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Abstract

In this paper, we assess whether attracting higher amounts of FDI induces a greater level of economic complexity in a country. Using a panel of 117 countries and 22 years, from 1995 to 2016, we test for the causal relationship between inward FDI and economic complexity using a panel Granger causality approach. We also estimate the short-run relationship between these two factors using a panel vector autoregressive model and an impulse response function approach. We find that accumulating a higher stock of inward FDI per capita Granger-causes a greater economic complexity in a country, and not vice versa. This causal effect is very small, however, and occurs only in countries with above average levels of GDP per capita, tertiary education, tertiarization or financial development. Looking at the FDI entry mode, we find that only greenfield FDIs Granger-cause economic complexity in developed countries, whereas mergers and acquisitions have no such effect. Finally, we find that knowledge-intensive greenfield projects are the only form of inward FDI that Granger-cause complexity in a less developed country, but the estimated effect is near zero and disappears after two years.

Keywords: economic complexity, foreign direct investment, panel Granger causality, panel VAR

JEL codes: C23, F21, F23, O19, O33

1. Introduction

This paper examines the existence of a causal relationship between inward foreign direct investments (FDI) and the degree of a country's economic complexity. Recent literature has suggested that what countries produce and export matters in shaping their growth patterns (Hausman and Rodrik, 2003; Hausman, Hwang and Rodrik, 2007): countries specializing in, and exporting, goods and services that are associated with a higher productivity or more sophisticated grow faster than others. The idea is simple: the underlying process of entrepreneurial discovery entails a series of costs that originate from the host economy's level of market uncertainty. The cost discovery process is subject to relevant knowledge externalities: in the case of successful entrepreneurial projects, other entrepreneurs can benefit from this information and engage in the profitable production of new goods. The larger the number of these entrepreneurs in the economy, the larger the number of high-productivity goods a country can produce, thus reducing the technology gap vis-à-vis more advanced economies. The policy implication is that stimulating risky entrepreneurial activities can increase the average degree of product sophistication in a country, thereby stimulating economic growth.

One way for developing countries to trigger such a cost discovery process, and improve the average sophistication of their products, is to attract FDI. Given the extent to which higher amounts of incoming FDI increase average product complexity, and this in turn stimulates economic growth, we can trace an indirect link between FDI and economic well-being, especially in less-developed countries.

Various studies have emphasized the mechanisms by which the operations of multinational enterprises (MNEs) can increase the quality of exports from developing regions. First, MNEs can use a country as an export platform, directly producing and exporting goods of higher quality than those produced domestically (Javorcik, 2004; Iacovone and Javorcik, 2008). There are three main reasons why: (i) on average, MNEs make better-quality products than their domestic rivals because they are endowed with more skills and technology; (ii) MNEs use high-quality inputs, helping local suppliers to upgrade their production standards, or indirectly making these inputs available to domestic competitors; (iii) MNEs can transfer technology, skills, managerial and organizational practices to local domestic suppliers, partners, and even rivals. A second explanation concerns the knowledge spillovers that come from MNEs' operations in the recipient economy (Rojec and Knell, 2018). So far, there have been reports of mixed results as regards the effect of FDI on product/export complexity. Positive spillovers can originate from two phenomena: (i) learning externalities from imitation and/or interaction between MNE affiliates and local firms (Javorcik, 2008; Brambilla et al., 2009; Swenson and Chen, 2014); or (ii) the adoption of higher production standards by local suppliers that become part of the MNEs' value chain (Iacovone et al., 2015), or the domestic rivals' improvements in productivity needed to compete with the global players.

The choice of location and presence of MNEs can also have negative consequences for the incumbent activities in the host countries, however. Greater exposure to MNEs can elbow out existing activities because of the increased competition in a given product market, or due to a rise in wages and input prices, or because MNEs' greater bargaining power may force local competitors to adopt cost-saving strategies (De Backer and Sleuwaegen, 2003).

Ultimately, whether attracting more FDI induces an increase in a country's average degree of economic complexity remains a matter of empirical research. In this paper, we adopt a panel Granger causality, and a panel vector autoregressive (VAR) model with an impulse response function (IRF) to test the direction of causality and the magnitude of the relationship between FDI and economic complexity for a sample of 117 countries over a period of 22 years. We also check for heterogeneity in the results by ranking the countries according to a series of variables that capture different aspects of their level of development, such as GDP per capita, tertiary education, degree of tertiarization, and level of financial development. We test whether the results can be affected by the type of FDI, separating mergers and acquisitions (M&A) from greenfield projects, looking at the business activity underlying the greenfield investment, distinguishing knowledge-intensive business services, R&D, design and ICT-related activities from other types of greenfield FDI, like those involving manufacturing operations.

Judging from our estimates, increasing the amount of inward FDI per capita Granger-causes an increase in a country's economic complexity. This result only holds, however, in countries with above average levels of GDP per capita, tertiary education, tertiarization or financial development, and only in the case of inward greenfield FDI. When we consider the business operations underlying the latter, we find that higher inflows for greenfield projects in knowledge-intensive activities (e.g. business services, R&D, design and ICT-related activities) are the only type of FDI that Granger-cause a greater economic complexity in countries with below average levels of development. Their estimated effect is small, however, and tends to zero within a few years. Our results point to a causal relationship between (greenfield) inward FDI per capita and economic complexity, but this relation holds only in the short term, and is small in magnitude.

The paper develops as follows. Section 2 presents the empirical literature on the determinants of economic complexity. Section 3 outlines our empirical strategy, with Section 3.1. describing the data, and Section 3.2 our econometric approach. In Section 4 we report our results. Section 5 discusses the results and concludes.

2. Related literature

The empirical evidence on the impact of MNEs, and FDI, on the quality of domestic production and exports is ambiguous. On the one hand, Brambilla (2009) finds that foreign subsidiaries of MNEs operating in China in 1998-2000 tended to introduce more than twice as many new goods as their domestic private rivals, to achieve higher sales from new varieties of goods, and to have a 3-6% advantage in the development costs of these products. Still on China, Swenson and Chen (2014) found that proximity of domestic firms to own-industry foreign MNEs raised the new export transaction prices, i.e. the unit values of new exports, and their frequency. Using panel data on Spanish manufacturing firms concerning the years between 1990 and 2006, Guadalupe et al. (2012) found that foreign-owned enterprises tended more than their domestic competitors to acquire the best firms within industries and, once they had done so, they tended to invest more in process and organizational innovation to increase the production and exports of new goods.

On the other hand, Wang and Wei (2008) found no significant role for inward FDI in raising the level of sophistication of Chinese exports, which was triggered instead by greater endowments of human capital, and by domestic policies such as the establishment of special high-tech zones with favorable tax conditions.

Harding and Javorcik (2012) reported mixed findings. In a sample of 105 countries, and considering the years between 1984 and 2000, they investigated whether attracting FDI increased the average quality of exports, with a focus on developing countries. Their estimates show a positive causal relationship between inward FDI and the unit value of these countries' exports. This relationship is no longer statistically significant, however, when they measure the degree of export sophistication with the Hausman et al. (2007) index, capturing the income associated with each export basket.

More recently, in a study on Turkish manufacturers in the years 2006 to 2009, Javorcik et al. (2018) showed that the firms' ability to upgrade the quality (and consequent complexity) of their products depended on the amount of inward FDI in downstream sectors in the region. MNEs act as agents of structural change (Neffke et al. 2018) and innovation by improving the average level of firms' product sophistication.

Inspired by this last study, we examine the effect of inward FDI on the level of product sophistication of a country's exports, as captured by its level of economic complexity.

In the last two decades, the concept of economic complexity has come back to the fore in economic disciplines. Starting from the seminal contributions of Hidalgo et al. (2007), and Hidalgo and Hausmann (2009), this concept has been increasingly associated with that of economic development. In the above-mentioned Authors' framework, complexity arises as the outcome of two factors: the diversity of a country's product/export portfolio; and the ubiquity of a product, which is greater the fewer the countries producing or exporting it. The underlying mechanism is that countries differ in their level of economic complexity, and therefore of their economic development, because they are endowed with different sets of skills and capabilities.

Adopting this framework, many scholars have tried in the last few years to judge the role of economic complexity in explaining aggregate economic outcomes, like growth in GDP per capita or income inequality (among others, see Hidalgo and Hausmann [2009], Felipe et al. [2012], Ferrarini and Scaramozzino [2016], Pugliese et al. [2017], Gao and Zhou [2018], and Sbardella et al. [2017, 2018]). Other studies have recently looked at the possible role of economic complexity in affecting a country's ability to diversify its product portfolio, or develop new specializations in unrelated industries (Pinheiro et al. 2018).

All these papers use complexity as an exogenous predictor, however, and postulate that it is a path-dependent process where the development of new products, or industries, is the outcome of a process that recombines existing skills and capabilities (Hidalgo et al., 2007). In other words, no study clearly explains why countries differ in their degree of knowledge complexity, or why some countries improve their level of economic complexity faster than others.

This paper tries to fill this gap by identifying one possible driver of economic complexity, focusing specifically on FDI. There are two mechanisms by which inward FDI can increase the degree of economic complexity in a country. One lies in that attracting more FDI can make countries increase the number of products for which they have a comparative advantage, which means further diversifying their product portfolio. The other lies in that, thanks to MNEs' superior technological endowment and greater innovativeness (compared with the average domestic firms), FDI can stimulate product innovation in a country, reducing the ubiquity of products in the world, and favoring the technological specialization of some countries rather than others. On the other hand, if FDI crowd out incumbent domestic activities and products without replacing them with new or technologically improved ones, then the aggregate level of economic complexity might be unaffected, or even reduced.

From an empirical standpoint, the impact that FDI might have on host economies has been investigated in several papers, using both macro- and micro-level data, and looking at both developing and developed countries (for a survey, see Iršová and Havránek [2013], and Rojec and Knell [2018], among others). Only two studies discuss the likely effect of FDI on economic complexity, however. The first, by Sweet and Eterovic Maggio (2015), examines whether a stronger intellectual property rights (IPR) system triggers aggregate innovation, proxied by the economic complexity index, in a sample of 94 countries over forty years, from 1965 to 2005. Their system GMM estimates show that more stringent IPR laws improve a country's ability to increase the level of sophistication of its products, but this only holds for countries where the levels of development, human capital and complexity are already high. These authors also include the yearly FDI inflow as a control variable in their estimates, but the corresponding estimated coefficient is not statistically significant. The second study, by Balland et al. (2020), finds a strong correlation between higher levels of complexity of the economic activities and greater spatial concentrations of activities, and technology, in US large cities.

3. Empirical analysis

3.1. Data

Our data on yearly inward FDI stocks (in millions of US dollars, from 1995 to 2016) come from the Annex Tables of the UNCTAD World Investment Report Database. According to the UNCTAD, these data correspond to the sum of the values of the shares of capital and reserves (including retained profits) attributable to a parent company and the net indebtedness of its affiliates. This corresponds approximately to the accumulated value of past FDI flows. To normalize the variable across countries, we divide it by total resident population, obtaining a measure of inward FDI stock per capita (*FDI*). We choose population, not GDP, as the denominator to avoid any potential correlations with our dependent variable, which would make the relationship between economic complexity and FDI endogenous by construction.

We also use data that enable us to differentiate the mode of entry of FDI: the value of inward announced greenfield FDI (in millions of US dollars) between 2003 and 2016, available on the UNCTAD website and coming from FDI markets; and the value of net cross-border mergers and acquisitions (M&A) by country of the seller, available from the UNCTAD cross-border M&A database for the whole period (1995-2016). While the former represents new investments (i.e. new plants, new activities) that a developing country attracts from scratch, the latter captures changes of ownership of existing activities, and possibly of their control and management. To build the corresponding stocks, we simply calculate the sum of the values of incoming greenfield FDI and M&A flows by country and year, applying the perpetual inventory method without depreciation[1]. To account for the size of the recipient country, we also divide both variables by the corresponding

[1] We also re-computed our greenfield and M&A FDI stock per capita using the perpetual inventory method with a 10% rate of depreciation for capital assets, finding no significant difference in the results.

stock of resident population, then proceed with the logarithmic transformation (*ln*M&A and *ln*GREEN)[2].

We merge this information with data on countries' economic complexity from the Atlas of Economic Complexity (http://atlas.cid.harvard.edu/) provided by Harvard University to obtain a ready-to-use economic complexity index (ECI). This index is computed using trade data from UN COMTRADE, and merging two elements: the number of products that a country can manufacture with its set of internal capabilities (*diversity*), and the number of countries that can manufacture a given product (*ubiquity*). The overall economic complexity of a country is obtained applying the method of reflections and is greater the higher the diversity of its product basket and/or the lower the ubiquity of its products.

Although it is computed starting from the "diversity" index, Kemp-Benedict (2014) and Mealy, Farmer and Teytelboym (2019) demonstrate that the ECI and the initial knowledge diversity index ($k_{c,0}$) are orthogonal. This means that the ECI captures a different kind of information from diversity: it is closely related to countries' specialization in high- or low-quality products, where high-ECI countries specialize more in technologically-advanced products, whereas low-ECI countries specialize in poorer-quality, more traditional products. Since the index originally ranges between -2.5 and +2.8, we reparametrize it as follows to obtain an index that varies between 0 and 1: $(ECI - \min)/(max - \min)$; then, we take its natural logarithm (*ln*ECI).

We also collect a set of information that captures different aspects of a country's level of development, drawn from the World Bank's World Development Indicators database. We consider GDP per capita in 1995, measured at constant 2010 US dollars. Then we look at education, defined as the proportion of the population (aged 25 years and over) that had completed at least a short

[2] We converted the few negative values in M&A and greenfield FDI to zero, and applied the logarithmic transformation adding one to their value.

cycle of tertiary-level education in 1995, considering this as a proxy for the level of human capital in a country and its capacity to absorb foreign investments (Borensztein et al., 1998). Third, we examine a country's degree of tertiarization, computed as the share of value added to GDP by services (S) vis-à-vis the sum of the shares of value added by manufacturing (M) and agriculture (A) (i.e. S/(M+A) in 1995. The higher this ratio, the greater the weight of services compared with the other two branches of economic activity. This variable can be taken either as a proxy for the level of a country's development (in line with the Fisher-Clark tertiarization hypothesis), or as a rough proxy for the degree of a country's diversification, that cannot be captured in other ways due to a lack of data on the sectoral composition of countries' economies. As a fourth measure, we use a proxy of the stage of development of a country's financial system. Following Alfaro et al. (2004), we adopt the *broad money* (BM) variable, which measures a country's liquid liabilities vis-à-vis its GDP, giving us a broad idea of the overall size of a country's financial system, without distinguishing between the different financial sectors. The BM variable is the sum of the amounts of currency outside banks, deposits other than those of the central government, savings and foreign currency of the resident sectors, bank and traveler's checks, and other securities. For this variable we take the average for the years 1993-1995 because of some missing observations in year 1995. According to Alfaro et al. (2004), it is in countries with a high level of financial development that the growth-enhancing effect of FDI is stronger.

Our final sample consists of 117 countries and spans 22 years (1995-2016)[3], for a total of 2,574 observations (the full list of countries is in the Appendix, Table A1). Figure 1 shows the evolution of inward FDI per capita, inward M&A per capita, and inward greenfield projects per capita (panel A), and of the ECI (panel B) for all countries. As expected, all the FDI stocks increase over time, while

[3] When referring to greenfield FDI, the sample is reduced to 117 countries and 14 years (2003-2016) for a total of 1,638 observations.

the ECI is quite volatile, and characterized by different trends: it decreases until the 2008 financial crisis, and increases afterwards.

FIGURE 1 ABOUT HERE

3.2. Econometric strategy

3.2.1. Unit root tests

Preliminary to the Granger causality analysis, we test for the stationarity of ln*FDI*, ln*M&A*, ln*GREEN*, and ln*ECI*. The so-called first-generation panel unit root tests are the most often used, but they are sensitive to the cross-sectional dependence that emerges because of shocks common to groups of countries, or because of spillovers across countries. The asymptotic convergence to normal distribution of the estimators of the first-generation panel unit root tests assumes that all the units of the panel are independent, so these first-generation tests are not reliable if there is cross-sectional dependence. To avoid this problem, we use a second-generation panel unit root test developed by Pesaran (2007), based on the Im, Pesaran and Shin (2003) unit root test.

To detect the presence of a unit root, we estimate the following equation:

(2) $\Delta y_{it} = \beta_i y_{it-1} + \gamma_i \overline{\Delta y_{it}} + \delta_i \overline{y_{it-1}} + \mu_i + \varepsilon_{it},$

which involves extending the individual augmented Dickey-Fuller (ADF) regressions with the cross-sectional means of the lagged levels and first differences of the individual regressor *y* (*ln*ECI, *ln*FDI, *ln*M&A, and *ln*GREEN, respectively) that are used as proxy for the unobserved common factors. The null hypothesis is that β_i=0, which is tested by averaging the t_i statistics corresponding to β_i in equation 2 (Pesaran, 2007; Burdisso and Sangiacomo, 2016). The alternative hypothesis is that β_i<0 for *i*=1,2,…,M and β_i=0 for *i*=M+1, M+2,…, N (with M<N).

The test is called the cross-sectional Im, Pesaran and Shin (CIPS) test, and it is based on the null hypothesis that the variable under investigation has a unit root. We first test for the presence of a unit root in our focal variables in levels, and then in their first differences. If the test does not reject H_0 when variables are in levels, but it does reject it when they are in first differences, we conclude that they are integrated of order 1, or non-stationary. If the test rejects the null hypothesis both when the variables are in levels and when they are in first differences, we conclude that they are integrated of order 0, or stationary. Table 1 shows the results of the CIPS tests, where we include a linear trend and an intercept.

TABLE 1 ABOUT HERE

For all three FDI variables in levels, the CIPS test never rejects the null hypothesis of non-stationarity, whereas it does reject it (at 1% level) for the variables in first differences. We therefore conclude that all our FDI variables are I(1), i.e. with a trend characterized by the presence of a unit root. Conversely, the CIPS test strongly rejects H_0 when economic complexity is measured in both levels and first differences, implying that *ln*ECI is I(0).

Since the Granger causality test requires variables to be stationary, we transform all of them into first differences and we test whether the growth rate in the stock of inward FDI per capita (Δ*ln*FDI, Δ*ln*M&A, Δ*ln*GREEN) Granger-causes the growth rate in a country's economic complexity (ΔlnECI).

3.2.2. The panel Granger causality test

The starting equation used to analyze the causal relationship between inward FDI and economic complexity is as follows:

(1) $\Delta lnECI_{it} = \alpha + \sum_{k=1}^{K} \beta_k \, \Delta lnECI_{it-k} + \sum_{k=1}^{K} \gamma_k \, \Delta lnFDI_{it-k} + \epsilon_{it}$

where i=1, …, N refers to the country, t=1,…,T to the year, and ϵ is the stochastic error term. To apply the Granger causality tests, both Δln*ECI* and Δln*FDI* must be stationary. In this case, Δln*FDI* Granger-causes Δln*ECI* if the past values of Δln*FDI* can predict the current values of Δln*ECI*, even once the past values of Δln*ECI* have been included in the model. This happens when the coefficients γ_k jointly differ statistically from zero. By swapping the two variables, we can test for causality in the opposite direction. In the Dumitrescu-Hurlin (2012) version of the Granger causality test, all the coefficients can vary across countries, but are invariant over time. The null hypothesis becomes:

(2) $H_0: \gamma_{i1} = \gamma_{i2} = \cdots = \gamma_{iK} = 0 \qquad \forall \, i = 1, \ldots, N$

which corresponds to the absence of causality for all the countries in the dataset. The alternative hypothesis is that there can be causality between Δln*FDI* and Δln*ECI* for some countries, but not necessarily for all of them. The test works as follows. After running the *N* individual regressions in (1), we perform the F-test of the *K* linear hypotheses in (2), and generate the individual Wald statistics W_i. Then we compute the average Wald statistic[4].

With large *N* and large *T*, Dumitrescu and Hurlin (2012) show that the standardized statistics $\bar{Z}$ follows a standard normal distribution. For panels with large *N* and small *T* (with $T > 5+3K$), however (as in our case), the test uses an approximated standardized statistic $\tilde{Z}$, which is normally distributed too. We choose the optimal lag order *K* using the whole sample of countries and the Akaike

[4] We adopt the user-written package *xtgcause* provided by Lopez and Weber (2017) for Stata 15.

information criterion. We also use the bootstrap procedure with 1000 replications, as suggested by Dumitrescu and Hurlin (2012), to avoid any cross-sectional dependence across countries.

We test for the opposite direction of causality, from Δln*ECI* to Δln*FDI*, as well. If the test rejects the null hypothesis, we conclude that FDI and economic complexity do influence one another. On the other hand, if the test does not reject H_0, this means that causality only runs from FDI to economic complexity.

To check for the general validity of our results, we also perform the Granger causality tests on four subsets of countries, selected on the basis of aggregate indicators of economic development like GDP per capita, tertiary education, tertiarization, and financial development. For each of these indicators, we compute the mean value in 1995 and we distinguish between countries with values above and below the mean[5].

3.2.3. Panel VAR and Impulse Response Function

Having established the Granger causality, we estimate the short-run relation between inward FDI per capita and economic complexity using a panel vector autoregression (PVAR) estimator, and the GMM approach suggested by Holtz-Etkin, Newey and Rosen (1988). We estimate the following equation:

(3) $lnECI_{it} = \sum_{k=1}^{K} \beta_k \, lnECI_{it-k} + \sum_{k=1}^{K} \gamma_k \, lnFDI_{it-k} + \mu_i + \epsilon_{it}$

[5] We also tested for the robustness of our results using the median of GDP per capita, tertiary education, and tertiarization in 1995, finding no relevant difference in the results, apart from education (see footnote 6).

where μ_i represents the vector of country-specific fixed effects, and ε_{it} the vector of idiosyncratic errors. Before proceeding with the estimation, we remove the fixed effects by first differencing each variable in equation 3, and we subtract their cross-sectional mean to remove time-specific fixed effects. Then we use the model selection criteria proposed by Andrews and Lu (2001) to find the optimum time lag *p*, which is based on three model selection criteria: the Akaike information criterion; the Hannan and Quinn information criterion; and the Bayesian information criterion. We apply the panel GMM approach, using lagged values (i.e. up to the fourth lag) of *ln*ECI and *ln*FDI as instruments to obtain consistent estimates of the coefficients.

We follow Lutkepohl (2005) to check for the stability condition of our PVAR model, and we compute the modulus of each eigenvalue of the estimated model. The model is stable if all moduli of the companion matrix are less than one or lie inside a unit circle. Figure A1 in Appendix confirms the stability of our PVAR model. Then we repeat the process, replacing the total stock of inward FDI per capita with the stock of inward M&A and greenfield FDI per capita.

Starting from our PVAR model, we also look at the impulse response functions (IRF), which describe the reaction of economic complexity to a one-standard-deviation (orthogonalized) shock in inward FDI per capita over a period of ten years. Standard errors and confidence intervals are computed using 200 Monte Carlo simulations.

4. Results

4.1. Granger causality

Table 2 shows the results of the Granger causality test on the full sample. We test both directions of causality, first from Δ*ln*FDI to Δ*ln*ECI, then from Δ*ln*ECI to Δ*ln*FDI. Then, we repeat the process for Δ*ln*M&A and Δ*ln*GREEN. In the first row, we find the p-value of the $\widetilde{Z}$ statistic significant (at 5% level) only in the case of Δ*ln*FDI, whereas it is not statistically significant when we divide the total FDI stock per capita into M&A and greenfield FDI. In the second row, the $\widetilde{Z}$ statistic is never significant. This implies a causality relationship from increasing inward FDI to increasing economic complexity, and not vice versa. In other words, higher stocks of inward FDI per capita Granger-cause economic complexity.

TABLE 2 ABOUT HERE

Table 3 shows the results of the Granger causality test after splitting the sample of countries by level of GDP per capita, education, tertiarization and financial development. We find the $\widetilde{Z}$ statistic significant (at 5% level) for: (i) countries with a GDP per capita, a proportion of tertiary-level educated population[6] (only in the case of greenfield FDI), a degree of tertiarization and of broad money above the mean; (ii) when the direction of causality is from inward FDI to economic complexity, and not vice versa; and (iii) in the case of total inward FDI per capita and greenfield FDI per capita. We find no evidence of a causal relationship between economic complexity and M&A. Here again, these findings support the hypothesis that attracting FDI Granger-causes economic complexity in a country, especially if the mode of entry is through greenfield projects. We also find, however, that such a relationship holds not for all countries, but only for those with an above average level of development.

TABLE 3 ABOUT HERE

[6] We find that the test rejects the null hypothesis (at 5% level) of no Granger causality when we consider countries as having a “high education level” when their share of tertiary-level educated population is above the median, while the null hypothesis is not rejected for countries with a share of tertiary-level educated population below the median.

As a further step, we investigate whether the type of activity underlying the stock of inward FDI can affect our results. To do so, we exploit the information provided by the fDi Markets dataset administered by The Financial Times Limited, which unfortunately only refers to greenfield FDI. For a given country, fDi Markets classifies each inward FDI project according to a series of indicators, including the sector of the investor company, the cluster of activity of end-users, and the business activity (or what the investing company is actually doing in the recipient country). fDi Markets identifies eighteen business activities, as follows: research and development (R&D); business services; construction; customer contact centers; design, development and testing; education and training; electricity; extraction; headquarters; ICT and internet infrastructure; logistics, distribution and transportation; maintenance and servicing; manufacturing; recycling; retail; sales, marketing and support; shared service centers; and technical support centers.

We take this information and first compute the share of greenfield projects belonging to each of the eighteen business activities out of the total amount of inward greenfield FDI projects, for each country and each year between 2003 and 2016. We thus obtain the weight of each business activity in each country and year. On average, the three business activities accounting for the largest proportion in our sample, if present in a country, are: sales, marketing and support (with an average weight of 0.203); manufacturing (0.203); and business services (0.196).

To reduce the number of business activities, we pool them according to how knowledge-intensive they are, distinguishing business services, R&D, design, development and testing, and ICT and internet infrastructure, which are characterized by professional, intangible and digital characteristics (*KIGREEN*), from the other activities (*OTHER*). Among the latter, we also pool together manufacturing, construction and extraction as industry-related activities (*MGREEN*).

Table 4 shows the distribution of these three types of greenfield FDI across countries. We find the presence of greenfield FDI lower (i.e. the percentage of zeros with respect to the total amount of inward FDI is higher), but their average intensity higher in countries with below average levels of GDP per capita, education, tertiarization, and BM.

TABLE 4 ABOUT HERE

We apply these weights to the yearly value of greenfield FDI stock per capita, obtaining the corresponding business-activity-weighted stock of inward FDI per capita. Finally, we transform our three variables into natural logarithms (ln*KIGREEN*, ln*OTHER* and ln*MGREEN*). Table 5 shows the results of the Granger causality test. Interestingly, the only cases where the test rejects the null hypothesis of no causality concern knowledge-intensive greenfield FDI in less developed countries, e.g. those with an initially below average level of GDP per capita, proportion of tertiary-level educated population, and BM[7]. The test never rejects the null hypothesis for the other two types of greenfield FDI, or for the most developed countries. We thus conclude that the only type of FDI that Granger-causes economic complexity in developing countries is greenfield and knowledge-intensive.

TABLE 5 ABOUT HERE

4.2 Short run estimates

Using the results of the panel Granger causality test, we now turn to the estimates of the short-run relationship between inward FDI and economic complexity. Since the Dumitrescu and Hurlin (2012) test shows that inward FDI, and greenfield FDI, Granger-cause economic complexity only in

[7]A weak Granger causality emerges between ln*KIGREEN* and ln*ECI* for countries with a level of tertiarization below the 75th percentile.

economies with a high GDP per capita, and high levels of education, tertiarization and financial development, we run our PVAR estimates only on these subsamples of countries.

Preliminary to the PVAR analysis, we select the optimal lag order in PVAR and moment condition. To do so, we use the Andrews and Lu (2001) three model selection criteria (the Bayesian, Akaike, and Hannan and Quinn), and we select the lag order that minimizes all three statistics. We apply this method to two specifications, one where the main regressor is ln*FDI*, and one where the main regressor is ln*GREEN*. In both cases, the preferable model is first-order PVAR (see Table A2 in the Appendix).

Table 6 shows the results of the PVAR regressions. We use up to four-time lags of the variables in levels as instruments for the corresponding variables in first differences. We apply the approach of Holtz-Eakin et al. (1988), which substitutes missing observations with zero, based on the assumption that the vector of the instruments does not correlate with the error terms. As explained in Section 3.2.3, we also subtract the cross-sectional mean from each variable to control for time-specific fixed effects.

TABLE 6 ABOUT HERE

All the columns in the table show a negative estimated coefficient of the two inward FDI variables[8]. In the short run, an increase in the stock of inward total FDI per capita corresponds to a decrease in the aggregate economic complexity, but the magnitude of the effect is very small. Instead, a negative, but much stronger effect is given by the increase in the stock of greenfield FDI per capita.

[8] This negative coefficient emerges also from the single countries' estimates used to compute the statistic with the Dumitrescu and Hurlin (2012) test. Interestingly, the only country where the estimated coefficients of all the lagged values of inward FDI are positive and statistically significant is Turkey, the country analyzed by Javorcik et al. (2018).

Figure 2 plots how economic complexity responds to a one-standard-deviation shock in inward FDI per capita. The top left part of the graph refers to the whole sample, the top right to countries with a large proportion of the population with a tertiary-level education, the bottom left to countries with a high GDP per capita, and the bottom right to countries with a high level of tertiarization. All the graphs show that the one-standard-deviation shock in inward FDI generates a small decrease in the level of economic complexity after one year, followed by an increase after two years. Afterwards, the influence of inward FDI tends to disappear.

FIGURE 2 ABOUT HERE

Figure 3 plots the response of economic complexity to a one-standard-deviation shock in inward greenfield FDI. The picture is much the same: after an initial decrease in the first year, the effect of greenfield FDI tends to fade, smoothly approaching zero in the longer run.

FIGURE 3 ABOUT HERE

Relying on the results in Table 5, we now analyze the effect of knowledge-intensive greenfield FDI on economic complexity in less-developed countries. The results are shown in Table 7. In each column, regardless of the proxy that we use to measure the level of economic development, attracting more knowledge-intensive greenfield FDI coincides with a decrease in economic complexity in the short run.

TABLE 7 ABOUT HERE

Figure 4 shows the corresponding IRF. As in the case of total inward FDI per capita, a one-standard-deviation greenfield FDI shock induces a decrease in economic complexity in the first year, followed by an increase in the second, and the effect tends to disappear after three years.

5. Conclusions

From our panel Granger causality tests and PVAR analysis we obtain three main results. The first is that a causal linkage can be established that goes from inward (greenfield) FDI to economic complexity, but not vice versa. This causal relationship only occurs in developed countries, however, with above average levels of income per capita, education, tertiarization, and financial development. For the other countries, the only type of FDI that Granger-causes economic complexity is knowledge-intensive greenfield FDI.

The second finding concerns the size and dynamics of this effect, which is very small for total inward FDI per capita, by comparison with greenfield FDI. Both effects follow a similar trend, however, and disappear after a couple of years. The effect of knowledge-intensive greenfield FDI per capita on the economic complexity of less-developed countries shows the same dynamics.

The third outcome is that M&A and non-knowledge-intensive greenfield FDI are not related to economic complexity.

These results seem to corroborate the literature, which has found no clear impact of inward FDI on product sophistication in developing countries (Harding and Javorcik, 2012; Wang and Wei, 2008). We can suggest two possible explanations for this. One, as mentioned in Section 2, is that FDI may increase the sophistication of a recipient country's products in two ways. The first is by creating new goods and services that increase the country's product specialization portfolio, or by increasing the production of existing goods so to generate new specializations in the host country. The second is by introducing very novel goods or services (not produced elsewhere) in host countries, and thereby increasing the ubiquity of these products. So, if FDI do not generate any brand-new varieties of goods, or are unable to increase the number of products for which a country has a comparative advantage, then the country's aggregate level of economic complexity does not change. These processes might also take much longer than that used for the PVAR analysis.

Another explanation has to do with inter-firm trade. If FDI, like knowledge-intensive greenfield projects, involve the production of semi-finished goods, software or services that are re-imported through inter-firm transactions, then the trade flows of the recipient country may not change. Since the ECI is built on countries' export flows, this means that inward FDI cannot have any direct effect on the aggregate level of product sophistication.

Taken together, these results point to a limited role of inward FDI in stimulating economic complexity. For developing countries in particular, the key to making their export structure upgrade does not seem to lie in attracting more FDI. On the other hand, the way in which inward FDI can affect recipient countries' patterns of economic development is probably not through an increase in their products' sophistication, but by improving the domestic firms' efficiency.

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TABLES AND FIGURES

Table 1. Panel unit root test

	Pesaran (2007) panel unit root test			
	lnFDI	*ln*M&A	*ln*GREEN	*ln*ECI
CIPS	-2.048	-1.708	-2.435	-3.236***
	Δ*ln*FDI	Δ*ln*M&A	Δ*ln*GREEN	Δ*ln*ECI
CIPS	-3.817***	-4.044***	-2.916***	-5.383***

Notes: *** significant at 1% level. All the tests include an intercept and a linear trend. The optimum number of lags is obtained using the Portmanteau test for white noise. The relevant 10%, 5%, and 1% critical values are -2.59, -2.65 and -2.77, respectively. For lnGREEN and Δ*ln*GREEN the critical values are -2.66, -2.75 and -2.91, respectively.

Table 2. Panel Granger causality test: full sample

	Δ*ln*FDI→Δ*ln*ECI	Δ*ln*M&A→Δ*ln*ECI	Δ*ln*GREEN→Δ*ln*ECI
$\widetilde{Z}$ statistic	1.886**	-0.847	0.055
(p-value)	(0.026)	(0.396)	(0.952)
	Δ*ln*ECI→Δ*ln*FDI	Δ*ln*ECI →Δ*ln*M&A	Δ*ln*ECI →Δ*ln*GREEN
$\widetilde{Z}$ statistic	0.059	-1.031	0.649
(p-value)	(0.954)	(0.345)	(0.531)

Notes: ** significant at 5% level.

Table 3. Panel Granger causality test by groups of countries

High GDP per capita	Δ*ln*FDI→Δ*ln*ECI	Δ*ln*M&A→Δ*ln*ECI	Δ*ln*GREEN→Δ*ln*ECI
	2.496**	-0.014	3.517***

	(0.011)	(0.989)	(0.000)
	Δ*ln*ECI→Δ*ln*FDI	Δ*ln*ECI →Δ*ln*M&A	Δ*ln*ECI →Δ*ln*GREEN
	-0.291	-0.529	-1.419
	(0. 771)	(0.597)	(0.156)
Low GDP per capita	Δ*ln*FDI→Δ*ln*ECI	Δ*ln*M&A→Δ*ln*ECI	Δ*ln*GREEN→Δ*ln*ECI
	0.661	-0.790	-0.885
	(0.509)	(0.429)	(0.376)
	Δ*ln*ECI→Δ*ln*FDI	Δ*ln*ECI →Δ*ln*M&A	Δ*ln*ECI →Δ*ln*GREEN
	0.174	-0.556	-0.669
	(0.862)	(0.620)	(0.504)
High education level	Δ*ln*FDI→Δ*ln*ECI	Δ*ln*M&A→Δ*ln*ECI	Δ*ln*GREEN→Δ*ln*ECI
	0.282	1.381	3.155***
	(0.739)	(0.167)	(0.002)
	Δ*ln*ECI→Δ*ln*FDI	Δ*ln*ECI →Δ*ln*M&A	Δ*ln*ECI →Δ*ln*GREEN
	0.101	-0.721	0.751
	(0.919)	(0.471)	(0. 453)
Low education level	Δ*ln*FDI→Δ*ln*ECI	Δ*ln*M&A→Δ*ln*ECI	Δ*ln*GREEN→Δ*ln*ECI
	2.248**	-0.932	-0.643
	(0.016)	(0.352)	(0.521)
	Δ*ln*ECI→Δ*ln*FDI	Δ*ln*ECI →Δ*ln*M&A	Δ*ln*ECI →Δ*ln*GREEN
	-0.009	-0.739	0.209
	(0.993)	(0.460)	(0.835)
High tertiarization	Δ*ln*FDI→Δ*ln*ECI	Δ*ln*M&A→Δ*ln*ECI	Δ*ln*GREEN→Δ*ln*ECI
	2.132**	0.083	2.689***
	(0.033)	(0.934)	(0.007)
	Δ*ln*ECI→Δ*ln*FDI	Δ*ln*ECI →Δ*ln*M&A	Δ*ln*ECI →Δ*ln*GREEN
	-0.021	-0.345	-0.747
	(0.983)	(0.729)	(0.455)
Low tertiarization	Δ*ln*FDI→Δ*ln*ECI	Δ*ln*M&A→Δ*ln*ECI	Δ*ln*GREEN→Δ*ln*ECI
	0.473	-0.298	-0.398
	(0.636)	(0.765)	(0.691)
	Δ*ln*ECI→Δ*ln*FDI	Δ*ln*ECI →Δ*ln*M&A	Δ*ln*ECI →Δ*ln*GREEN
	0.050	-1.144	1.761
	(0.961)	(0.253)	(0.063)
High BM	Δ*ln*FDI→Δ*ln*ECI	Δ*ln*M&A→Δ*ln*ECI	Δ*ln*GREEN→Δ*ln*ECI
	1.571**	-0.346	2.536***
	(0.033)	(0.633)	(0.000)
	Δ*ln*ECI→Δ*ln*FDI	Δ*ln*ECI →Δ*ln*M&A	Δ*ln*ECI →Δ*ln*GREEN
	-0.508	-0.625	-0.708
	(0.667)	(0.531)	(0.400)
Low BM	Δ*ln*FDI→Δ*ln*ECI	Δ*ln*M&A→Δ*ln*ECI	Δ*ln*GREEN→Δ*ln*ECI
	1.089	-0.859	-0.839
	(0.167)	(0.391)	(0.433)
	Δ*ln*ECI→Δ*ln*FDI	Δ*ln*ECI →Δ*ln*M&A	Δ*ln*ECI →Δ*ln*GREEN
	0.606	-0.834	1.656
	(0.400)	(0.404)	(0.167)

Notes: ** significant at 5% level; *** significant at 1% level.

Table 4. Distribution of inward greenfield FDI by business activity, 2003-2016

	High GDP p.c.	Low GDP p.c.	High education	Low education	High tertiarization	Low tertiarization	High BM	Low BM
KIGREEN=0	9	195	22	182	77	127	41	163
KIGREEN>0	717	1653	1078	1292	1309	1061	1279	1091
Ave % KIGREEN	0.261	0.251	0.232	0.275	0.248	0.263	0.235	0.279
OTHER=0	2	43	2	43	21	24	7	38
OTHER>0	724	1805	1098	1431	1365	1164	1313	1216
Ave % OTHER	0.740	0.796	0.770	0.787	0.769	0.792	0.759	0.731
MGREEN=0	20	109	19	110	67	62	34	95
MGREEN>0	706	1739	1081	1364	1319	1126	1286	1159
Ave % MGREEN	0.184	0.403	0.256	0.402	0.278	0.408	0.257	0.323
Total obs.	726	1848	1100	1474	1386	1188	1320	1254

Notes: KIGREEN=0, OTHER=0, and MGREEN=0 refer respectively to the number of inward knowledge-intensive, non-knowledge-intensive, and industry-related greenfield FDI projects absent in a country between 2003 and 2016. KIGREEN>0, OTHER>0 and MGREEN>0 refer respectively to the number of inward knowledge-intensive, non-knowledge-intensive, and industry-related greenfield FDI projects present in a country between 2003 and 2016.

Ave % KIGREEN, Ave % OTHER and Ave % MGREEN refer respectively to the average share of inward knowledge-intensive, non-knowledge-intensive, and industry-related greenfield FDI, if any, out of the total amount of inward greenfield FDI projects in a country between 2003 and 2016.

Table 5. Panel Granger causality test by groups of countries and business activities

High GDP per capita	Δ*ln*KIGREEN→Δ*ln*ECI	Δ*ln*OTHER→Δ*ln*ECI	Δ*ln*MGREEN→Δ*ln*ECI
	1.604	0.494	0.784
	(0.109)	(0.622)	(0.433)
	Δ*ln*ECI→Δ*ln*KIGREEN	Δ*ln*ECI →Δ*ln*OTHER	Δ*ln*ECI →ΔlnMGREEN
	-0.199	0.350	0.832
	(0. 842)	(0.726)	(0.406)
Low GDP per capita	Δ*ln*KIGREEN→Δ*ln*ECI	Δ*ln*OTHER→Δ*ln*ECI	ΔlnMGREEN→Δ*ln*ECI
	1.948**	0.394	0.149
	(0.045)	(0.694)	(0.881)
	Δ*ln*ECI→Δ*ln*KIGREEN	Δ*ln*ECI →Δ*ln*OTHER	Δ*ln*ECI →ΔlnMGREEN
	-0.605	0.573	-0.796
	(0.546)	(0.567)	(0.426)
High education	Δ*ln*KIGREEN→Δ*ln*ECI	Δ*ln*OTHER→Δ*ln*ECI	ΔlnMGREEN→Δ*ln*ECI
	-1.079	0.651	0.635
	(0.298)	(0.515)	(0.525)
	Δ*ln*ECI→Δ*ln*KIGREEN	Δ*ln*ECI →Δ*ln*M&A	Δ*ln*ECI →ΔlnMGREEN
	-0.490	-1.108	-0.140
	(0. 624)	(0.268)	(0. 889)
Low education	Δ*ln*KIGREEN→Δ*ln*ECI	Δ*ln*OTHER→Δ*ln*ECI	ΔlnMGREEN→Δ*ln*ECI
	3.325***	0.545	0.178
	(0.005)	(0.586)	(0.859)
	Δ*ln*ECI→Δ*ln*KIGREEN	Δ*ln*ECI →Δ*ln*OTHER	Δ*ln*ECI →ΔlnMGREEN
	-0.392	1.254	-1.213
	(0.695)	(0.210)	(0.225)
High tertiarization	Δ*ln*KIGREEN→Δ*ln*ECI	Δ*ln*OTHER→Δ*ln*ECI	ΔlnMGREEN→Δ*ln*ECI
	0.518	0.407	-0.163
	(0.604)	(0.684)	(0.870)
	Δ*ln*ECI→Δ*ln*KIGREEN	Δ*ln*ECI →Δ*ln*OTHER	Δ*ln*ECI →ΔlnMGREEN
	-0.041	0.389	0.478
	(0.967)	(0.698)	(0.633)
Low tertiarization	Δ*ln*KIGREEN→Δ*ln*ECI	Δ*ln*OTHER→Δ*ln*ECI	ΔlnMGREEN→Δ*ln*ECI
	1.370	0.442	0.998
	(0.171)	(0.659)	(0.350)
	Δ*ln*ECI→Δ*ln*KIGREEN	Δ*ln*ECI →Δ*ln*OTHER	Δ*ln*ECI →ΔlnMGREEN
	-0.871	0.062	-0.832
	(0.134)	(0.950)	(0.406)
High BM	Δ*ln*KIGREEN→Δ*ln*ECI	Δ*ln*OTHER→Δ*ln*ECI	ΔlnMGREEN→Δ*ln*ECI
	0.540	0.832	0.796
	(0.467)	(0.267)	(0.300)
	Δ*ln*ECI→Δ*ln*KIGREEN	Δ*ln*ECI →Δ*ln*OTHER	Δ*ln*ECI →ΔlnMGREEN
	0.166	0.263	0.319
	(0.900)	(0.793)	(0.749)
Low BM	Δ*ln*KIGREEN→Δ*ln*ECI	Δ*ln*OTHER→Δ*ln*ECI	ΔlnMGREEN→Δ*ln*ECI
	3.037***	0.350	-0.030
	(0.000)	(0.700)	(0.967)
	Δ*ln*ECI→Δ*ln*KIGREEN	Δ*ln*ECI →Δ*ln*OTHER	Δ*ln*ECI →ΔlnMGREEN
	-1.053	0.203	-0.599
	(0.167)	(0.839)	(0.549)

0Notes: ** significant at 5% level; *** significant at 1% level.

Table 6. Panel VAR estimates

	Full sample		High education		High GDP p.c.		High tertiarization		High BM	
Dep Var. Δ*lnEC*I	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Δ*lnEC*I_{t-1}	-0.353***	-0.341***	-0.397***	-0.462***	-0.343**	-0.466***	-0.217**	-0.327**	-0.441***	-0.389**
	(0.081)	(0.089)	(0.056)	(0.063)	(0.014)	(0.170)	(0.097)	(0.013)	(0.109)	(0.130)
Δ*ln*FDI_{t-1}	-0.033**		-0.057***[1]		-0.054*		-0.053**		-0.063***	
	(0.015)		(0.017)		(0.032)		(0.022)		(0.018)	
Δ*ln*$GREEN_{t-1}$		-82.69***		-27.79***		-56.74***		-48.14***		-55.16***
		(8.480)		(2.874)		(7.102)		(5.211)		(5.305)
N obs	2223	1404	1180	600	660	396	1260	756	1200	720
N countries	117	117	59	50	33	33	63	63	60	60

Notes: robust standard errors in parentheses. * significant at 10% level, ** significant at 5% level; *** significant at 1% level. In columns 1, 3, 5 and 7, the instruments are the 1 to 4 lagged values of ln*ECI* and ln*FDI*. In columns 2, 4, 6 and 8, the instruments are the 1 to 4 lagged values of ln*ECI* and ln*GREEN*.

[1] This estimated coefficient is obtained on a sample of countries with a proportion of tertiary-level educated population above the median.

Table 7. Panel VAR estimates: the impact of knowledge-intensive greenfield FDI

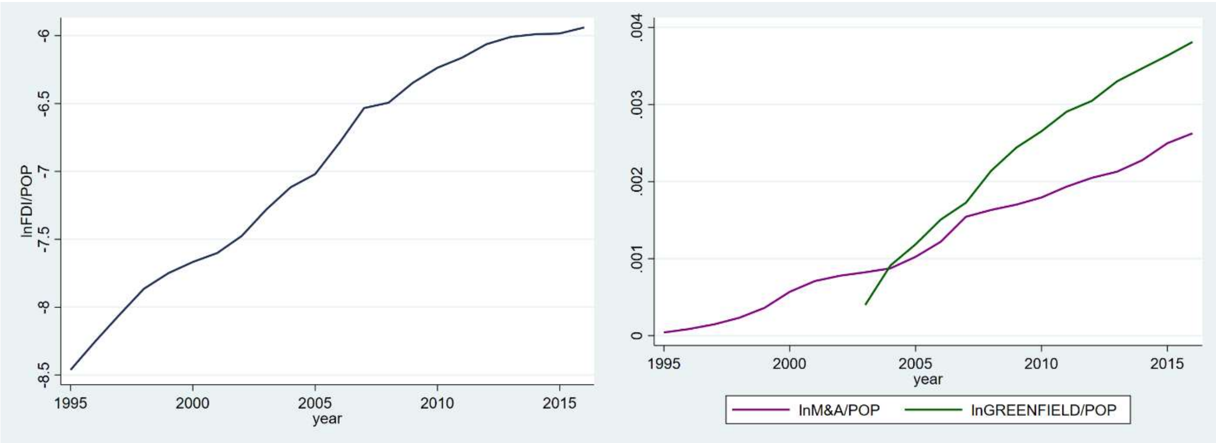
Dep Var. Δ*lnEC*I	Low education	Low GDP p.c.	Low tertiarization	Low BM
Δ*lnEC*I_{t-1}	-0.312***	-0.335***	-0.422***	-0.296***
	(0.092)	(0.062)	(0.073)	(0.072)
Δ*ln*$KIGREEN_{t-1}$	-106.8***	-106.6***	-147.6***	-133.5***
	(32.33)	(24.31)	(54.45)	(44.01)
N obs	780	960	612	660
N countries	65	80	51	55

Notes: robust standard errors in parentheses. * significant at 10% level, ** significant at 5% level; *** significant at 1% level. The instruments are the 1 to 4 lagged values of ln*ECI* and ln*KIGREEN*.

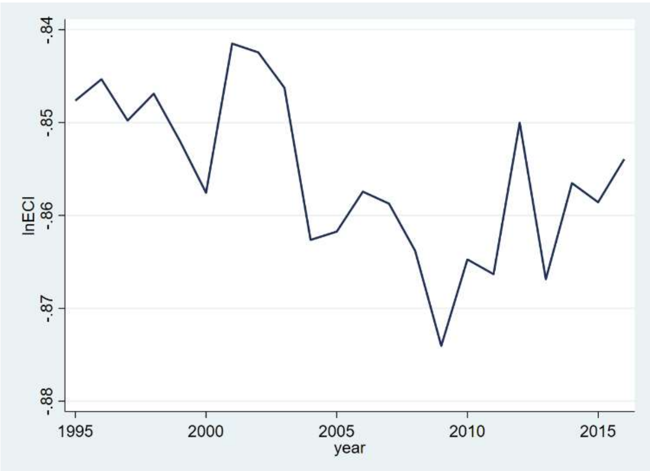
FIGURES

Figure 1. Dynamics of inward FDI and economic complexity

Panel A



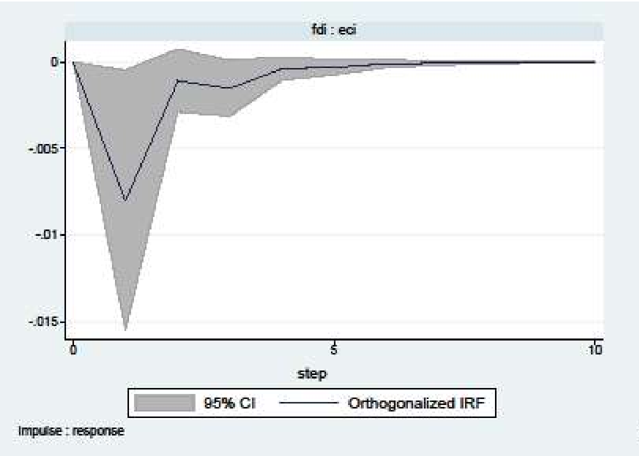
Panel B



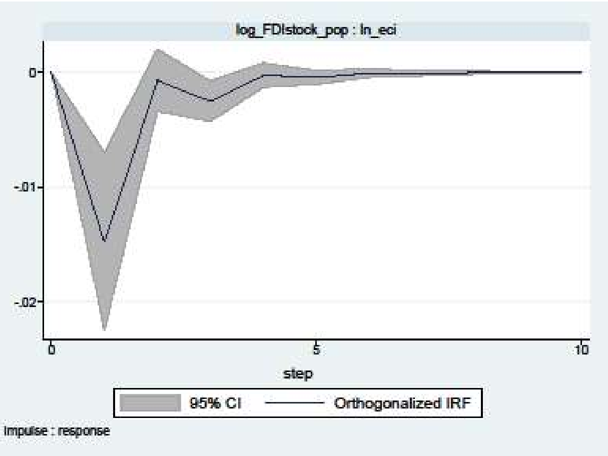
Notes: authors' elaborations

Figure 2. IRF for one-lag PVAR: total inward FDI per capita

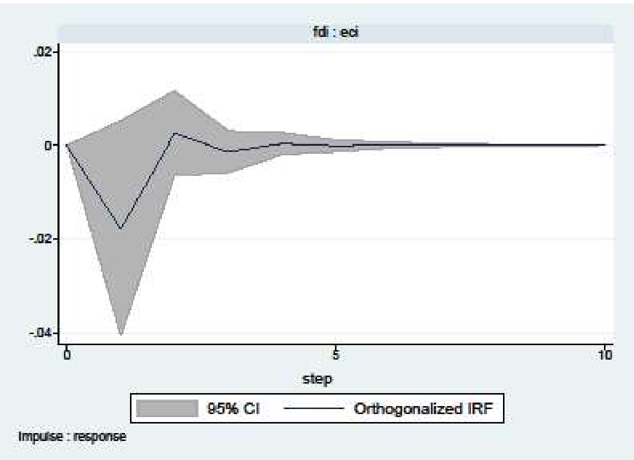
Full sample



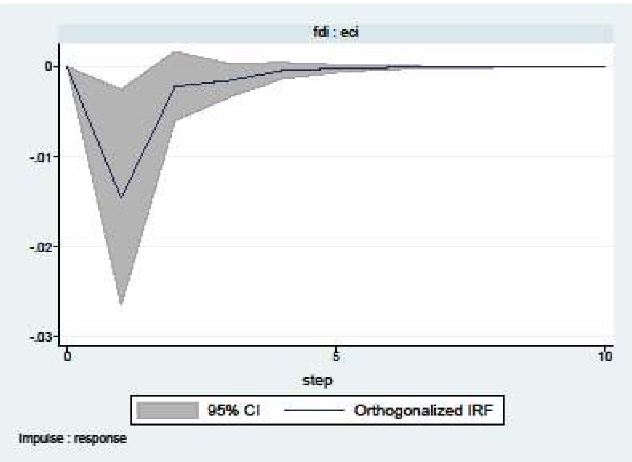
High education level (median)



High GDP per capita



High tertiarization



High financial development

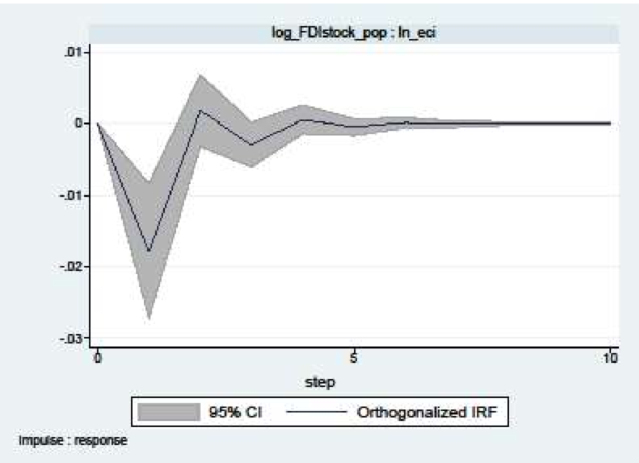
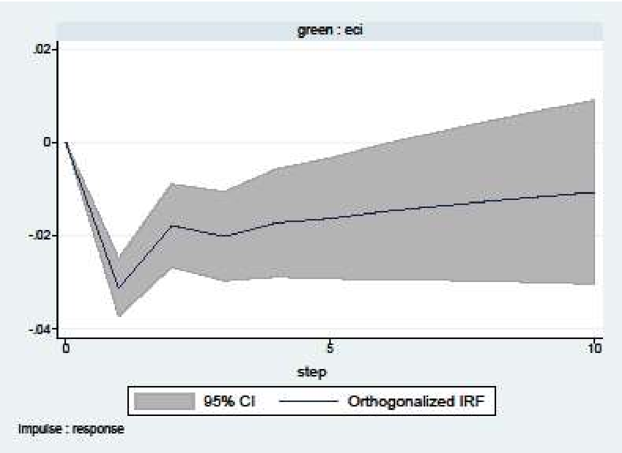
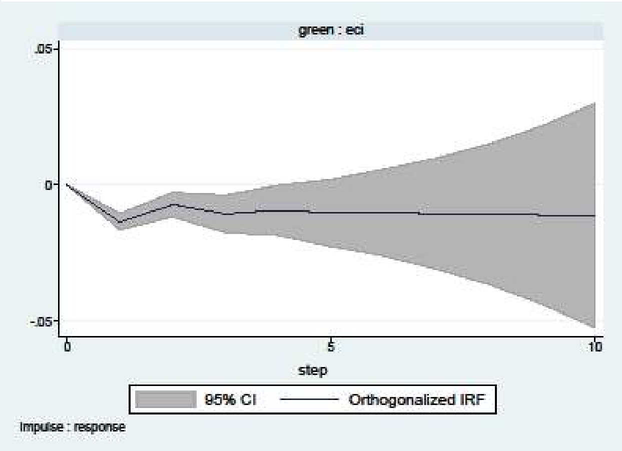


Figure 3. IRF for one-lag PVAR: inward greenfield FDI per capita

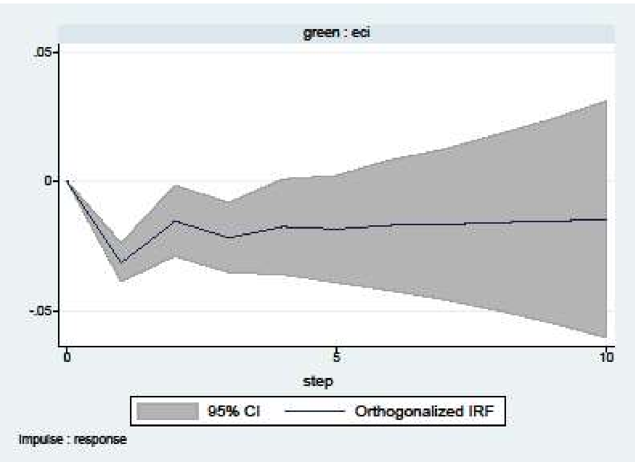
Full sample



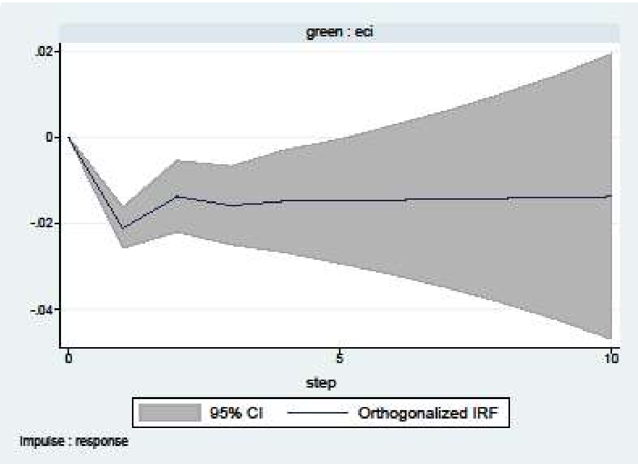
High education level



High GDP per capita



High tertiarization



High financial development

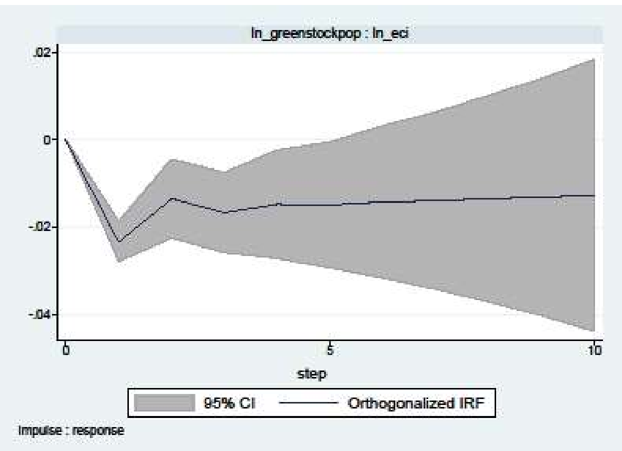
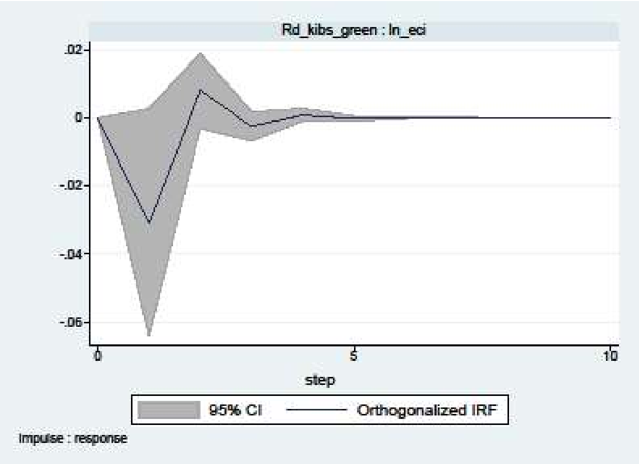
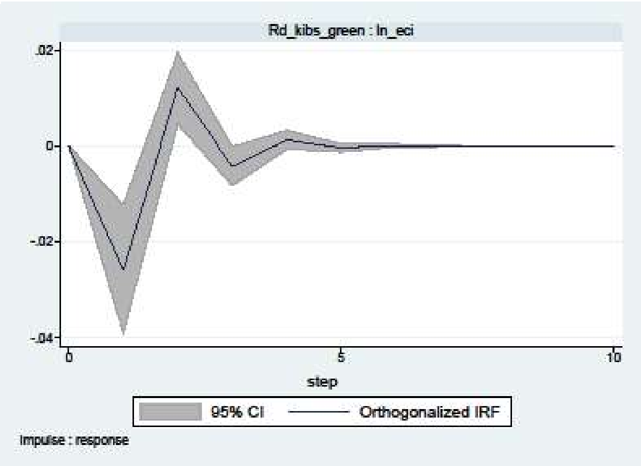


Figure 4. IRF for one-lag PVAR: inward knowledge-intensive greenfield FDI per capita

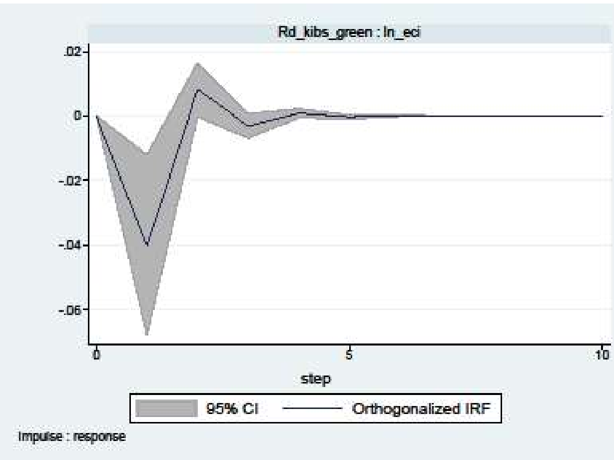
Low education level



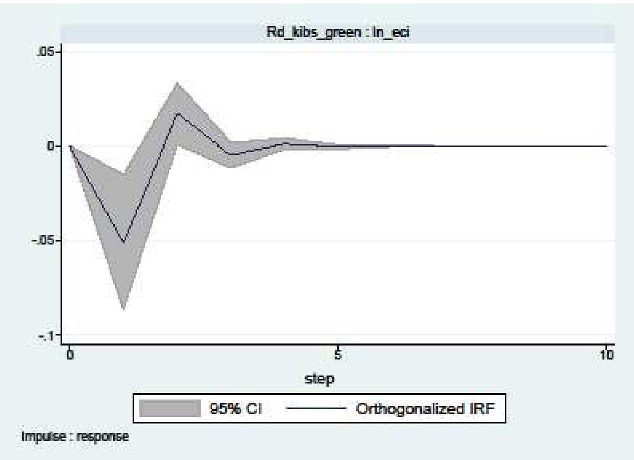
Low GDP per capita



Low tertiarization



Low financial development



Source: authors' elaborations

APPENDIX

Table A1. List of countries

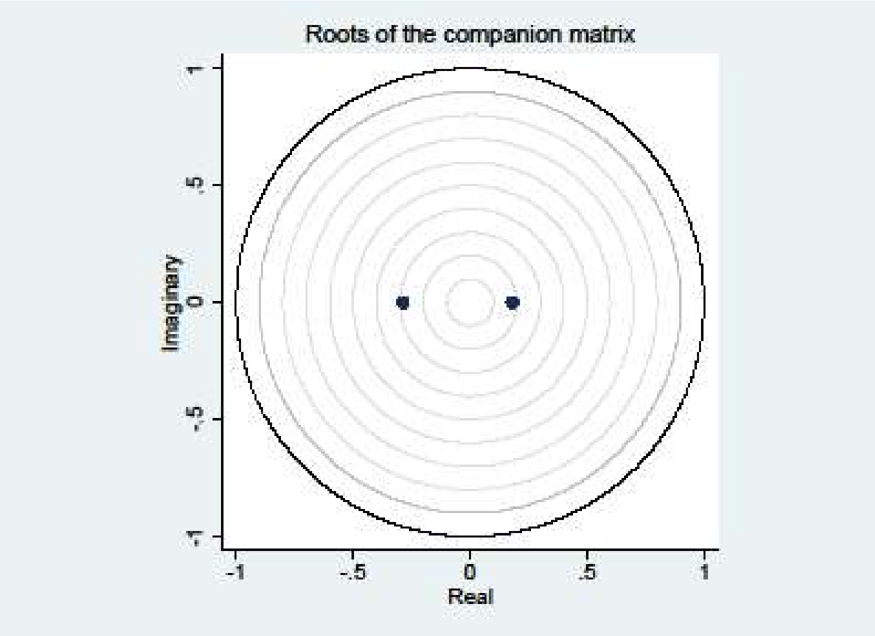
Albania	Estonia	Kyrgyzstan	Papua New Guinea	Turkmenistan
Algeria	Ethiopia	Lao PDR	Paraguay	Uganda
Argentina	Finland	Latvia	Peru	Ukraine
Australia	France	Lebanon	Philippines	UEA
Austria	Georgia	Liberia	Poland	United Kingdom
Azerbaijan	Germany	Libya	Portugal	United States
Bangladesh	Ghana	Lithuania	Qatar	Uruguay
Belarus	Greece	Madagascar	Romania	Uzbekistan
Bolivia	Guatemala	Malawi	Russian Federation	Venezuela, RB
Brazil	Guinea	Malaysia	Saudi Arabia	Vietnam
Bulgaria	Honduras	Mali	Senegal	Yemen, Rep.
Cambodia	Hong Kong	Mauritania	Singapore	Zambia
Cameroon	Hungary	Mauritius	Slovak Republic	Zimbabwe
Canada	India	Mexico	Slovenia	
Chile	Indonesia	Moldova	South Africa	
China	Iran, Islamic Rep.	Mongolia	Spain	
Colombia	Ireland	Morocco	Sri Lanka	
Congo, Rep.	Israel	Mozambique	Sudan	
Costa Rica	Italy	Netherlands	Sweden	
Croatia	Jamaica	New Zealand	Switzerland	
Czech Republic	Japan	Nicaragua	Tajikistan	
Cote d'Ivoire	Jordan	Nigeria	Tanzania	
Denmark	Kazakhstan	Norway	Thailand	
Ecuador	Kenya	Oman	Trinidad and Tobago	
Egypt	Korea, Rep.	Pakistan	Tunisia	
El Salvador	Kuwait	Panama	Turkey	

Table A2. Optimum lag selection

	Lags	MBIC	MAIC	MQIC
ln*FDI* → ln*ECI*	1	-76.51875	-9.374106	-34.03509
	2	-49.75132	-4.988222	-21.42888
	3	-25.07172	-2.690175	-10.9105
ln*GREEN* → ln*ECI*	1	-75.01938	-15.50659	-38.06883
	2	-47.74863	-8.073446	-23.11493
	3	-23.82771	-3.990119	-11.51086

Notes: MBIC = model/moment selection Bayesian information criterion; MAIC = model/moment selection Akaike information criterion; MQIC = model/moment selection Hannan and Quinn information criterion.

Figure A1. Graph of the eigenvalue of the companion matrix



Source: authors' elaborations.