and extensive (the number of FDI affiliates) margins estimated using OLS. The marginal effect of patents is positive and significant, with a larger effect for the intensive margin. Part of the effect of patents on

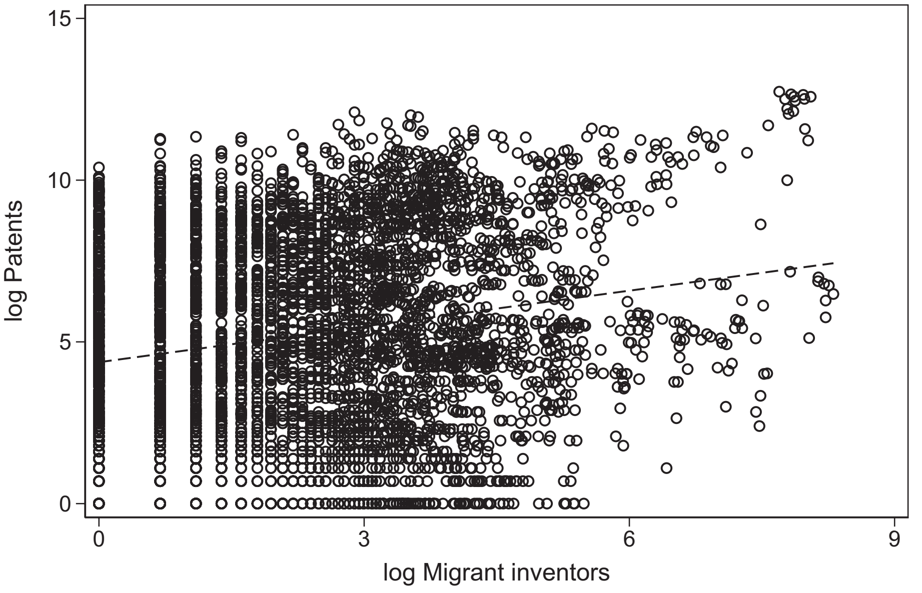

FIGURE 3 Migrant inventors and FDI

bilateral flows is attributable to the creation of new investment partners (extensive margin effect) and larger investments with existing partners (intensive margin).

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 of Table 3 and for the intensive margin and column 4 of Table 3 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 0.16% (OLS) and by 0.14% (PPML) on average. However, in the extensive margin, where the count nature of the dependent variable would advise a Poisson count model, we observe that the OLS coefficient (0.094) is significantly lower than the PPML coefficient (0.146).

In our theory, we considered a particular type of investment in innovation, which is destination 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 for both the intensive and the extensive margin. On the one hand, the intensive margin share is the volume of investment made by country i in 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 established by country i in 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 results in a relatively larger increase in FDI towards the country where those migrants are coming from. Conversely, if innovation was affecting all countries generally (as with a cost-reduction innovation, for example) the effect of patents on FDI will be the same across all countries and the shares will not be affected.[12]

[12]Furthermore, as noted by Larch et al. (2019), PPML places relatively more weight than OLS on large countries, which is partly corrected with a share specification.

TABLE 3 Baseline results

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS		**PPML**			
Dep. Variable →	**Int. Margin**	**Ext. Margin**	**Int. Margin**	**Ext. Margin**	**Int. Quota**	**Ext. Quota**
$\ln PatStock_{ki\tilde{j}t}$	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

Notes: Robust standard errors in parentheses, clustered by country pair.

*$p < .10$; **$p < .05$; ***$p < .01$.

TABLE 4 2S-IV gravity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	First stage (OLS)	**Second stage (OLS)**		**Second stage (PPML)**			
Dep. Variable →	**$\ln PatStock_{k\tilde{i}\tilde{j}t}$**	**Int. Margin**	**Ext. Margin**	**Int. Margin**	**Ext. Margin**	**Int. Quota**	**Ext. Quota**
$\ln MigraInvStock_{kjit}$	0.572***						
	(0.04)						
$\ln \widehat{PatStock}_{k\tilde{i}\tilde{j}t}$		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***						

Notes: Robust standard errors in parentheses, clustered by country pair.

*$p < .10$; **$p < .05$; ***$p < .01$.

Columns 5 and 6 of Table 3 report our results when we use the shares rather than the levels. In column 5, we used the investment share rather than the share of the invested capital volume, and in column 6, we employ the share of the total number of projects. 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 raises the share of the volume of FDI invested in existing subsidiaries by 0.14 percentage points and the share of expected investment in new plants by the same amount.

The baseline evidence presented in Table 3 supports the basic implications of the model. However, as discussed above, the patents are endogenous, and therefore, the estimates might be biased. The model proposes that migrants increase the laboratory's productivity; consequently, we use migrant inventors as an instrument, as discussed in the empirical section. The results of regressing patents against migrant inventors in (3b) and then FDI against the instrumented patents in (3a) 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 values and the Anderson LM statistic allows us to reject the null hypothesis of weak instrument and under-identification.

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

We observe larger results in terms of magnitude for the intensive margin: Increasing the number of patents by 1% increases the volume of FDI by 0.31% (2S-IV - Table 4 column 4) and by 0.14% (baseline - Table 3 column 3) on average. Similarly for the extensive margin: increasing the number of patents by 1% increases the volume of FDI by 0.37% (2S-IV - Table 4 column 5) and by 0.15% (baseline - Table 3 column 4) on average. The effect on FDI shares is similar: 0.289 versus 0.140 for the intensive margin and 0.307 versus 0.139 for the extensive margin.

The increase in the coefficient estimates is the indirect effect of migrant inventors, which we attributed to better performance in the country-sector-specific innovation. We compute the marginal effects of the stock of migrant inventors on FDI through its effects on patents. Column 1 reports the first stage results, in which the stock of patents is regressed on the stock of migrant inventors with a marginal effect of 0.572. Therefore, increasing the stock of migrant inventors by 1% should increase the intensive and extensive FDI margins by 0.18% and 0.22%, respectively.[13] These 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 (2022) report a marginal effect of 0.404 of patent stock on trade. Our results lie in between their highest 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 data set and econometric specification, Cuadros, Martín-Montaner, and Paniagua (2019) report marginal effects of 1.1 for migrant managers, 0.53 for professionals, and 0.6 for highly educated migrants, regardless of occupation.

Standard models of FDI and migration suggest that migrants in the host country reduce transaction costs and information asymmetries. Therefore, our baseline results may suffer from omitted variable bias. To address this, we introduce the flow of migrant inventors from the source to the destination (in a particular sector) in Table 5.[14]

[13]Calculated by $0.572 \times 0.311 = 0.178$

[14]We use the flow rather than the stock to prevent collinearity with the stock of migrants a the source. Furthermore, it might be possible that the effect of these migrants is not well identified due to endogeneity. However, we aim to control for their effect to identify our variable of interest better.

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
$\widehat{\ln\text{PatStock}}_{ki\tilde{j}t}$	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

Notes: Robust standard errors in parentheses, clustered by country pair.

$^*p < .10$; $^{**}p < .05$; $^{***}p < .01$.

TABLE 6 Sectoral results

	(1)	(2)	(3)	(4)	(5)	(6)
	Chemistry		Electrical engineering		Mechanical engineering	
$\widehat{\ln PatStock}_{ki\tilde{j}t}$	−0.013	−0.417	1.681*	0.568*	−0.330	−0.521
	(1.56)	(0.55)	(0.99)	(0.32)	(1.15)	(0.49)
$\ln MigraInv_{kijt}$	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

Notes: Robust standard errors in parentheses, clustered by country pair. PPML.
*$p<.10$; **$p<.05$; ***$p<.01$.

Focussing directly on our preferred PPML results in the last 4 columns of Table 5, we observe that the effect of migrant inventors in the host country is positive and significant, but only for the intensive margin. The coefficients are smaller 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 in the host country through patents (0.17). However, the impact of the host's migrant stock on the extensive margin is not significant. This means that the effect of migrant inventors is mostly amplified by their innovator and patenting role rather than by cost reduction when it comes to creating new investment partners.

Our empirical test of the model concludes in Table 6 with a sectoral decomposition of the variables to investigate additional sources of heterogeneity. It can be readily seen that the effect is only significant for electrical engineering (we report the second stage for brevity). In sectors where quality does not matter for the consumers, firms do not invest in quality. Furthermore, recall that electrical engineering was composed of Communications, Electronic Components, Software & IT, Consumer Electronics, and Semiconductors. These activities rely heavily on the quality and, more specifically, on adapting the quality to their end customers' tastes, language and culture worldwide.

4.1 | Validity and sensitivity analysis

This subsection presents validity tests for the exclusion restriction, external validity and sensitivity analyses. Our first test is to validate the exclusion restriction, which will not be fulfilled if there were alternative channels through which migrant inventors affected FDI. The estimates of the marginal effect of migrant inventor stocks on FDI presented in Table 7 suggests orthogonality between the instrument and the dependent variable.

The marginal effect of our instrument (the stock of migrant inventors in the firm's country of origin) is not significant for the intensive margin (in levels and shares) and in the share of the extensive margin. We do find, however, a significant and positive effect of the instrument for 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

TABLE 7 Instrument validity

	(1)	(2)	(3)	(4)		(5)	(6)
	Intensive Margin		**Extensive Margin**			**Int. Quota**	**Ext. Quota**
$\ln MigraInvStock_{kjit}$	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)
$\ln PatStock_{ki\tilde{j}t}$	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)
$\ln PatStock_{ki\tilde{j}t} \times \ln MigraInvStock_{kjit}$		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

Notes: Robust standard errors in parentheses, clustered by country pair. PPML.

*$p < .10$; **$p < .05$; ***$p < .01$.

TABLE 8 External validity: Out of sample estimates

	(1)	(2)	(3)	(4)
	Second stage (PPML)			
Dep. Variable →	Int. Margin	Ext. Margin	Int. Quota	Ext. Quota
$\ln\widehat{\text{PatStock}}_{ki\tilde{j}t}$	0.217**	0.257***	0.192**	0.231***
	(0.09)	(0.03)	(0.08)	(0.03)
Observations	26,977	26,977	26,977	26,977
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

Notes: Robust standard errors in parentheses, clustered by country pair.
*$p < .10$; **$p < .05$; ***$p < .01$.

absorbed by the interaction. This means that migrant inventors have a positive effect only for 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 attributed 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 8, we estimate a larger sample by predicting all possible patents for all sector-country-pairs. This considerably increases the number of 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.

Our final exercise presents some sensitivity analyses. Our stock variables are constructed with initial values that might not represent the stocks if prior distributions of migrants or patents were structurally different. However, we are not particularly concerned about this issue, since the technological cycles of companies in the sectors considered here are generally shorter than the time span used to construct our stock data. Additionally, adaptive innovation may occur before the investment and, therefore, we lag the flow variables one period.

Table 9 reports 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.

5 | CONCLUSIONS

This paper examines a new channel through which globalisation may affect MNEs, namely migration-fueled innovation. Foreign inventor enhances firms' adaptive innovation strategy, increasing the firm's multinational investment.

TABLE 9 Robustness: Variables in flows

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	First stage (OLS)	**Second stage (OLS)**		**Second stage (PPML)**			
Dep. Variable →	**$\ln PatStock_{k\tilde{i}\tilde{j}t}$**	**Int. Margin**	**Ext. Margin**	**Int. Margin**	**Ext. Margin**	**Int. Quota**	**Ext. Quota**
$\ln MigraInv_{kjit-1}$	0.580***						
	(0.09)						
$\ln \widehat{Pat}_{k\tilde{i}\tilde{j}t-1}$		0.395***	0.252***	0.235***	0.067**	0.224***	0.460 ***
		(0.10)	(0.05)	(0.05)	(0.03)	(0.05)	(0.03)
$\ln MigraInv_{kijt}$		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***						

Notes: Robust standard errors in parentheses, clustered by country pair.

$^{*}p<.10$; $^{**}p<.05$; $^{***}p<.01$.

We perform a theoretically consistent estimation of the effect of innovation on FDI by using migrant inventors as the instrument for a firm's investment in innovation. Our gravity estimates on a novel FDI-patent-migration data set at the country-pair-sector level reveal significant and sizable effects. Robustness checks confirm the results and validate the instrument.

This paper makes several different contributions to the existing literature on the effects of migration on innovation and FDI. First, using a theoretically consistent estimation strategy, it proposes a novel instrument to estimate destination-specific effects of innovation on FDI. Second, the study broadens the existing literature by providing multi-country evidence. Besides, we identify the indirect effects of migrant inventors rather than ethnic innovators.

The outcomes reported in this paper may help to design and evaluate migration policies associated with innovation policies (e.g. efforts to attract talent). This question seems to be particularly important in the current situation of increasing economic and policy uncertainty. Our paper reveals that migrants can boost the internationalisation activities of the firms in their host country by alleviating informational issues and shaping their innovation strategy. Recent work has outlined the importance of talent allocation for economic growth (Hsieh et al., 2019). We believe that further contributions to this direction constitute a fruitful future research avenue.

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DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from FDIMarkets (The Financial Times Ltd). Restrictions apply to the availability of these data, which were used under license for this study. Data are available from www.fdimarkets.com.

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APPENDIX

A | Theoretical Appendix

In this section, we briefly describe the preferences and technology behind the gravity Equations (1a) and (1b). These functional forms will help the reader to understand each of the parameters discussed in the gravity equations provided in the main section of the paper.

The model developed in Cuadros, Paniagua, and Navas (2019), which provides a full formal derivation of the equations, is a multi-country multi-sector model of trade and FDI with firm heterogeneity. There are J small open economies. In each of these countries, $K+1$ final goods are produced, denoted with subscript k. The Consumers derive utility from the consumption of these goods. The following Cobb–Douglas utility function describes preferences across these goods:

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

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,

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

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 have the case of the traditional CES utility function used in the gravity literature (see, Anderson & Van Wincoop, 2003; Chaney, 2008, among others).

The homogeneous good is produced in perfect competition using labour and a constant returns to scale technology represented by the following production function $q_{0i} = \varphi_i' L_{0i}$. Let $\varphi_i' = \varepsilon_i$ denote the productivity of country i in the homogeneous good. The assumption of perfect competition together with linear technology implies 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 labour. Firms in each sector produce goods 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' Total Factor Productivity (TFP) and, as it is common in the literature on firm heterogeneity, we assume 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 labour 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 its productivity from a common productivity distribution which follows a Pareto functional form. More precisely, we have:

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

where κ controls for the degree of productivity dispersion. The ingredients presented in this section should be sufficient for identifying each of the parameters that enter the gravity equations described above. For specific details about the computations and the other ingredients of the theoretical see Cuadros, Paniagua, and Navas (2019).

B | Empirical Appendix: Robustness

This section contains several robustness checks which aim to reinforce the empirical analysis presented in the main manuscript. The data set is rich in country and sectoral variation, which allows us to include different combinations of fixed effects. Table B1 allows the country pair and sector characteristics to be time-variant. The results obtained align with the previous results in terms of magnitude, sign, and statistical significance.

The analysis continues by using a different instrument, then involves checking the exclusion restriction and ends by specifying the variables in flows instead of stocks. We have also weighted the patents by family size, that is 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 the sake of brevity.[15]

Instead of using migrant inventors, we instrument patents with the stock of foreign population by nationality and the stock of foreign labour by nationality sourced from the DIOC-E

TABLE B1 Robustness: Fixed-effects

	(1)	(2)	(3)	(4)
	Second stage (PPML)			
Dep. Variable →	**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

Notes: Robust standard errors in parentheses, clustered by country pair.
*$p < .10$; **$p < .05$; ***$p < .01$.

[15]Results are available upon request.

TABLE B2 Robustness: Non-migrant inventors (2SLS)

	(1)		(2)	(3)	(4)	(5)
	First stage		Second stage (Migrants)		Second stage (Labour Migrants)	
Dep Variable	$\ln PatStock_{\tilde{i}\tilde{j}t}$		**Intensive Margin**	**Extensive Margin**	**Intensive Margin**	**Extensive Margin**
$\ln Migrants_{jit}$	−0.003					
	(0.06)					
$\ln LaborMigrants_{jit}$		−0.028				
		(0.15)				
$\ln \widehat{PatStock}_{\tilde{i}\tilde{j}t}$			0.982	−16.880	−5.993	−3.097
			(26.22)	(252.57)	(33.66)	(17.03)
Observations	8242	1326	8242	8242	1326	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				

Notes: Robust standard errors in parentheses, clustered by country pair.

*$p < .10$; **$p < .05$; ***$p < .01$.

data set from the OECD. We do so to obtain more evidence that the innovation-migration mechanism 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 B2. First, the IV post-estimation statistics reveal that the instrument choice is rather weak in both cases. Furthermore, there is no significant relationship between the stock of migrants or labour 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.