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From FDI to economic complexity: a panel Granger causality analysis

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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 VAR approach and Impulse Response Functions. 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. We also find that only greenfield FDIs Granger-cause economic complexity in developed countries. Finally, knowledge-intensive greenfield projects are the only type of FDI that Granger-cause complexity in a less developed country, but the estimated effect is near zero and disappears after two years.

1. Introduction

Using a panel vector autoregressive (PVAR) analysis and Impulse Response Functions (IRF), this paper examines the existence of a (Granger) causal relationship between inward foreign direct investments (FDI) and the degree of a country's economic complexity (EC). We conceive this latter as reflecting the average complexity of production, which, in turn, depends on two elements: the diversity and the exclusivity of products. Products differ by the amount of the required knowledge and capabilities: simple products, like raw natural resources, need very little amount of such capabilities, whereas complex products, like mainframes, robots or aircrafts, ask for large amounts of knowledge. In this respect, the complexity of a product corresponds to the amount of knowledge required for its production. The degree of EC of a country increases as the range of complex products becomes more diversified, and as such products are exclusive, or sophisticated, because they are produced in a few countries.

This idea of EC is relatively new and rests on the structural properties of global trade networks (Mealy, Farmer & Teytelboym, 2019). Since the beginning of the 21st century, scholars have realized the need to combine economics with complexity science to overcome certain possible limitations of the neoclassical economic theory (Blume and Durlauf, 2006; Fontana, 2010). Originating from the "Santa Fe perspective" in the US at the end of the 1980s, the research program on complexity in economics has developed through three theoretical and methodological approaches (Fontana, 2010): dynamic complexity, computational complexity, and connective complexity. The concept of dynamic complexity is mainly mathematical and goes back to the notions of non-linear systems, bifurcation theory and transition to chaos. Computational complexity, instead, refers to the computational and cognitive skills of decision makers, especially when trying to decipher the surrounding environment. In this respect, complexity is related to concepts like bounded and procedural rationality or to cognitive theory, as well as to undecidability and computational costs. Connective complexity, instead, is mainly based on the social interactions among the elements of a system, and on those forces that tend to keep the order or to create disorder: from the interactions between these two forces, new types of relations can emerge, destroying the old (social) structures and making the whole system evolve.

After a period of silence at the beginning of the new Millennium, the concept of EC has (re)emerged thanks to the seminal contributions of Hidalgo et al. (2007) and Hidalgo and Hausmann (2009), who draw elements from computer science, net-

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work theory and evolutionary economic geography. In their view, EC emerges as the main explanation of the differences in the level of development across countries. The fact that some capabilities, like institutions, specific skills, infrastructures or natural resources, are not tradable across borders makes them available to production only at local level. Therefore, countries' productivity differences originate from the different endowment of capabilities, on their diversity and interactions. In this sense, EC increases as far as a country specializes and exports a wider variety of products that are also exclusive, i.e. that are produced by a few countries, following a circular and iterative pattern.

To explain the mechanics of EC, Hidalgo and Hausmann (2009) use the Lego analogy. If we assume that a single Lego piece represents a capability, and a Lego model a single product, we can represent countries as buckets of Lego pieces. The ability to produce more complex products depends on the availability of capabilities and the way they are combined, such as the ability of a child to generate a new Lego model depends on the availability of pieces in the bucket. The more diversified, and exclusive, are the Lego pieces, the more complex is the model that a child can create; using the same reasoning, the more diversified, and exclusive, are the available capabilities, the more complex are the products that a country can produce and export competitively.

Following this idea, there is a growing consensus among scholars that EC is related to wealth: countries producing a more diversified portfolio of highly sophisticated and exclusive products experience higher levels of income per capita. EC also explains countries' and regions' convergence in income per capita (Hausmann and Hidalgo, 2011), product and export diversification (Cicerone et al., 2020; Pinheiro, Alshamsi, Hartmann, Boschma, & Hidalgo, 2018), GDP per capita growth and speed of industrialization (Ferrarini & Scaramozzino, 2016; Hidalgo & Hausmann, 2009; Pugliese, Chiarotti, Zaccaria, & Pietronero, 2017; Sbardella, Pugliese, Zaccaria, & Scaramozzino, 2018), economic development and income/wage inequality (Gao & Zhou, 2018; Hartmann et al., 2017; Sbardella, Pugliese, & Pietronero, 2017).

In presenting their complexity-based model of economic development, however, Hidalgo and Hausmann (2009) remain silent on the underlying mechanisms through which countries accumulate new capabilities and recombine them with the capabilities already existing in the country. Therefore, a key question remains unanswered: why is the level of EC higher in some countries, or regions, than in others? What explains the level of EC in a country?

In this paper we posit that one way to accumulate and (re)combine capabilities is by attracting FDI from foreign-owned investors, like foreign multinational enterprises. This idea dates to Romer (1992), who uses an endogenous growth model to explain how foreign investments represent one of the most important channels for the introduction of new ideas, and new products, into an economy that lacks the know-how to produce them. The interaction between foreign MNEs and local suppliers in the host country is a way for the latter to expand and improve its set of capabilities and, indirectly, to upgrade production processes and introduce new and more sophisticated products in the market.

In this paper, we adopt a panel Granger causality, and a PVAR model with IRF to test the direction of causality and the magnitude of the relationship between FDI and EC 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 EC. 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 of 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-causes a greater EC 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 EC, but this relation holds only in the short term, and is small in magnitude.

Our contribution is twofold. On the one hand, we contribute to the literature on EC by showing, in a cross-country setting, one of the possible channels through which economies can accumulate capabilities and recombine them to increase the average sophistication of their production. On the other hand, we test for a possible new interpretation of the FDI-growth relationship, that passes through EC: by attracting more FDI, countries can increase product diversity and exclusivity, raising the average complexity of their production. To the extent in which a higher EC is the ultimate cause of economic growth, we can trace a link between inward FDI and economic development that passes through EC.

The paper develops as follows. Section 2 presents the theoretical background, discussing the mechanisms through which inward FDI might affect the average EC of a country and revising the empirical literature on the determinants of EC. 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 concludes.

2. Background theory and literature

2.1. The mechanisms through which FDI contribute to economic complexity

Inward FDI can improve the average EC of a country in a direct and an indirect way. On the one hand, foreign-owned multinationals can directly contribute to increase the sophistication of the recipient country's production structure by producing more technology- and knowledge-intensive goods and services that were not previously produced in the country itself (Romer, 1992). The larger the amount of FDI attracted by a country, the higher should be the possibility to *directly* increase the diversity and the exclusivity of domestic production. On the other hand, foreign-owned MNEs can *indirectly* affect the economic complexity of the host country through the knowledge spillovers that can occur between foreign MNEs and local firms, being them fully domestic organizations or domestically owned MNEs. These spillovers are generated by different phenomena. First, by the transfer of tangible and intangible technology from MNEs to their foreign affiliates operating in the recipient country, which increases their efficiency and propensity to introduce new products and production processes (Arnold and Javorcik, 2009). Second, positive spillovers might originate from imitation or demonstration effects, and/or direct and indirect interactions between MNEs' foreign affiliates and local firms (Javorcik, 2008; Brambilla et al., 2009; Swenson and Chen, 2014), where these latter might take advantage from the innovative of the former that reduces the average cost of R&D (Javorcik, 2008; Guadalupe, Kuzmina & Thomas, 2012). A third source of knowledge spillovers is the adoption of higher production standards by local suppliers that become part of the MNEs' value chain

(Iacovone et al., 2015; Rojec & Knell, 2018), or the domestic rivals' improvements in productivity needed to compete with the global players. In this respect, Javorcik, et al. (2018) describe the cases of two important foreign multinationals operating in Turkey and how the sharing of tacit knowledge, information processes, instructions and superior organizational procedures helped local domestic suppliers to upgrade the complexity of their production. A fourth channel of knowledge transmission is represented by labour mobility. Especially when knowledge is tacit and uncodified, the mobility of skilled personnel becomes a key vehicle to transfer experience and know-how from business-to-business (Agrawal et al., 2006). Therefore, the flows of skilled employees and managers that go from foreign-owned MNEs to local domestic firms, being them incumbent or new entrants, represent a channel for transferring superior knowledge and more efficient production and organizational methods to the recipient country, increasing its average level of innovativeness (Fosfuri et al., 2001; Görg and Strobl, 2005; Braunerhjelm et al., 2016).

The presence of foreign MNEs can also have negative consequences for the incumbent activities in the host countries, however. Greater exposure to foreign 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 & Sleuwaegen, 2003; Agosin & Machado, 2005; Kosová, 2010).

Ultimately, whether attracting more FDI induces an increase in a country's average degree of economic complexity remains a matter of empirical research.

2.2. The literature on the determinants of economic complexity

In the last few years, many scholars have tried to judge the role of EC 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 EC 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 EC faster than others.

The literature investigating the role of FDI on the level of sophistication of domestic production 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 products as their domestic private rivals, to achieve higher sales from new varieties of goods and services, 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 FDIs increased the average quality of exports, with a focus on developing countries. Their estimates show a positive causal relationship between inward FDIs 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 Hidalgo 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 FDIs 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.

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 Irsova and Havranek, 2013, and Rojec and Knell, 2018, among others). Only three studies discuss the likely effect of FDIs on EC, however. The first, by Sweet and Eterovic Maggio (2015), examines whether a stronger intellectual property rights (IPR) system triggers aggregate innovation, proxied by the EC 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 and greater spatial concentrations of activities, and technology, in US large cities. The third study is that provided by Khan et al. (2020), who apply a time series analysis to investigate the direction of causality between inward FDIs and EC in China from 1985 to 2017. They find a long-run bidirectional relationship between inward FDIs and EC, but the Granger causal effect of EC on FDIs holds only in the short run.

This paper moves from the empirical and anecdotical evidence provided by Javorcik et al. (2018), and extends their analysis to a cross-country setting to assess the effect of inward FDI on the level of product sophistication of a country's exports, as captured by its level of EC. In doing so, we adopt a similar approach to Khan et al. (2020), but we extend the analysis to a wider cross-country setting and to a PVAR analysis.

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

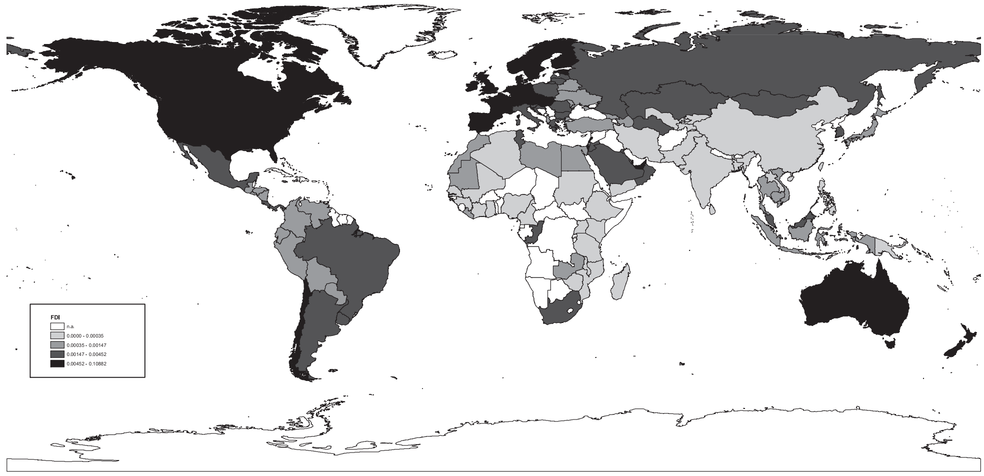


Fig. 1. Geography of inward FDI stock per capita. Source: authors' elaborations on UNCTAD data.

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[1]. Figure 1 shows the geographical distribution of *FDI* (averaged across 1995-2016) across the available countries.

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 Financial Times fDi Markets database; 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[2]. To account for the size of the recipient country, we also divide both variables by the corresponding stock of resident population, then proceed with the logarithmic transformation (*ln*M&A and *ln*GREEN)[3]. Table A1 in Appendix shows the correlation among the three FDI variables.

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. Specifically, the first step is to compute the revealed comparative advantage index as follows:

$$RCA_{ij} = \frac{X_{ij}}{\sum_i X_{ij}} / \frac{\sum_i X_{ij}}{\sum_{ij} X_{ij}} \tag{1}$$

where X_{ij} represents the value of exports of country i and in product j. If the index is higher than 1, the country is competitive in producing, and exporting, product j. Then second step consists in defining a country-product matrix M, the elements of which are M_{ij} =1 if the country i has a revealed comparative advantage in product j, and M_{ij} =0 otherwise. Third, from the proximity matrix M it is possible to derive the ubiquity and diversity measures: the former corresponds to the number of countries with RCA>1 in a product, while the latter is the number of products in which a country has a comparative advantage[4]. The ECI is obtained through an iterative method of reflections, which corresponds to finding the eigenvalue of the following normalized similarity matrix, which reflects how similar the export baskets of countries are:

$$\tilde{M}_{ii'} \equiv \sum_j \frac{M_{ij} M_{i'j}}{k_i^{(0)} k_j^{(0)}} = \frac{1}{k_i^{(0)}} \sum_j \frac{M_{ij} M_{i'j}}{k_j^{(0)}}, \tag{2}$$

where the rows sum to one, and where each entry can be interpreted as conditional transition probabilities in a Markov transition matrix (Kemp-Benedict, 2014). The ECI corresponds to the second largest right eigenvalue (K_i) of the matrix $\tilde{M}$ (Mealy, Farmer and Teytelboym, 2019). The final ECI is obtained after standardizing the vector K_i as follows, so to allow for comparisons across regions and years:

$$ECI_i = \frac{K_p - \bar{K}}{std(K)} \tag{3}$$

where $\bar{K}$ is the mean value of K_i. Figure 2 shows the geographical distribution of *ECI* (averaged across 1995-2016) across countries.

Since the index ranges between -2.5 and +2.8, we reparametrize it as follows to obtain an index that varies be-

[1] We are aware that the use of these data can be problematic, as stressed by Bellak and Cantwell (1989), especially when FDI stocks are reported on a historical cost basis because they do not take into consideration of the specific age distribution of those stocks. This is confirmed in the empirical exercise of the authors as they recalculate the value of FDIs for older and younger investors finding that the effect is more important for older investors. In our cross-country analysis, however, it is impossible to distinguish the age of the investors.

[2] 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.

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

[4] 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 ($k_{i,0}$) 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.

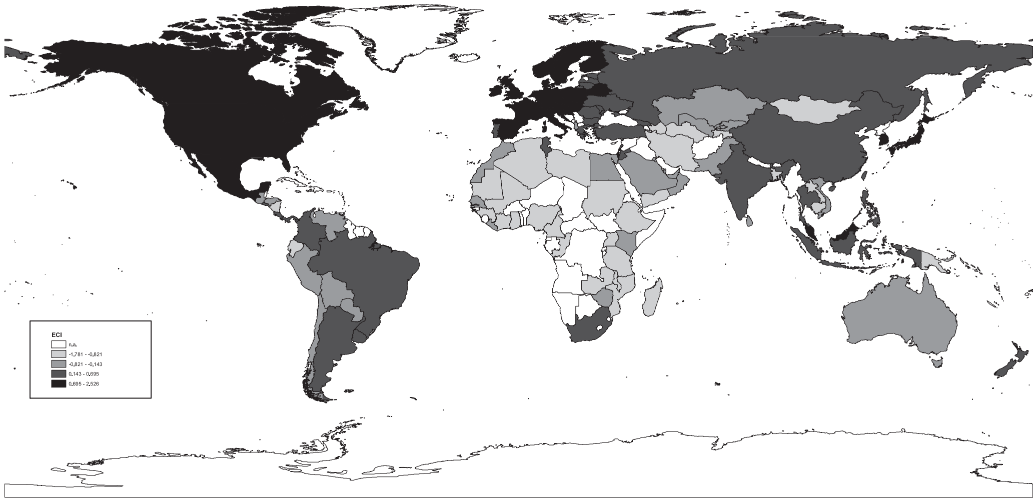


Fig. 2. Geography of economic complexity. Source: authors elaborations on Harvard University data.

tween 0 and 1: $(ECI - \min)/(max - \min)$; then, we take its natural logarithm (*ln*ECI)[5].

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 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. In this respect, we have also to admit that S can capture a quite different series of activities in developed and developing countries, like a higher amount of knowledge-intensive business services in the former vis-a-vis a larger amount of traditional, or low-skill intensive, activities in the latter. 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 a balanced panel of 117 countries and 22 years (1995-2016)[6], for a total of 2,574 observations (the full list of countries is in the Appendix, Table A3). Figure 3 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 the ECI is quite volatile, and characterized by different trends: it decreases until the 2008 financial crisis and increases afterwards.

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:

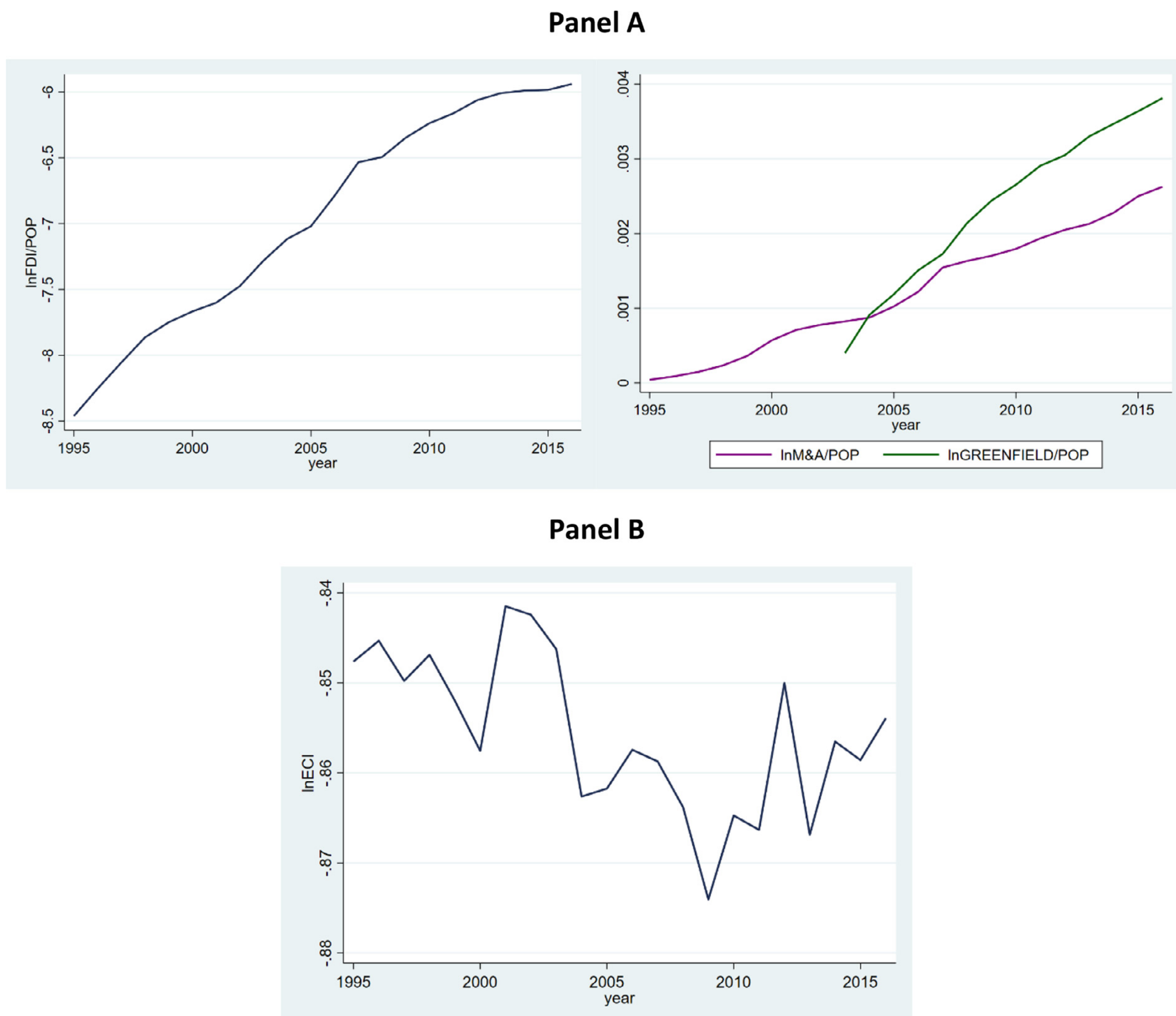
$$\Delta y_{it} = \beta_i y_{it-1} + \gamma_i \overline{\Delta y_{it}} + \delta_i \overline{y_{it-1}} + \mu_i + \varepsilon_{it}, \tag{4}$$

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

[5] To check whether these transformations could have generated a bias in the analysis, we have run our panel unit root tests on *ECI and* Δ*ECI* too. The CIPS test statistics (i.e. -3.387*** and -5.425*** respectively) are very similar to those of ln*ECI* and Δ*lnECI in* Table 2. This confirms that *ECI* is I(0) too. Table A2 in Appendix provides the summary statistics of all the three versions of our EC index.

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



Source: authors' elaborations

Fig. 3. Dynamics of inward FDI and economic complexity.

Table 1
Panel unit root test.

	Pesaran (2007) panel unit root test			
	*ln*FDI	*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.

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.

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 EC 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 EC (ΔlnECI).

3.2.2. The panel Granger causality test

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

$$\Delta lnECI_{it} = \alpha + \sum_{k=1}^{K} \beta_k \Delta lnECI_{it-k} + \sum_{k=1}^{K} \gamma_k \Delta lnFDI_{it-k} + \varepsilon_{it} \qquad (5)$$

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 $\Delta \ln ECI$ and $\Delta \ln FDI$ must be stationary. In this case, $\Delta \ln FDI$ Granger-causes $\Delta \ln ECI$ if the past values of $\Delta \ln FDI$ can predict the current values of $\triangle \ln ECI$, even once the past values of $\triangle \ln ECI$ 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 version of the Granger causality test, all the coefficients can vary across countries, but are invariant over time. The null hypothesis becomes:

$$H_0 : \gamma_{i1} = \gamma_{i2} = \ldots = \gamma_{iK} = 0 \, \forall \, i = 1, \ \ldots, \ N \tag{6}$$

which corresponds to the absence of causality for all the countries in the dataset. The alternative hypothesis is that there can be causality between $\triangle \ln FDI$ and $\triangle \ln ECI$ for some countries, but not necessarily for all of them. The test works as follows. After running the N individual regressions in (5), we perform the F-test of the K linear hypotheses in (6) and generate the individual Wald statistics W_i. Then we compute the average Wald statistic[7].

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 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 $\triangle \ln ECI$ to $\triangle \ln FDI$, 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[8].

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-Eakin et al. (1988). We estimate the following equation:

$$lnECI_{it} = \sum_{k=1}^{K} \beta_k lnECI_{it-k} + \sum_{k=1}^{K} \gamma_k lnFDI_{it-k} + \mu_i + \varepsilon_{it} \tag{7}$$

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 7, 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 $\triangle ln$FDI to $\triangle ln$ECI, then from $\triangle ln$ECI to $\triangle ln$FDI. Then, we repeat the process for $\triangle ln$M&A and $\triangle ln$GREEN. In the first row, we find the p-value of the $\tilde{Z}$ statistic significant (at 5% level) only in the case of $\triangle ln$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 $\tilde{Z}$ statistic is never significant. This implies a causality relationship from increasing inward FDI to increasing EC, and not vice versa. In other words, higher stocks of inward FDI per capita Granger-cause EC[9].

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 $\tilde{Z}$ statistic significant (at 5% level) for: (i) countries with a GDP per capita, a proportion of tertiary-level educated population[10] (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 EC in a country, especially if the mode of entry is through greenfield projects. These results are in line with our expectations: assuming that they do not displace incumbent activities, greenfield FDI represent the way through which foreign MNEs might directly increase the average EC of the host country, as they represent new productive facilities that add to those already existing. On the contrary, M&As do not create any new capacity or increase in physical capital, but, in the short run, they can simply represent a change in ownership for a domestic company (Agosin and Machado, 2005). Moreover, the motivations behind the two types of FDI are very different: while greenfield FDI are usually undertaken to generate new activities, or launch new products into a foreign market, in the case of M&As a key motive may be to reduce competition and the productive capacity in the industry. From Table 3, we also find, however, that such a relationship holds not for all countries, but only for those with an above average level of development.

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

[8] 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).

[9] We have also tested for the Granger causality between ln*FDI* and ln*ECI* between 2003 and 2016. The results are similar, albeit slightly less significant, to those presented in Table 3, as shown in Appendix, Table A5.

[10] 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.

Table 2
Panel Granger causality test: full sample.

	ΔlnFDI→ΔlnECI	ΔlnM&A→ΔlnECI	ΔlnGREEN→ΔlnECI
$\widetilde{Z}$ statistic (p-value)	1.886** (0.026)	-0.847 (0.396)	0.055 (0.952)
	ΔlnECI→ΔlnFDI	ΔlnECI →ΔlnM&A	ΔlnECI →ΔlnGREEN
$\widetilde{Z}$ statistic (p-value)	0.059 (0.954)	-1.031 (0.345)	0.649 (0.531)

Notes: ** significant at 5% level.

Table 3
Panel Granger causality test by groups of countries.

High GDP per capita	ΔlnFDI→ΔlnECI	ΔlnM&A→ΔlnECI	ΔlnGREEN→ΔlnECI
	2.496** (0.011)	-0.014 (0.989)	3.517*** (0.000)
	ΔlnECI→ΔlnFDI	ΔlnECI →ΔlnM&A	ΔlnECI →ΔlnGREEN
	-0.291 (0. 771)	-0.529 (0.597)	-1.419 (0.156)
Low GDP per capita	ΔlnFDI→ΔlnECI	ΔlnM&A→ΔlnECI	ΔlnGREEN→ΔlnECI
	0.661 (0.509)	-0.790 (0.429)	-0.885 (0.376)
	ΔlnECI→ΔlnFDI	ΔlnECI →ΔlnM&A	ΔlnECI →ΔlnGREEN
	0.174 (0.862)	-0.556 (0.620)	-0.669 (0.504)
High education level	ΔlnFDI→ΔlnECI	ΔlnM&A→ΔlnECI	ΔlnGREEN→ΔlnECI
	0.282 (0.739)	1.381 (0.167)	3.155*** (0.002)
	ΔlnECI→ΔlnFDI	ΔlnECI →ΔlnM&A	ΔlnECI →ΔlnGREEN
	0.101 (0.919)	-0.721 (0.471)	0.751 (0. 453)
Low education level	ΔlnFDI→ΔlnECI	ΔlnM&A→ΔlnECI	ΔlnGREEN→ΔlnECI
	2.248** (0.016)	-0.932 (0.352)	-0.643 (0.521)
	ΔlnECI→ΔlnFDI	ΔlnECI →ΔlnM&A	ΔlnECI →ΔlnGREEN
	-0.009 (0.993)	-0.739 (0.460)	0.209 (0.835)
High tertiarization	ΔlnFDI→ΔlnECI	ΔlnM&A→ΔlnECI	ΔlnGREEN→ΔlnECI
	2.132** (0.033)	0.083 (0.934)	2.689*** (0.007)
	ΔlnECI→ΔlnFDI	ΔlnECI →ΔlnM&A	ΔlnECI →ΔlnGREEN
	-0.021 (0.983)	-0.345 (0.729)	-0.747 (0.455)
Low tertiarization	ΔlnFDI→ΔlnECI	ΔlnM&A→ΔlnECI	ΔlnGREEN→ΔlnECI
	0.473 (0.636)	-0.298 (0.765)	-0.398 (0.691)
	ΔlnECI→ΔlnFDI	ΔlnECI →ΔlnM&A	ΔlnECI →ΔlnGREEN
	0.050 (0.961)	-1.144 (0.253)	1.761 (0.063)
High BM	ΔlnFDI→ΔlnECI	ΔlnM&A→ΔlnECI	ΔlnGREEN→ΔlnECI
	1.571** (0.033)	-0.346 (0.633)	2.536*** (0.000)
	ΔlnECI→ΔlnFDI	ΔlnECI →ΔlnM&A	ΔlnECI →ΔlnGREEN
	-0.508 (0.667)	-0.625 (0.531)	-0.708 (0.400)
Low BM	ΔlnFDI→ΔlnECI	ΔlnM&A→ΔlnECI	ΔlnGREEN→ΔlnECI
	1.089 (0.167)	-0.859 (0.391)	-0.839 (0.433)
	ΔlnECI→ΔlnFDI	ΔlnECI →ΔlnM&A	ΔlnECI →ΔlnGREEN
	0.606 (0.400)	-0.834 (0.404)	1.656 (0.167)

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

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.

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 popu-

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

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

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

lation, and BM[11]. 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.

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 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 A4 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 instru-

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

Table 6
Panel VAR estimates.

Dep Var. $\Delta lnECI$	Full sample (1)	(2)	High education (3)	(4)	High GDP p.c. (5)	(6)	High tertiarization (7)	(8)	High BM (9)	(10)
$\Delta lnECI_{t-1}$	-0.353*** (0.081)	-0.341*** (0.089)	-0.397*** (0.056)	-0.462*** (0.063)	-0.343** (0.014)	-0.466*** (0.170)	-0.217** (0.097)	-0.327** (0.013)	-0.441*** (0.109)	-0.389** (0.130)
$\Delta lnFDI_{t-1}$	-0.033** (0.015)		-0.057***[1] (0.017)		-0.054* (0.032)		-0.053** (0.022)		-0.063*** (0.018)	
$\Delta lnGREEN_{t-1}$		-82.69*** (8.480)		-27.79*** (2.874)		-56.74*** (7.102)		-48.14*** (5.211)		-55.16*** (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.

ments 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.

All the columns in the table show a negative estimated coefficient of the two inward FDI variables[12]. In the short run, an increase in the stock of inward total FDI per capita corresponds to a decrease in the aggregate EC, 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.

Figure 4 plots how EC 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 EC after one year, followed by an increase after two years. Afterwards, the influence of inward FDI tends to disappear.

Figure 5 plots the response of EC 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.

Relying on the results in Table 5, we now analyze the effect of knowledge-intensive greenfield FDI on EC 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 EC in the short run.

Figure 6 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 EC 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

[12] 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).

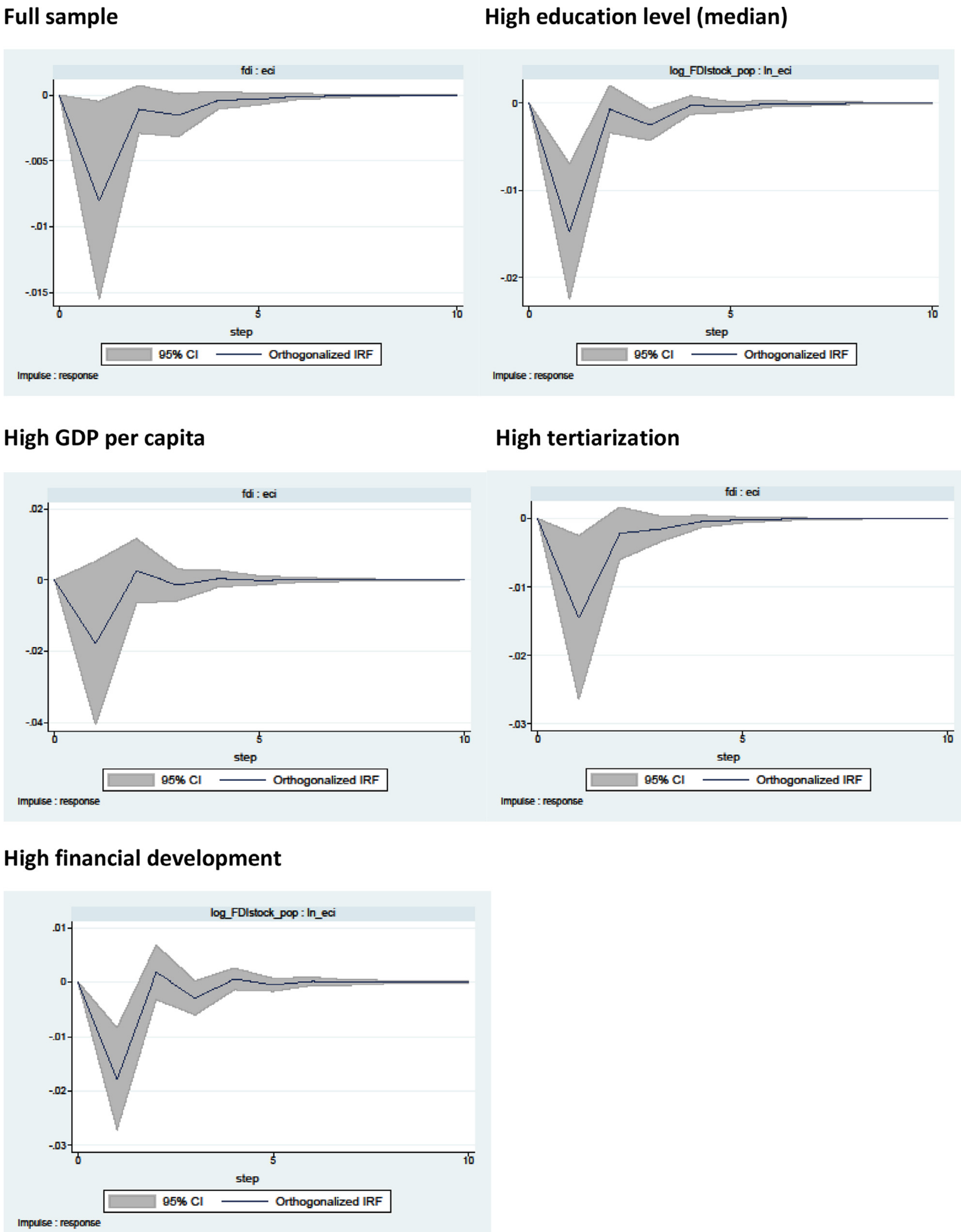
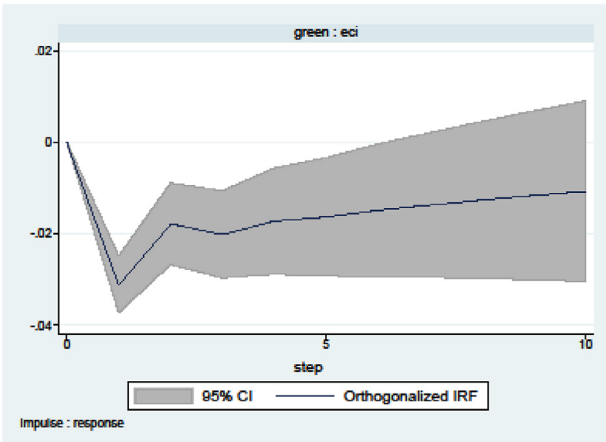
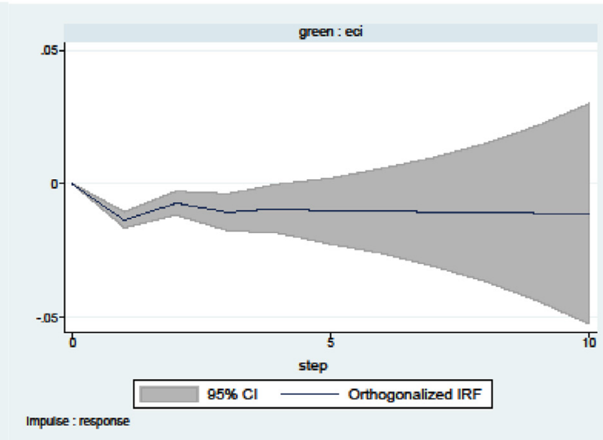


Fig. 4. IRF for one-lag PVAR: total inward FDI per capita.

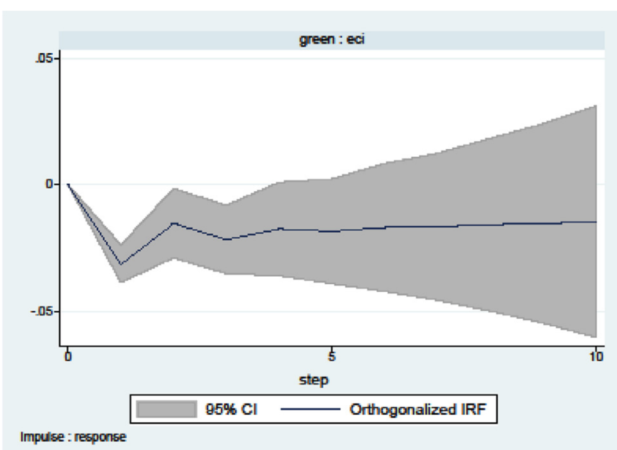
Full sample



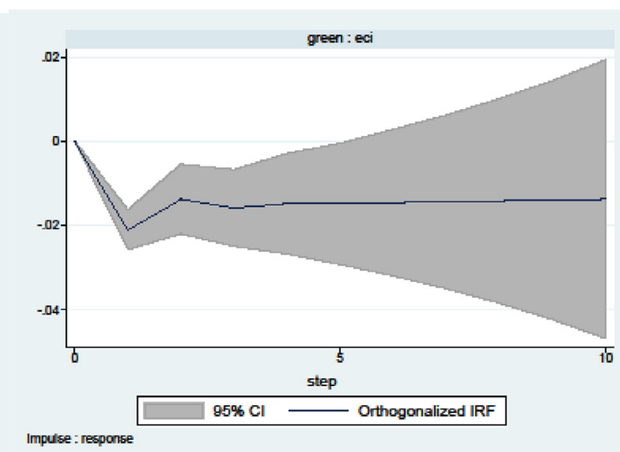
High education level



High GDP per capita



High tertiarization



High financial development

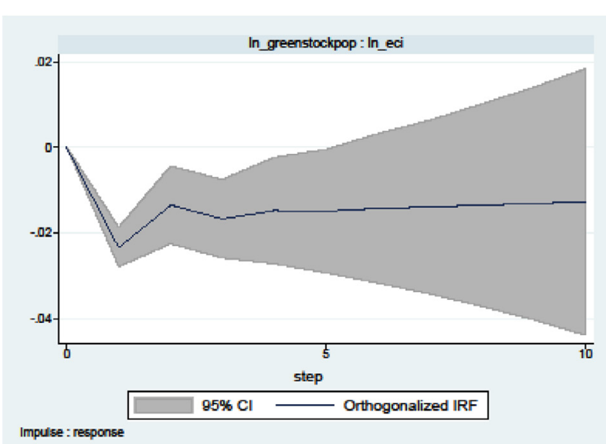


Fig. 5. IRF for one-lag PVAR: inward greenfield FDI per capita.

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

Dep Var. $\Delta lnECI$	Low education	Low GDP p.c.	Low tertiarization	Low BM
$\Delta lnECI_{t-1}$	-0.312*** (0.092)	-0.335*** (0.062)	-0.422*** (0.073)	-0.296*** (0.072)
ΔlnKIGREEN$_{t-1}$	-106.8*** (32.33)	-106.6*** (24.31)	-147.6*** (54.45)	-133.5*** (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*.

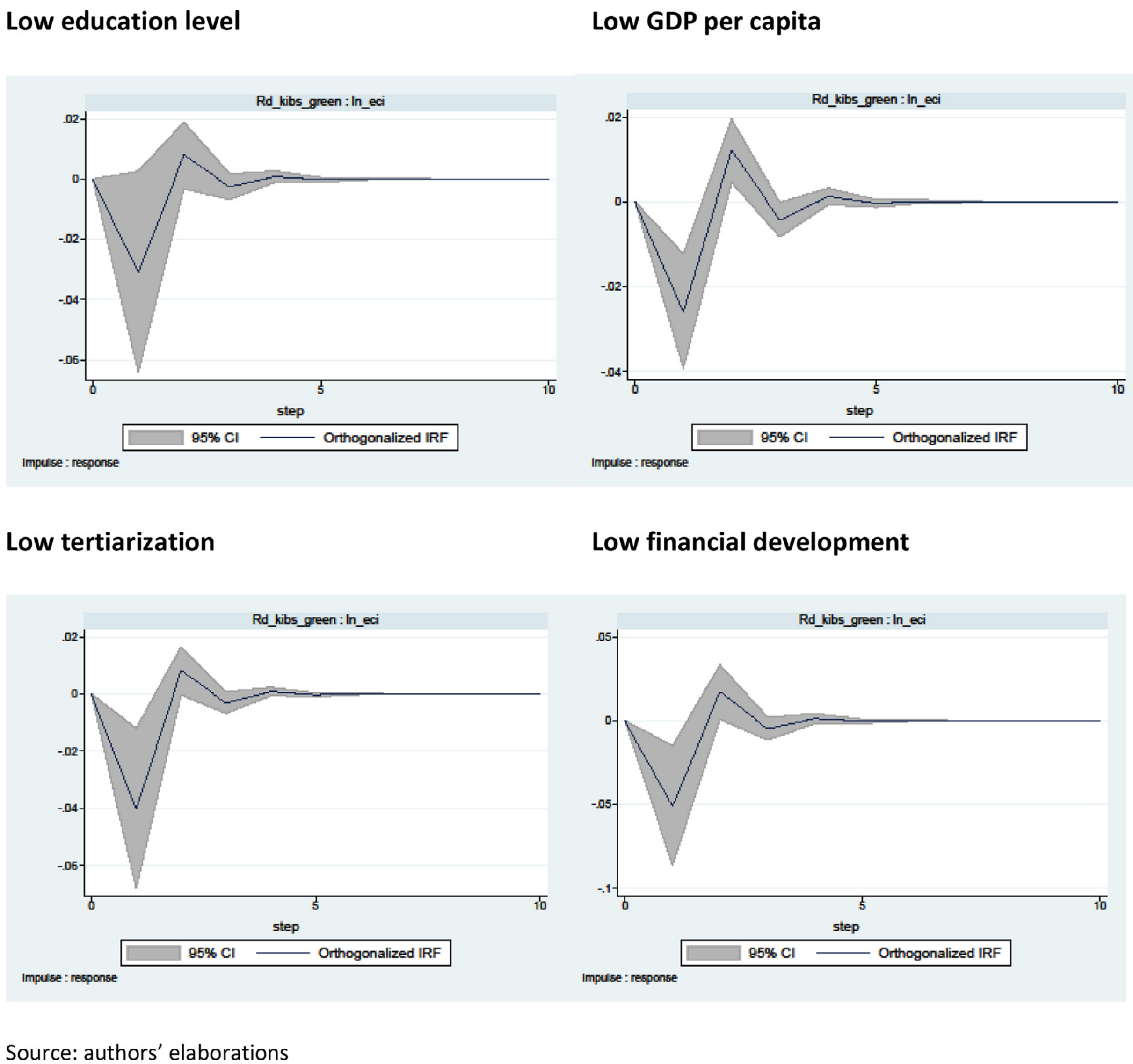


Fig. 6. IRF for one-lag PVAR: inward knowledge-intensive greenfield FDI per capita. Source: authors' elaborations.

existing goods in order 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.

Declaration of Competing Interest

We hereby declare that we do not have any actual or potential conflict of interest, including any financial, personal or other relationships with other people or organizations.

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Appendix

Table A1, A2, A3, A4 and A5, Figure A1.

Table A1
Correlation matrix: FDI variables.

	lnFDI	lnM&A	lnGREEN
lnFDI	1		
lnM&A	0.567***	1	
lnGREEN	0.453***	0.240***	1

Table A2
Summary statistics: ECI variables.

	Mean	Std. Dev.	Min	Max
ECI (original)	0.014	1.008	-2.435	2.814
ECI (normalized)	0.467	0.192	0	1
lnECI (log normalized)	-0.855	0.455	-3.697	0

Table A4
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.

Table A5
Panel Granger causality test: full sample, 2003-16.

	Δ*ln*FDI→Δ*ln*ECI
$\tilde{Z}$ statistic (p-value)	1.865* (0.064)
	Δ*ln*ECI→Δ*ln*FDI
$\tilde{Z}$ statistic (p-value)	-0.039(0.967)

Notes: * significant at 10% level.

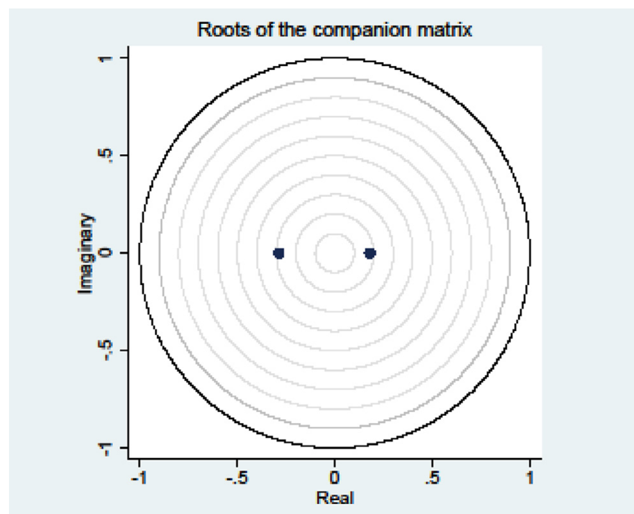

Fig. A1. Graph of the eigenvalue of the companion matrix. Source: authors' elaborations.

Table A3
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	

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