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Abstract

In recent years, India has emerged as a leading foreign direct investment (FDI) player, featuring prominently as both an origin and a destination of FDI. This study takes a firm-level perspective to empirically address the relationship between inward FDI, outward FDI, and firm-level performance in India. Using the Orbis database, our estimates reveal that Indian firms that have at least one foreign shareholder and/or one foreign subsidiary outperform those that do not. Controlling for endogeneity through propensity score matching and difference-in-difference techniques, we show that the deeper the FDI involvement, the larger the performance differentials. Moreover, compared with investing abroad, receiving foreign capital can contribute more toward enhancing the performance of Indian firms.

JEL: F23, L25, O53

Keyword: India, Foreign Direct Investment (FDI), inward, outward, firm-level performance

Introduction

In recent years, India has emerged as a leading foreign direct investment¹ (FDI) player, featuring prominently as both an origin and a destination of FDI. In 2016, India contributed USD 144,134 million to global outward FDI stocks, up from \$109,508 million in 2011, ranking 31st in the list of top investor countries worldwide and 10th in the group of developing economies. During the same year, India's share of global inward FDI stocks accounted for USD 318,502 million, up from \$206,354 million, ranking 21st in the list of top receiving countries worldwide and 9th among developing economies (UNCTAD 2018).

These figures contradict the traditional view of India as a mere manufacturing location. In fact, the geography of FDI is rapidly evolving and developing countries are becoming major hubs for outward and inward FDI (Ramamurti 2008, 2012; Ramamurti and Singh 2008; Sauvart 2008; Hattari and Rajan 2010; Pradhan 2017).

This study takes a firm-level perspective to empirically address the relationship among inward FDI, outward FDI, and firm-level performance in India.

Our data, which were downloaded from the Orbis database, cover industrial companies listed on the stock market and headquartered in India in 2015 and 2016, for 5,387 observations overall.

Our research question is related to the fervent debate on the internationalization–performance nexus. Starting with the seminal contribution of Bernard and Jensen (1995), many researchers have documented that, although there are few internationalized firms, they outperform domestic enterprises. The novelties of this study's approach lie in the geographical context and definition of internationalization.

Concerning the geographical context, the literature on internationalization and performance mostly focuses on advanced countries because firm-level datasets on developing economies have only become available recently. Although this is encouraging new academic research on the topic, evidence is still restricted to a few countries. This includes China (Yang and Mallick 2010; Dai and Yu 2013; Ma, Tang, and Zhang 2014; Huang and Zhang 2017), Chile (Pavcnik 2002; Alvarez and

Lopez 2005; Kandilov 2009), Colombia (Roberts and Tybout 1997; Fernandes and Isgut 2005; Sanghamitra, Roberts, and Tybout 2007), and Indonesia (Blalock and Gertler 2004; Arnold and Javorcick 2009; Yang and Chen 2012). To help fill this gap, this study focuses on India, a developing country for which the internationalization–performance nexus has remained largely unexplored, with the exceptions of the empirical analyses of Banga (2004), Pradhan (2004), Goldar, Banga, and Renganathan (2004), Haidar (2012), Demirbas, Patnaik, and Shah (2013), Petkova (2013), Mallick and Yang (2013), Thomas and Narayanan (2017), Gupta, Patnaik, and Shah (2018), and Goldar and Banga (2020).

Concerning the definition of internationalization, previous contributions mostly focus on trade (Blalock and Gertler 2004; Alvarez and Lopez 2005; Fernandes 2007; Yang and Mallick 2010; Haidar 2012; Du et al. 2012; Dai and Yu 2013; Mallick and Yang 2013; Gupta, Patnaik, and Shah 2018), whereas evidence on FDI is scanty. Moreover, studies investigating the FDI–performance nexus focus either on inward FDI (Doms and Jensen 1998; Banga 2004; Goldar, Banga, and Renganathan 2004; Salis 2008; Arnold and Javorcick 2009; Petkova 2013; Goldar and Banga 2020) or outward FDI (Pradhan 2004; Hijzen, Jean, and Mayer 2011; Demirbas, Patnaik, and Shah 2013; Huang and Zhang 2017; Thomas and Narayanan 2017), without attempting to build an integrated framework. To address this issue, this study focuses on FDI, rather than trade, and allows firms to both receive and promote FDI, thereby analyzing inward and outward FDI in a joint empirical model.

To the best of our knowledge, this is the first study to estimate the effects of inward and outward FDI on firm-level performance in India.

As the most notable finding, our measures of FDI turn out to be positive and statistically significant. This implies that Indian firms having at least one foreign shareholder and/or one foreign subsidiary record higher productivity, sales, value-added, return on equity, and return on capital employed and pay better wages than their domestic counterparts. Considering mutually exclusive classes of FDI involvement, firms engaged in both inward and outward FDI outperform those engaged in inward FDI only, which in turn outperform those engaged in outward FDI only. By controlling for

endogeneity through propensity score matching (PSM) and difference-in-difference (DID) techniques, this study shows that receiving foreign capital, more than investing abroad, helps Indian firms achieve outstanding performance.

In the remaining sections of the paper, we review the literature and provide a brief overview of inward and outward FDI in India. Then, we introduce our dataset, describe the econometric models, and present the estimation results. The last section concludes the paper, discusses policy implications, and suggests future lines of research.

Literature review

The seminal contribution of Bernard and Jensen (1995) drew researchers' attention to the relationship between internationalization and firm-level performance. Irrespective of the year and the country of analysis, vast empirical evidence reveals that although there are few internationalized firms, they outperform domestic enterprises. This result is robust to different internationalization strategies and performance measures (for a survey, refer to Singh 2010; Hayakawa, Kimura, and Machikita 2012; and Wagner 2016).

In what follows, we review studies examining the relationships among inward FDI, outward FDI, and firm-level performance.

Theoretical contributions

From a theoretical point of view, two alternative hypotheses help in framing the existence of a positive correlation between FDI involvement and firm-level performance.

According to the first hypothesis, known as "self-selection," ex-ante performance differences exist between firms that will and will not engage in FDI. The theoretical foundation of the self-selection mechanism can be traced to Head and Ries (2003), Helpman, Melitz, and Yeaple (2004), and Grossman, Helpman, and Szeidl (2006), who extend the benchmark framework of Melitz (2003) to analyze the intra-industry effects of outward FDI. In Helpman, Melitz, and Yeaple (2004), upon entry into the market, firms draw a productivity level from a known distribution function and, subsequently,

decide whether to internationalize or to operate domestically. Internationalization entails considerable fixed costs, which are higher in the case of (horizontal) outward FDI than in the case of exports. As the model shows, exposure to international markets induces the most productive firms to engage in outward FDI and the least productive firms to operate domestically; firms with intermediate productivity levels self-select into export operations. Head and Ries (2003) consider a richer framework in which firms are allowed to engage in both horizontal and vertical outward FDI. In this case, firms engaging in the former are driven by market access and those engaging in the latter are driven by cost savings. This model indicates that the most productive firms engage in horizontal FDI in advanced countries to serve the local demand directly and the least productive firms engage in vertical FDI in emerging countries to reduce labor costs. Given that firms may follow mixed strategies, Grossman, Helpman, and Szeidl (2006) consider combinations of horizontal and vertical outward FDI, allowing an interaction between market access and cost saving considerations. Many factors, including the foreign-market dimension, transportation costs, and fixed costs of production and assembly, become key determinants of the strategy that a firm should undertake.

According to the second hypothesis, known as “learning,” ex-post performance differences emerge because of firms’ exposure to international markets. Compared with the self-selection mechanism, the learning process presents less profound theoretical foundations because the model by Clerides, Lach, and Tybout (1998), regarded as a cornerstone in the literature on learning, deals exclusively with export. Despite the absence of a specific theoretical framework, one could imagine several factors explaining a learning-by-outward-FDI mechanism. For instance, by interacting with foreign competitors and customers, firms might derive information about processes to reduce cost and improve quality (De Loecker 2007). They might increase their scale and efficiency (Baldwin and Gu 2009) and get the motivation to innovate (Aw and Lee 2008). In some cases, operating abroad might even become a substitute for importing (access to) better institutions, thereby contributing toward correcting credit constraints and a weak institutional environment in the home-country (Van Biesebroeck 2005).

To summarize, all theoretical models reviewed in this sub-section rationalize the existence of a positive correlation between FDI involvement and firm-level performance, the former being defined as outward FDI. The major difference between theorists of self-selection and theorists of learning lies in the direction of causality.

Empirical contributions

In this sub-section, we review the empirical contributions that address the FDI–performance nexus using firm-level data.

First, we focus on the sub-literature inspired by the self-selection hypothesis. Consistent with Helpman, Melitz, and Yeaple (2004), a positive and statistically significant correlation between productivity and FDI has been detected (see, for instance, Doms and Jensen 1998; Pradhan 2004; Kimura and Kiyota 2006; Demirbas, Patnaik, and Shah 2013; Thomas and Narayanan 2017). In these papers, most productive firms engage in outward FDI. The exception is for Doms and Jensen (1998), whose findings show most productive firms receiving inward FDI.

Refinements of these simple analyses follow two broad research trajectories. On the one hand, Federico (2010), Kohler and Smolka (2011), and Gattai and Trovato (2016) characterize heterogeneous firms' mapping into different sourcing strategies, including outward FDI. Consistent with the theoretical argument of Antras and Helpman (2004), these studies show that most productive firms self-select into outward FDI, sourcing intermediate components within the boundaries of a foreign subsidiary. On the other hand, outward FDI is dissected according to the destination and ownership structure. Regarding the destination, Aw and Lee (2008) and Damijan, Polanec, and Prasnikar (2007) find that most productive firms invest in developed—rather than developing—countries, supporting the theoretical predictions of Grossman, Helpman, and Szeidl (2006). Concerning the ownership structure, the theoretical and empirical analysis of Raff, Ryan, and Stähler (2012) suggests that most productive firms engage in wholly owned enterprises, followed by joint-ventures and mergers and acquisitions (M&As).

Second, we focus on the sub-literature inspired by the learning hypothesis. Evidence of a learning effect of outward FDI is available for Italy (Castellani and Zanfei 2007; Castellani, Mariotti, and Piscitello 2008; Borin and Mancini 2016), France (Navaretti, Castellani, and Disdier 2010; Hijzen, Jean, and Mayer 2011), Japan (Ito 2007; Hijzen, Inui, and Todo 2010), and China (Huang and Zhang 2017). Although sophisticated econometric techniques are applied to account for endogeneity, results are not straightforward. Castellani, Mariotti, and Piscitello (2008), Borin and Mancini (2016), and Huang and Zhang (2017) find that outward FDI has a positive impact on a wide array of performance variables, whereas Ito (2007) and Hijzen, Inui, and Todo (2010) do not detect any significant effect. Contributions testing the learning hypothesis in the context of inward FDI typically focus on cross-border M&As. Applying proper econometric tools to address endogeneity, a few studies identify a causal link from inward FDI to firm-level performance (Bertrand and Zitouna 2008; Fukao et al. 2008; Salis 2008; Arnold and Javorcik 2009; Goldar and Banga 2020). Refinements of this simple approach inspire two main research trajectories. The first trajectory identifies multinationals that exercise a high influence on the acquired firm's performance. In this context, Chen (2011) finds that acquisitions by developed countries' multinationals enhance the target firms' profits more than acquisitions by developing countries' multinationals. The second trajectory investigates the domestic firms that experience the highest positive impact of acquisition. Particularly, Girma et al. (2015) show that the rate of productivity change is sensitive to the pre-acquisition productivity level of the target firm. Moreover, beyond some critical level of pre-acquisition productivity, the rate of technology transfer through inward FDI starts declining.

To summarize, two results emerge from the empirical literature on FDI and performance. First, there is evidence of self-selection for both inward and outward FDI; second, there is conclusive evidence of learning only in case of inward FDI.

Related studies on India

Until now, the literature on internationalization and firm-level performance has predominantly focused on advanced countries. This poses a severe limitation to our understanding of the self-

selection and learning mechanisms because multinationals from developing economies might behave differently from those headquartered in advanced countries (Ramamurti 2008, 2012; Ramamurti and Singh 2008; Hattari and Rajan 2010).

Among developing economies, China, Chile, Colombia, and Indonesia have received considerable attention (Pavcnik 2002; Blalock and Gertler 2004; Fernandes and Isgut 2005; Fernandes 2007; Arnold and Javorcick 2009; Yang and Mallick 2010; Dai and Yu 2013; Huang and Zhang 2017).

Considering India, some studies focus on the export–performance nexus using firm-level data and confirming the self-selection (Haidar 2012; Mallick and Yang 2013; Gupta, Patnaik, and Shah 2018) or the learning hypotheses (Mallick and Yang 2013). Others address the relationship between FDI and firm-level performance focusing solely on outward FDI (Demirbas, Patnaik, and Shah 2013; Pradhan 2004; Thomas and Narayanan 2017) or inward FDI (Banga 2004; Goldar, Banga, and Renganathan 2004; Petkova 2013; Goldar and Banga 2020). To the best of our knowledge, Indian inward and outward FDI have not been integrated in a joint empirical framework yet.

For outward FDI, using a panel of Indian firms over the period 2001–2011, Demirbas, Patnaik, and Shah (2013) find significant performance differences between domestic firms and firms that internationalize through export or outward FDI. Consistent with Helpman, Melitz, and Yeaple (2004), firms with certain characteristics—in terms of productivity, value-added, total assets, R&D intensity, and return on equity—embark on exporting, and an intensification of these characteristics yields outward FDI. This indicates that self-selection is at play, although issues of reverse causality are not addressed econometrically. Consistent results are those of Pradhan (2004) and Thomas and Narayanan (2017).

For inward FDI, using a panel of Indian firms over the period 2000-2015, Goldar and Banga (2020) document a strong and significant productivity enhancing effect of inward FDI among manufacturing firms, which is particularly pronounced when inward FDI originates from developed countries. Controlling for endogeneity through treatment effect methods, both direct and indirect effects are

detected. Consistent evidence is reported by Banga (2004), Goldar, Banga, and Renganathan (2004), Petkova (2013), and Goldar and Sharma (2015).

Considering previous literature, Demirbas, Patnaik, and Shah (2013) is perhaps the closest to our study. However, we introduce novelties that widen our perspective and mark a clear departure from it. First, this study's focus is not restricted to outward FDI; we consider a richer framework in which Indian firms may engage in inward and/or outward FDI. Second, we depart from Demirbas, Patnaik, and Shah (2013) by considering the learning rather than the self-selection hypothesis, a side of causality that has not been convincingly addressed. Our econometric models draw on the assumption that FDI involvement may foster firm-level performance. This implies that significant differences in performance between domestic firms and firms engaged in FDI may be the consequence, not the cause, of FDI.

Inward FDI and outward FDI in India: Overview

The attitude of Indian policymakers toward FDI has undergone a dramatic change over the last century (Cooper 2006; Prime 2009; Chakravorty 2012; Shaw 2012). During the pre-liberalization period (1948–1991), the volume of inward FDI was rather low. If not completely hostile, India was not very receptive toward foreign capital (CUTS 2003). This attitude translated into restrictive measures toward inward FDI, aimed at protecting the domestic base of the created assets. During this period, the volume of outward FDI was also low. Although the emergence of Indian multinationals started in the 1960s, it involved only a few conglomerates, such as the Birla group and the Shriram group.

However, there was a reversal in policy stance during the 1980s (CUTS 2003). The liberalization of industrial and trade policy during this decade was accompanied by an increasingly receptive attitude toward FDI. On the one hand, the Indian Government realized that multinationals were key to the modernization of the Indian economy because of the intangible assets they could transfer to local firms upon opening local subsidiaries. This, of course, fostered inward FDI. On the other hand, Indian

policymakers recognized that the future growth of local enterprises could be influenced by the share of the world market they could earn through outward FDI. This, in turn, provided the initial momentum to outward FDI.

Full-scale liberalization measures were introduced in the 1990s with a view to integrating the Indian economy with the world economy (Hattari and Rajan 2010; Nijman 2012; Pandit 2012). During the post-liberalization period (1991–), many policies were implemented to favor inward FDI, such as the automatic approval system for priority industries and the liberalization of the procurement and licensing of foreign technology. Sector-specific caps for foreign ownership were defined but were gradually relaxed over time. A comprehensive review of the Indian inward FDI policy occurred in 2006 and new measures were introduced to consolidate existing liberalization efforts and further rationalize FDI (Aoyama and Parthasarathy 2012). A further boost in inward FDI followed the implementation of the “Make in India” campaign of 2014, which aimed at enhancing India’s image as a preferred destination for FDI (Export-Import Bank of India 2014). By providing foreign investors with unrestricted access to most industries, this reform has been contributing toward improving India’s “ease of doing business” World Bank ranking since 2015. Finally, the Department of Industrial Policy and Promotion issued the revised FDI policy in 2017, with the explicit goal of encouraging inward FDI by removing multiple layers of bureaucracy and processing proposals under the government approval route in a more streamlined, positive, and expeditious manner. India’s new FDI policy has eased 87 FDI rules across 21 sectors in the last three years, opening up traditionally conservative sectors like infrastructure, agriculture, and defense.

As the Indian economy liberalized and the policy framework evolved, inward FDI rose significantly. Global inward FDI has steadily increased over the last few decades, with flows moving from USD 205 billion in 1990 to USD 1,746 billion in 2016. According to UNCTAD 2018, the share of developing economies in the global inward FDI flows rose from 29% in 2006 to 37% in 2016, reaching a peak of 54% in 2014. Inward FDI flows to developing economies also witnessed an exceptional increase in absolute terms, moving from USD 412 billion to USD 646 billion. The

growing importance of developing countries in global inward FDI flows reflects in the shares of stocks directed to developing countries. Global inward FDI stocks amounted to USD 14,090 billion in 2006 and peaked at USD 26,728 billion USD in 2016—a growth rate of 90% in a 10-year period. Likewise, inward FDI stocks to developing economies rose from USD 3,309 billion to USD 9,078 billion, growing at a rate of 174% during the same period. Within the group of developing economies, Brazil, Russia, India, and China—the so-called BRIC countries—featured prominently. In fact, they accounted for 36% (22%) of inward FDI flows (stocks) to developing economies in 2001, which rose to 42% (29%) in 2016. Concerning inward FDI flows, India ranked 11th in the 2016 list of top receiving countries worldwide, 7th among developing economies, and 3rd in the group of BRIC countries. Concerning inward FDI stocks, in the same year, it ranked 21st, 9th, and 4th, respectively. Inward FDI flows to India were at USD 237 million in 1990; they steadily increased during the next few decades up to USD 44,486 million in 2016. Inward FDI stocks to India, amounting to USD 1,657 million in 1990, peaked at USD 318,502 million in 2016 (Figure 1).

[Figure 1]

With the gradual liberalization of the Indian economy and the evolving regulatory regime, an increasing number of domestic firms started viewing the global market as an opportunity to improve their growth prospects and achieve a higher growth trajectory. While the first wave of Indian outward FDI (during the pre-liberalization phase) involved a handful of firms and concentrated on Asian and African developing countries, the second wave (during the post-liberalization phase) saw the participation of many firms, which mostly targeted developed countries (Brienen, Burger, and van Oort 2010; Hattari and Rajan 2010; Pradhan 2017).

Global outward FDI has witnessed an upsurge during the last decade, with flows increasing from USD 244 billion in 1990 to USD 1,452 billion in 2016. A notable trend in the geography of outward FDI illuminates the centrality of developing economies as key contributors (UNCTAD 2018). The share of developing economies in the global outward FDI flows rose from 15% in 2006 to 26% in 2016. In fact, during this period, outward FDI flows from developing economies doubled in absolute

terms, increasing from USD 209 billion to USD 383 billion. The centrality of developing countries in global outward FDI flows also reflects in their shares of global outward FDI stocks. While the global outward FDI stocks increased from USD 15,008 billion in 2006 to USD 26,160 billion in 2016, a growth rate of 74%, outward FDI stocks from developing economies shot up from less than USD 1,669 billion to USD 5,809 billion—a growth rate of 248% during the same period. In particular, the share of BRIC countries in developing countries' outward FDI flows (stocks) amounted to 14% (17%) in 2001, rising to 53% (33%) in 2016. Within the group of BRIC countries, India proved to be an important home-country for FDI. Concerning outward FDI flows, in 2016, India ranked 36th in the list of top investor countries worldwide, 15th in the group of developing economies, and 3rd in the group of BRIC countries. Concerning outward FDI stocks, in the same year, it ranked 31st, 10th, and 4th, respectively. Outward FDI flows from India amounted to USD 6 million in 1990, gradually rising to USD 5,120 million in 2016. Likewise, outward FDI stocks from India, starting at a negligible USD 124 million in 1990, reached USD 114,134 million in 2016 (Figure 2).

[Figure 2]

Although quite active as both a receiver and a promoter of FDI, India remains a net FDI receiver.

Econometric analysis

Data

Our econometric analysis rests on firm-level longitudinal data downloaded from the Orbis database, issued by Bureau van Dijk. Bureau van Dijk collects public data from national administrative sources and publishes them in a standard format to allow for cross-company comparisons (Ribeiro, Menghinello, and De Backer 2010). From 2017, Orbis contains administrative dataⁱⁱ on 300 million firms across the globe; moreover, it presents several distinctive features that make the database particularly suitable for this study. Unlike other administrative firm-level databases, Orbis covers small and large firms, listed and unlisted companies, all sectors of the economy, and all continents. Additionally, unlike census-type firm-level databases, Orbis reports financial and real variables and

exhaustive information regarding firms' ownership structure, including complete lists of shareholders and subsidiaries. This means that all of the information needed to perform our empirical exercise are available in the database, which avoids merging potentially non-harmonized data sources.

Our data, which were downloaded in 2016 and 2017, cover industrial companies listed on the stock market and headquartered in India in 2015 and 2016, for 8,516 observations overall. However, due to the large number of missing values, our working sample is restricted to those firms that are not missing the information regarding value-added, sales, and wages. Applying this adjustment, we have 5,387 observations in the pooled sample, with 2,750 firms in 2015 and 2,637 firms in 2016. Industrial companies are selected from a long list of company types to study the behavior of heterogeneous firms within a relatively homogeneous class. Furthermore, we restrict attention to listed firms because they are surveyed in more detailed. In Ribeiro, Menghinello, and De Backer (2010), Orbis is said to assign the company location (country, region, and city) by the location of its headquarters: This means that our data does not include Indian subsidiaries of multinationals headquartered outside India.

Our panel covers only two years because Orbis provides historical data about balance sheet items—which we use to measure performance—but only contemporaneous data about shareholders and subsidiaries—which we use to construct our FDI measures. Since our balance sheet data cover the 2011-2016 period, but our shareholders and subsidiaries data cover only 2015 and 2016, we end up having a 2-year panel dataset.

From a geographical point of view, 36% of our sample is from the 10 most prosperous cities in India, namely Chandigarh, Panaji, Delhi, Valparai, Greater Mumbai, Pune, Ludhiana, Chennai, Shimla, and Jalandhar. If we adopt the NACE 1-digit classificationⁱⁱⁱ, most firms belong to the manufacturing sector, accounting for 65% of our sample; this is followed by the information and communication (8%), wholesale and retail trade (6%), professional, scientific and technical activities (4%), construction (3%), mining and quarrying (2%), agriculture, forestry and fishing (2%) and electricity, gas, steam, and air conditioning supply (2%) sectors. Firm-level diversity is also relevant. Being listed on the stock market, all firms in our sample are “very large” companies, according to the Orbis

classification of size.^{iv} Still, they turn out to be quite heterogeneous in terms of age, with the minimum being 0 years, maximum 159 years, and the average age being around 32 years.

Table 2 summarizes the FDI involvement of Indian firms in our sample along two dimensions. The first dimension concerns the distinction between current versus first FDI involvement, thus producing “status” FDI variables and “start” FDI variables. The second dimension pertains to the general versus specific FDI involvement, thus resulting in “general” FDI variables and “mutually exclusive” FDI variables (Table 1). To capture the current FDI involvement, we define several measures of FDI status. In particular, a firm is said to engage in FDI if it has at least one foreign shareholder or one foreign subsidiary in the current year.^v Drawing on this definition, the label *FDI* denotes those firms engaged in inward and/or outward FDI at year *t*. *FDI* firms are further dissected into three mutually exclusive classes of current FDI involvement: *only_inwardFDI* are those firms engaged only in inward FDI; *only_outwardFDI* are those firms engaged only in outward FDI; *twoways_FDI* are those firms engaged in both inward and outward FDI. Additionally, we denote as *non FDI* those firms engaged in neither inward nor outward FDI in *t*. To characterize the first FDI involvement, we consider several measures of FDI start. More precisely, a firm is said to start engaging in FDI if it has at least one foreign shareholder or one foreign subsidiary in the current year, but has neither in the previous year. Therefore, we denote as *start FDI* those firms engaged in inward and/or outward FDI for the first time at year *t*. *start FDI* firms are further dissected into mutually exclusive classes of first FDI involvement: *start_only_inwardFDI* are those firms that started engaging only in inward FDI; *only_outwardFDI* are those firms that started engaging only in outward FDI; *twoways_FDI* are those firms that started engaging in both inward and outward FDI. For the sake of completeness, we denote as *non FDI start* those firms that started engaging in neither inward nor outward FDI in *t*.

As the most notable finding, current FDI involvement in India is quite deep: 71% (50%) of our firms engage in FDI in 2015 (2016), against 29% (50%) that have neither foreign subsidiaries nor foreign shareholders in the same year. Considering the mutually exclusive classes of FDI status, *only_inwardFDI* firms make up 43% (16%) of the sample, *only_outwardFDI* firms account for 1%

(8%) whereas *twoways_FDI* firms amount to 27% (26%) in 2015 (2016). This evidence is consistent with the aggregated data presented before: irrespective of the recent evolution in policy framework, India remains a net FDI receiver. Considering the first FDI involvement, out of 796 *non FDI* firms in 2015, only 713 have data for the relevant variables information in 2016. Of these, 95 firms engage in FDI for the first time in 2016 (*start FDI*), meaning that they had neither foreign subsidiaries nor foreign shareholders in 2015 and have at least one in 2016.^{vi} Coming to the mutually exclusive classes of FDI start, we notice that the largest percentage accrue to *start_only_inwardFDI* (6%) and *start_only_outwardFDI* firms (6%), followed by *start_twoways_FDI* firms (1%).

[Tables 1, 2]

Econometric models and estimation results

To establish the effect of inward and outward FDI on firm-level performance, according to the learning hypothesis, we consider the first FDI involvement through the FDI start variables in a panel regression framework. Our attention is restricted to those firms that do not have any FDI involvement in $t-1$, namely those firms that could potentially start engaging in FDI in t . Equation 1 is set as follows:

$$performance_{it} = \alpha start_FDI_{it} + \beta IA_{it} + \gamma age_{it} + \delta city_{it} + \theta industry_{it} + \varepsilon_{it} \quad (1)$$

The dependent variable *performance* is a measure of firm i 's performance at time t . Consistent with the literature, *performance* is primarily meant to capture firm-level productivity. Productivity, in its broadest interpretation, reflects the efficiency by which inputs are turned into outputs (Hulten 2001). Labor productivity—defined as the ratio between value-added and the number of employees—does not control for differences in capital intensity across firms, whereas total factor productivity (TFP) does. In this paper, productivity is evaluated in terms of the total factor productivity under the estimation-based approach to address the simultaneity and selection bias, following Levinsohn and Petrin (2003). Accordingly, we assume the production function of firm i at time t to be Cobb-Douglas. In this framework, the logarithm of firm i 's output at time t can be expressed as a function of the

logarithm of the freely variable input labor, the logarithm of the intermediate input, and the logarithm of the state-variable capital. We measure the firm's output in terms of value-added, the input labor as the cost of employees^{vii}, the intermediate input as material costs, and the capital stock through fixed assets. As in Goldar, Banga, and Renganathan (2004), Petkova (2013) and Thomas and Narayanan (2017), we compute the latter according to the Perpetual Inventory Method—accounting for depreciation and new investments. All variables are in logarithms. At this stage, it is worth mentioning that the entire 2011-2016 time series for value-added, cost of employees, material costs, fixed assets, and depreciation is exploited to implement the “levpet” routine available in Stata. As a robustness check, we consider alternative measures of performance, including sales (*SALES*), wages (*WAGES*), value-added (*VALUE-ADDED*), return on equity (*ROE*) and return of capital employed (*ROCE*). All performance variables are in logarithms.

On the right-hand side of Equation 1, *start_FDI* denotes our main variable of interest, capturing firm *i*'s first involvement in FDI in *t*. Particularly, the dummy *start_FDI* equals 1 when firm *i* has neither foreign subsidiaries nor foreign shareholders in *t-1* and has at least one in *t*; it equals 0 otherwise. In the spirit of the literature supporting the learning hypothesis, we expect *start_FDI* to be positive and statistically significant, meaning that the first FDI involvement fosters firm-level performance.

To check the robustness of our results, additional controls at the firm-, space-, and industry-level are considered. Firm-level controls include the logarithm of firm's intangible assets (*IA*) and age (*age*). According to the International Accounting Standards Board 38, intangible assets are those lacking physical substance, including patents and R&D expenditures; therefore, they can be considered as a measure of innovation (Griliches 1990). The relationship between innovation and performance at the firm level is well established from both a theoretical and an empirical standpoint (Crepon, Duguet, and Mairesse 1998; Hall and Sena 2014), and previous evidence about India confirms that innovation is positively correlated with performance (Sharma 2010, 2011; Ambrammal and Sharma 2016). The variable *age* is defined as the difference between year *t* and the firm's year of foundation. Space-level controls are accounted for with the dummy *city* that equals 1 if firm *i* is headquartered in one of the

ten most prosperous cities in India; the industry-level controls, grouped in the vector *industry*, take the form of NACE 2 digit-industry dummies that should be suitable to account for industry-specific heterogeneity due to market structure and financial factors.^{viii} The Orbis database does not provide data on the firm's export status and, therefore, we cannot control for it.

Our results from panel OLS estimates of Equation 1 are shown in Table 3; standard errors are clustered at the firm level. For every performance variable, four columns are shown: in (a) we consider a parsimonious specification in which performance is regressed only on first FDI involvement; in (b) we control for age, space and industry dummies; in (c) we re-run the previous estimation on the restricted sample of firms that do not miss the information regarding intangible assets; in (d) we control for *IA*, age, space, and industry dummies on the restricted sample of firms that do not miss the information regarding intangible assets. Our *IA* variable suffers from many missing values, compared with value-added, sales, and wages. On the one hand, having *IA* on the right-hand side of Equation 1 is challenging considering the role played by innovation in enhancing firm-level productivity (see above); on the other hand, this comes at the expense of dramatically fewer observations. To address this trade-off, in columns (a) and (b) we consider our entire working sample without controlling for innovation, whereas in columns (c) and (d) we restrict our attention to the smaller sample of firms for which the *IA* information is available and explore its effect on firm-level performance.

[Table 3]

As the most notable finding, *start_FDI* turns out to be a positive and statistically significant determinant of firm-level performance: Indian firms engaging in FDI for the first time do exhibit higher *TFP*, *VALUE-ADDED*, *SALES*, *WAGES*, *ROE*, and *ROCE* compared with non-starters. Moreover, this result is robust to firm-, space-, and industry-level controls, as we may appreciate moving from column (a) to columns (b), (c), and (d) of Table 3. Put another way, controlling for the firm's age, innovation, location, and industry does not undermine the role of *start_FDI* as a major driver of firm's performance. Adding to this, *IA* is positive and statistically significant. However, its

explicative power is restricted to the *VALUE-ADDED*, *SALES*, and *WAGES* equations. As for *age*, this variable is significant only when performance is evaluated in terms of *VALUE-ADDED* and *WAGES*, and its sign is positive.

To go deeper into estimating the relationship among inward FDI, outward FDI, and firm-level performance, in Equation 2 we consider the mutually exclusive classes of first FDI involvement, in a panel regression framework:

$$\begin{aligned}
 performance_{it} &= \alpha_1 start_only_inwardFDI_{it} + \alpha_2 start_only_outwardFDI_{it} \\
 &+ \alpha_3 start_twoways_FDI_{it} + \beta IA_{it} + \gamma age_{it} + \delta city_{it} \\
 &+ \theta industry_{it}
 \end{aligned} \tag{2}$$

On the right-hand side of Equation 2, our main variables of interest are *start_only_inwardFDI*, *start_only_outwardFDI*, and *start_twoways_FDI*, capturing firm *i*'s first involvement in inward FDI only, outward FDI only, or in both, respectively. Particularly, the dummy *start_only_inwardFDI* (*start_only_outwardFDI*) equals 1 when firm *i* has neither foreign subsidiaries nor foreign shareholders in *t-1* and it has at least one foreign shareholder (subsidiary) but no foreign subsidiaries (shareholders) in *t*; it equals 0 otherwise. Similarly, the dummy *start_twoways_FDI* equals 1 when firm *i* has neither foreign subsidiaries nor foreign shareholders in *t-1* and it has at least one foreign shareholder and one foreign subsidiary in *t*; it equals 0 otherwise. To check the robustness of our results, performance is evaluated in terms of *TFP*, *VALUE-ADDED*, *SALES*, *WAGES*, *ROE*, and *ROCE* and the same controls at the firm-, space-, and industry-level are considered, as in Equation 1. Our results from panel OLS estimates of Equation 2 are shown in Table 4; standard errors are clustered at the firm level and year (2016) fixed effect is considered.

[Table 4]

From Table 4, *start_only_inwardFDI*, *start_only_outwardFDI*, and *start_twoways_FDI* turn out to be positive and statistically significant drivers of *SALES*, *VALUE-ADDED*, and *WAGES*, whereas their impact on *TFP*, *ROE*, and *ROCE* looks less pronounced and mainly confined to the *start_only_inwardFDI* or *start_only_outwardFDI* dummies. Being robust to the inclusion of firm-, space-, and industry-level controls, this suggests that Indian firms engaging for the first time in any of the mutually exclusive classes of FDI outperform those non-engaging in FDI, which confirms that a learning mechanism is at play, allowing Indian firms to benefit from their first FDI involvement. At this stage, it should be noticed that *IA* is positive and significant in most specifications, showing that innovation fosters performance of Indian firms in terms of *SALES*, *VALUE-ADDED*, and *WAGES*; the impact of *age* is instead restricted to the *VALUE-ADDED* and *WAGES* equations.

Our findings of a positive effect of *start_only_outwardFDI* on firm-level performance are in line with previous evidence reported for advanced countries (Castellani and Zanfei 2007; Castellani, Mariotti, and Pischitello 2008; Borin and Mancini 2016) and for developing countries (Huang and Zhang 2017). Our findings of a positive effect of *start_only_inwardFDI* on firm-level performance confirm previous evidence on advanced countries (Bertrand and Zitouna 2008; Fukao et al. 2008; Girma et al. 2015) and developing countries (Arnold and Javorcik 2009; Salis 2008). However, analyzing inward and outward FDI in a joint empirical framework allows deriving some additional results that are original of the present study. In our estimates, the coefficient of *start_twoways_FDI* is systematically larger than those of *start_only_inwardFDI* and *start_only_outwardFDI*. This suggests that the deeper the FDI involvement, the larger the performance differential in terms of productivity, sales, value-added, wages, return on equity, and return on capital employed. Deeper FDI involvement leaves more room for learning.

Although we show firms engaged in FDI for the first time outperforming those that do not engage, in the spirit of the learning hypothesis, this might not indicate a causal effect if self-selection is at play. In this case, firms exhibiting superior performance self-selected into FDI in the past and remained so

over time. Hence, the positive correlation detected after estimating Equations 1 and 2 might be the result of pure self-selection rather than learning.

To deal with reverse causality suitably, it would be essential to procure data for the counterfactual situation to observe whether, without foreign direct investment, firms engaged in FDI would have performed better than non-FDI firms. Unfortunately, we cannot follow the same firm as either it engages in FDI or it does not, therefore we resort to matching techniques. For the purpose of the present analysis, we exploit the PSM procedure (Becker and Ichino 2002; Caliendo and Hujer 2006; Caliendo and Kopeinig 2008; and Imbens and Wooldridge 2009). The rationale for this statistical approach can be summarized as follows. Since it is not possible to observe the same firm in the event it engages in FDI and in the event it does not, we match each firm engaged in FDI with another firm that is ex-ante similar to the first, but is not engaged in FDI. Subsequently, we proceed to evaluate the differences between the performances of the former and the latter, which serves as a proxy for the unobservable counterfactual situation. Roughly speaking, the PSM controls for the selection bias by restricting the comparison to differences within carefully selected pairs of firms with similar observable characteristics before FDI involvement has been started. Its purpose is to construct the missing counterfactual of how the FDI firms would have behaved had they not been involved in FDI. The underlying assumption for the validity of the procedure is that conditional on the observable characteristics that are relevant for the FDI decision, potential outcomes for the FDI and non-FDI firms are orthogonal to the treatment status.

In the context of our study, the propensity score is the predicted probability of an Indian firm engaging in FDI for the first time. Ex-ante similarity is established by estimating the probability that firm i engages in FDI for the first time in t conditional on firm's characteristics, as observed in $t - 1$, the so-called propensity score. We estimate the propensity score by using a logit model.^{ix} The set of variables capturing firms' characteristics includes the same controls used before, namely firms' age, city, and industry.^x A standard test of the so-called balancing hypothesis confirms that the

observations with the same propensity score have the same distribution of observable characteristics independent of the treatment.

Following Caliendo and Kopeinig (2008), after estimating the propensity score, we select a matching algorithm. For the present analysis, firms engaged in FDI for the first time—called “treated” firms—are matched with the most ex-ante similar firms not engaged in FDI—called “control” firms—via the single nearest neighbor matching (NNM) and kernel matching (KM) algorithms, using the routine provided by Becker and Ichino (2002) and available in Stata. Our treatment is the variable *start_FDI*, already employed in Equation 1; control firms are selected out of the group of firms having neither foreign subsidiaries nor foreign shareholders in $t-1$ and t . According to Caliendo and Kopeinig (2008), the nearest neighbor is the most straightforward matching estimator. Under the NNM, the firm from the control group is chosen as a matching partner for the treated firm that is closest in terms of propensity score. However, this means that only a few observations from the control group are used to construct the counterfactual outcome of a treated firm, which is a major drawback of this approach. KM is a non-parametric matching estimator that uses weighted averages of all individuals in the control group to construct the counterfactual outcome, assigning more weight if control observations are closer in terms of propensity score of a treated firm and less on more distant observations. Therefore, a major advantage of KM, compared with NNM, is the lower variance achieved by using more information. In light of the above discussion, we believe that exploiting both matching algorithms is an important robustness check for our analysis. As in Mallick and Yang (2013), the common support option is imposed, to avoid matching bias and improve the matching quality.

Finally, we proceed to evaluate the difference in performance between the treated and control firms by estimating the average treatment effects on the treated (ATTs), which corresponds to the difference between the average performance of the treated firms and the propensity-score weighted average performance of the control firms. Our results from NNM^{xi} and KM are shown in Table 5, having *start_FDI* as a treatment and using the common support option and bootstrapped standard errors.

[Table 5]

Our most notable finding is that the estimated ATTs are positive and statistically significant. This result is robust to the different matching algorithms and the various performance measures, suggesting that Indian firms do learn from their first FDI involvement. Our treated and control firms do differ in terms of *TFP*, *VALUE-ADDED*, *SALES*, *WAGES*, *ROE*, and *ROCE* meaning that the first FDI involvement significantly matters in explaining firm-level performance. Interestingly, the largest difference is observed in terms of *VALUE-ADDED* whereas the smallest concern *TFP*, *ROE*, and *ROCE*. Although Table 3 provided some insights about the learning effect of FDI, our estimates of Equation 1 could not be considered conclusive due to endogeneity concerns. These concerns are rigorously addressed through the PSM approach, providing a better identification strategy and, thus, having a more influential say on causality matters.

To go deeper into assessing the casual effect of FDI on firm-level performance, we dissect our *start_FDI* into the *start_only_inwardFDI*, *start_only_outwardFDI*, and *start_twoways_FDI* mutually exclusive classes of first FDI involvement that serve as a treatment in the PSM framework.

[Tables 6, 7, 8]

Two results stand out from our PSM estimations shown in Tables 6, 7, and 8. First, the estimated ATTs are positive and statistically significant when differences in *VALUE-ADDED*, *SALES*, and *WAGES* are analyzed. However, treated and control firms do not significantly differ in terms of *TFP* (*ROE* and *ROCE*) unless in the *start_only_inwardFDI* (*start_only_inwardFDI* and *start_only_outwardFDI*) treatment case. This seems to suggest that for most performance measures, a learning mechanism is at play, induced by any of the mutually exclusive classes of first FDI involvement. At the same time, when performance is evaluated in terms of total factor productivity (*ROE* and *ROCE*), first involvement in inward (inward or outward) FDI alone leaves more room for learning. Consistent with our evidence shown in Table 5, the largest difference between treated and control firms is observed in terms of *VALUE-ADDED*, whereas the smallest concern *TFP*, *ROE*, and *ROCE*. Second, the estimated ATTs tend to be larger when the treatment is *start_twoways_FDI*,

which suggests that Indian firms learn more when they engage in both inward and outward FDI. Put another way, the deeper the FDI involvement, the more pronounced the impact of foreign direct investment on firm-level performance. Notice also that the estimated ATTs in Table 6 tend to be larger than those reported in Table 7, meaning that receiving foreign capital pays off more than investing abroad. These results are consistent with our previous findings disclosed in Table 4, and prove to be robust to alternative measures of performance. This evidence is an original contribution of our study that compares inward FDI with outward FDI in a joint empirical analysis.

As a last step in our empirical strategy, we use a DID method to compare the performance of FDI firms with that of non-FDI firms. To do so, we introduce firm fixed-effects into Equations (1) and (2) to control for unobserved firm-level heterogeneity. As our sample is a panel of two years, the introduction of firm fixed effects, along with the time fixed effects, provides us with DID estimators (Angrist and Pischke 2008). Through DID, we eliminate the influence of all observable and unobservable non-random elements of the FDI decision that are constant or strongly persistent over time. We acknowledge that this comparison, in principle, is vulnerable to problems of non-random sample selection. To address the selection issue, following Chabe-Ferret (2015), we combine the DID approach with PSM, thus restricting the comparison to narrowly defined groups of firms.

Roughly speaking, applying DID means estimating the difference in performance Δ between treated and control firms after and before the first FDI involvement by the former. More formally, Δ can be defined as follows:

$$\Delta \equiv (\text{performance}_{treated,after} - \text{performance}_{treated,before}) - (\text{performance}_{control,after} - \text{performance}_{control,before}) \quad (3)$$

Table 9 reports our DID estimates of Δ . For the consistency, NNM is considered as a matching algorithm, and estimates are weighted by multiple matches.^{xii}

[Table 9]

Following Caliendo and Kopeinig (2008), mean standardized bias of variables are shown in Table 10, to assess the quality of our matching. Matching validation is needed because we do not condition on all covariates but on the propensity score; therefore, it has to be checked if the matching procedure is able to balance the distribution of the relevant variables in both the control and treatment group. The underlying idea is to compare the situation before and after the matching and check if there remain any differences after conditioning on the propensity score. One suitable indicator to assess the distance in the marginal distributions of the relevant variables is the standardized mean bias suggested by Rosenbaum and Rubin (1985). For each covariate used to estimate the propensity score, it is defined as the difference of sample means in the treated and (matched) control subsamples as percentage of the square root of the average sample variances in both groups (Caliendo and Kopeinig 2008). One possible problem with this approach is that we do not have a clear indication for the success of the matching procedure. We follow Imbens and Rubin (2015) in considering a standardized mean bias after matching below 0.20 sufficient to validate the matching.

[Table 10]

From Table 10, we see that the after match standardized mean bias between the two groups is below 0.20 for all variables except for the construction industry dummy, where it is slightly above.^{xiii} Therefore, our matching is successful and we proceed to estimate Δ as a function of the start FDI variables.

Column (i) of Table 9 considers *start_FDI* as our main covariate; column (ii) looks instead at the *start_only_inwardFDI*, *start_only_outwardFDI*, and *start_twoways_FDI* mutually exclusive classes of first FDI involvement. Notice that the effect of *IA* is not accounted for due to the limited number of observations. Other control variables previously considered in Equations 1 and 2 are absorbed by the inclusion of firm- and time-fixed effects. However, we use the same variables in PSM at the baseline (in 2015) to balance the composition of treated and control firms before the former engage in FDI in 2016.

In terms of *TFP* and *ADDED VALUE*, we observe positive and significant increases in the relative performance of firms engaged in FDI for the first time in 2016, compared with the non-starters. Indeed, *start_FDI* turns out to be positive and statistically significant in the *TFP* and *VALUE-ADDED* equations. When it comes to the mutually exclusive classes of first FDI involvement, *start_only_inwardFDI* and *start_only_outwardFDI* significantly affect the differences in *TFP* and *VALUE-ADDED*, whereas the role of *start_twoways_FDI* seems to be limited to the *SALES* equation. Consistent with our previous results reported in Tables 6, 7, and 8, the coefficient of *start_only_inwardFDI* is systematically larger than that of *start_only_outwardFDI*, meaning that first involvement in inward FDI alone leaves more room for learning than first involvement in outward FDI alone. At this stage, we acknowledge that our DID estimates suffer from a modest sample size, which might explain some of the borderline insignificant results reported in Table 9. Still, from an identification point of view, they represent our most rigorous analysis of the causal effect of FDI on firm-level performance.

To conclude, our findings summarized in Tables 6, 7, 8, and 9 are in line with the evidence of learning-by-outward FDI reported by Navaretti, Castellani, and Disdier (2010), Hijzen, Jean, and Mayer (2011), and Borin and Mancini (2016) for advanced countries; and by Huang and Zhang (2017) for developing countries. They are also consistent with the learning-by-inward FDI mechanism unveiled by Bertrand and Zitouna (2008), Fukao et al. (2008), and Girma et al. (2015) for advanced countries; and by Salis (2008) and Arnold and Javorcik (2009) for developing countries. Our novel contribution is allowing for comparability between inward and outward FDI as major drivers of firm-level performance. Interestingly, the importance of receiving foreign capital over investing abroad persists as long as we refine our identification strategy.

Conclusion

This study deals with inward FDI, outward FDI, and firm-level performance in India relying on the Orbis database. Controlling for endogeneity through PSM and DID techniques, we show that Indian

firms having at least one foreign shareholder and/or one foreign subsidiary record higher productivity, sales, value-added, ROE, and ROCE, and pay better wages than their domestic counterparts. This evidence suggests a learning-by-FDI mechanism, as described in the existing literature. Moreover, deeper FDI involvement leaves more room for learning in our sample, since the largest differences in performance accrue to those firms engaged in both inward and outward FDI. When it comes to the comparison between inward and outward FDI, we find that, compared with investing abroad, receiving foreign capital can contribute more toward enhancing the performance of Indian firms. Being robust to different identification strategies and performance measures, these results are novel to our study.

Our findings might contribute to the scant literature on internationalization and firm-level performance in India along two dimensions. On the one hand, by considering FDI an internationalization strategy, our estimates complement previous evidence on the export–performance nexus (Haidar 2012; Mallick and Yang 2013; Gupta, Patnaik, and Shah 2018). On the other hand, by accounting for both inward and outward FDI in a learning, rather than a self-selection perspective, our findings complement previous results on the outward FDI–performance nexus (Pradhan 2004; Dermirbas, Patnaik, and Shah 2013; Thomas and Narayanan 2017) and the inward FDI–performance nexus (Banga 2004; Goldar, Banga, and Renganathan 2004; Petkova 2013; Goldar and Sharma 2015).

We believe that our analysis can contribute to interpreting the policy framework governing FDI in India. Since 1990s, the Indian government has played an active role in promoting inward and outward FDI as major channels of liberalization and growth. Our result of learning-by-FDI shows the effectiveness of these policies. Another implication of our study is that inward FDI should be promoted more because the performance premium of inward FDI is systematically larger than that of outward FDI.

When formulating these policy recommendations, we recognize data limitations that plague our current analysis and limit its scope. For instance, there is an issue of external validity. Although Orbis

coverage is quite broad, it is not exhaustive. This means that the results discussed here hold within the sample used for empirical purposes and cannot be over-generalized. Moreover, the unavailability of information on incoming and outgoing capital prevents us from measuring FDI directly. In other words, our proxies for inward and outward FDI are rough measures and might not capture the exact FDI involvement of the sampled firms. At the same time, considering different levels of equity participations—such as 10%, 25% and 50%—could help in exploring the sensitivity of our analysis with respect to the intensive margin of FDI. Finally, the short horizon in our panel does not allow tracking firms over a long time period, which would be preferable to account for temporal variations in our measures of FDI start. Future research could address these limitations.

References

- Alvarez, R., and R. A. Lopez. 2005. “Exporting and Performance: Evidence from Chilean Plants.” *The Canadian Journal of Economics* 38: 1384-1400.
- Ambammal, S. K., and R. Sharma. 2016. “Impact of Patenting on Firm’s Performance: An Empirical Investigation Based on Manufacturing Firms in India.” *Economics of Innovation and New Technology* 25: 14-32.
- Angrist, J. D., and J. S. Pischke. 2008. *Mostly Harmless Econometrics: An Empiricist's Companion*. Princeton University Press.
- Antras, P., and E. Helpman. 2004. “Global Sourcing.” *Journal of Political Economy* 112: 552-580.
- Aoyama, Y., and B. Parthasarathy. 2012. “Research and Development Facilities of Multinational Enterprises in India.” *Eurasian Geography and Economics* 53: 713-730.
- Arnold, J. M., and B. Javorcik. 2009. “Gifted Kids or Pushy Parents? Foreign Acquisitions and Plant Performance in Indonesia.” *Journal of International Economics* 79: 42-53.
- Aw, B. J., and Y. Lee. 2008. “Firm Heterogeneity and Location Choice for Taiwanese Multinationals.” *Journal of International Economics* 75: 167-179.
- Baldwin, J., and W. Gu. 2009. “The Impact of Trade on Plant Scale, Production-Run Length and Diversification.” In *Producer Dynamics: New Evidence from Micro Data*, edited by Dunne, J. B. Jensen, and M. J. Roberts, Chapter 15. Chicago: University of Chicago Press.
- Banga, R. 2004. “Impact of Japanese and US FDI on Productivity Growth.” *Economic and Political Weekly* 39: 453-460.

- Becker, S., and A. Ichino. 2002. "Estimation of Treatment Effects Based on Propensity Score." *The Stata Journal* 2: 358-377.
- Bernard, A. B., and J. B. Jensen. 1995. "Exporters, Jobs and Wages in US manufacturing: 1976-1987." *Brookings Papers on Economic Activity, Microeconomics*: 67-119.
- Bertrand, O., and H. Zitouna. 2008. "Domestic Versus Cross-Border Acquisitions: Which Impact on the Target Firm's Performance?" *Applied Economics* 40: 2221-2238.
- Blalock, G., and P. J. Gertler. 2004. "Learning from Exporting Revisited in A Less Developed Setting." *Journal of Development Economics* 75:397-416.
- Borin A., and M. Mancini. 2016. "Foreign Direct Investment and Firm Performance: An Empirical Analysis of Italian Firms." *Review of World Economics* 152: 705-732.
- Brienen, M. J., M. J. Burger, and F.G. van Oort. 2010. "The Geography of Chinese and Indian Greenfield Investments in Europe." *Eurasian Geography and Economics* 51: 254-273.
- Caliendo, M., and R. Hujer. 2006. "The Microeconometric Estimation of Treatment Effects. An Overview." *Allgemeines Statistisches Archiv* 90: 197-2012.
- Caliendo, M., and S. Kopeinig. 2008. "Some Practical Guidance for the Implementation of the Propensity Score Matching." *Journal of Economic Surveys* 22: 31-72.
- Castellani, D., and A. Zanfei. 2007. "Internationalisation, Innovation and Productivity: How Do Firms Differ in Italy?" *The World Economy* 30: 156-176.
- Castellani, D., I. Mariotti, and L. Piscitello. 2008. "The Impact of Outward Investments on Parent Company's Employment and Skill Composition. Evidence from the Italian Case." *Structural Change and Economic Dynamics* 19: 81-94.
- Chabé-Ferret, S. 2015. "Analysis of the Bias of Matching and Difference-in-Difference Under Alternative Earnings and Selection Processes" *Journal of Econometrics* 185: 110-123.
- Chakravorty, S. 2012. "Regional Development in India: Paradigms Lost in A Period of Great Change." *Eurasian Geography and Economics* 53: 21-43.
- Chen, W. 2011. "The Effect of Investor Origin on Firm Performance: Domestic and Foreign Direct Investment in the United States." *Journal of International Economics* 83: 219-228.
- Clerides, S. K., S. Lach, and J. R. Tybout. 1998. "Is Learning by Exporting Important? Micro-Dynamic Evidence from Colombia, Mexico and Morocco." *Quarterly Journal of Economics* 113: 903-947.
- Cooper, J. 2006. "Of BRICs and Brains: Comparing Russia with China, India, and Other Populous Emerging Economies." *Eurasian Geography and Economics* 47: 255-284.
- Crepon, B., E. Duguet, and J. Mairesse. 1998. "Research, Innovation and Productivity: An Econometric Analysis at the Firm Level." *Economics of Innovation and New Technology* 7: 115-158.

- CUTS. 2003. "Investment Policy in India. Performance and Perceptions" *CUTS Centre for Competition, Investment & Economic Regulation Discussion Paper* 332.
- Dai, M., and M. Yu. 2013. "Firm R&D, Absorptive Capacity and Learning by Exporting: Firm-Level Evidence from China." *World Economy* 36: 1131-1145.
- Damijan J. P., S. Polanec, and J. Prasnikar. 2007. "Outward FDI and Productivity: Micro-Evidence from Slovenia." *World Economy* 30: 135-155.
- De Loecker, J. 2007. "Do Exports Generate Higher Productivity? Evidence from Slovenia." *Journal of International Economics* 73: 69-98.
- Demirbas, D., I. Patnaik, and A. Shah. 2013. "Graduating to Globalisation: A Study of Southern Multinationals." *Indian Growth and Development Review* 6: 242-259.
- Doms, M., and J. B. Jensen. 1998. "Comparing Wages, Skills and Productivity Between Domestically and Foreign-Owned Manufacturing Establishments in the United States." In *Geography and Ownership as Bases for Economic Accounting*, edited by R. E. Baldwin, R. E. Lipsey, and J.D. Richardson, Chapter 7. Chicago: University of Chicago Press.
- Du, J., Y. Lu, Z. Tao, and L. Yu. 2012. "Do Domestic and Foreign Exporters Differ in Learning by Exporting? Evidence from China." *China Economic Review* 23: 296-315.
- Export-Import Bank of India. 2014. "Outward Direct Investment from India: Trends, Objectives and Policy Perspectives." *Occasional Paper* 165.
- Federico, S. 2010. "Outsourcing versus Integration at Home or Abroad and Firm Heterogeneity." *Empirica* 37: 47-63.
- Fernandes, A. M. 2007. "Trade Policy, Trade Volumes and Plant-Level Productivity in Colombian Manufacturing Industries." *Journal of International Economics* 71: 52-71.
- Fernandes, A. M., and A. Isgut. 2005. "Learning-by-Doing, Learning-by-Exporting, and Productivity: Evidence from Colombia." *World Bank Policy Research Working Paper* 3544.
- Fukao, K., K. Ito, H. U. Kwon, and M. Takizawa. 2008. "Cross-Border Acquisitions and Target Firms' Performance: Evidence from Japanese Firm-Level Data." *International Financial Issues in the Pacific Rim: Global Imbalances, Financial Liberalization, and Exchange Rate Policy* 17: 347-389.
- Gattai, V., and V. Trovato. 2016. "Estimating Sourcing Premia Using Italian Regional Data." *The B.E. Journal of Economic Analysis and Policy* 16: 1029-1067.
- Girma, S., Y. Gong, H. Görg, and S. Lancheros. 2015. "Estimating Direct and Indirect Effects of Foreign Direct Investment on Firm Productivity in the Presence of Interactions between Firms." *Journal of International Economics* 95: 157-169.
- Goldar B., and K. Banga. 2020. "Country Origin of Foreign Direct Investment in Indian Manufacturing and Its Impact on Productivity of Domestic Firms." In *FDI, Technology and Innovation*, edited by N. Siddharthan, K. Narayanan. Springer, Singapore.

- Goldar, B., and A. K. Sharma. 2015. "Foreign Investment in Indian Industrial Firms and Its Impact on Firm Performance." *The Journal of Industrial Statistics* 4: 1-18.
- Goldar, B., R. Banga, and V.S. Renganathan. 2004. "Ownership and Efficiency in Engineering Firms, 1990-91 to 1999-2000." *Economic and Political Weekly* 39: 5-35.
- Griliches, Z. 1990. "Patent Statistics as Economic Indicators: A survey." *Journal of Economic Literature* 28: 1661–1707.
- Grossman, S. J., E. Helpman and A. Szeidl. 2006. "Optimal Integration Strategies for the Multinational Firm." *Journal of International Economics* 70: 216-238.
- Gupta A., I. Patnaik, and A. Shah. 2018. "Exporting and Firm Performance: Evidence from India." *Indian Growth and Development Review*, <https://doi.org/10.1108/IGDR-04-2018-0036>.
- Haidar, J. I. 2012. "Trade and Productivity: Self-Selection or Learning-by-Exporting in India." *Economic Modelling* 29: 1766-1773.
- Hall, B. H., and V. Sena. 2014. "Appropriability Mechanisms, Innovation and Productivity: Evidence from U K." *NBER Working Paper* 20514.
- Hattari, R., and R. Rajan. 2010. "India as a Source of Outward Foreign Direct Investment." *Oxford Development Studies* 38: 497-518.
- Hayakawa, K., F. Kimura, and T. Machikita. 2012. "Globalization and Productivity: A Survey of Firm-Level Analysis." *Journal of Economic Surveys* 26: 332-350.
- Head, K., and J. Ries. 2003. "Heterogeneity and the Foreign Direct Investment versus Exports Decision of Japanese Manufacturers." *Journal of the Japanese and International Economics* 17: 448-467.
- Helpman, E., M. Melitz, and S. Yeaple. 2004. "Export versus FDI." *American Economic Review* 94: 300-316.
- Hijzen, A., T. Inui, and Y. Todo. 2010. "Does Offshoring Pay? Firm-Level Evidence from Japan." *Economic Inquiry* 48: 880-895.
- Hijzen, A., S. Jean, and T. Mayer. 2011. "The Effects at Home of Initiating Production Abroad: Evidence from Matched French Firms." *Review of World Economics* 147: 457-483.
- Huang Y., and Y. Zhang. 2017. "How Does Outward Foreign Direct Investment Enhance Firm Productivity? A Heterogeneous Empirical Analysis from Chinese Manufacturing." *China Economic Review* 44: 1-15.
- Hulten, C. R. 2001. "Total Factor Productivity. A Short Biography." *New Developments in Productivity Analysis: National Bureau of Economic Research, Inc:* 1-54.
- Imbens, G. W., and J. M. Wooldridge. 2009. "Recent Developments in the Econometrics of Program Evaluation." *Journal of Economic Literature* 47: 5-86.

- Imbens, G. W., and D. B. Rubin. 2015. *Causal Inference in Statistics, Social, and Biomedical Sciences*. Cambridge University Press.
- Isgut, A. E. 2005. "What's Different about Exporters? Evidence from Colombian Manufacturing." *Journal of Development Studies* 37: 57-82.
- Ito, Y. 2007. "Choice for FDI and Post-FDI Productivity." *RIETI Discussion Paper* E049.
- Kandilov, I. T. 2009. "Do Exporters Pay Higher Wages? Plant-level Evidence from an Export Refund Policy in Chile." *The World Bank Economic Review* 23: 269-294.
- Kimura, F., and K. Kiyota. 2006. "Exports, FDI, and Productivity: Dynamic Evidence from Japanese Firms." *Review of World Economics* 142: 695-719.
- Kohler, W. K., and M. Smolka. 2011. "Sourcing Premia with Incomplete Contracts: Theory and Evidence." *The B.E. Journal of Economics Analysis and Policy* 11: 1-39.
- Levinsohn, J., and A. Petrin. 2003. "Estimating Production Functions Using Inputs to Control for Unobservables." *Review of Economic Studies* 70: 317-342.
- Ma, Y., H. Tang, and Y. Zhang. 2014. "Factor Intensity, Product Switching, and Productivity: Evidence from Chinese Exporters." *Journal of International Economics* 92: 349-362.
- Mallick, S. K., and Y. Yang. 2013. "Productivity Performance of Export Market Entry and Exit: Evidence from Indian Firms." *Review of International Economics* 21: 809-824.
- Melitz, M. J. 2003. "The Impact of Trade on Intra-Industry Reallocations and Aggregate Industry Productivity." *Econometrica* 71: 1661-1694.
- Navaretti, G. B., D. Castellani, and A. C. Disdier. 2010. "How Does Investing in Cheap Labour Countries Affect Performance at Home? Firm-level Evidence from France and Italy." *Oxford Economic Papers* 62: 234-260.
- Nijman, J. 2012. "India's Urban Challenge." *Eurasian Geography and Economics* 53: 7-20.
- OECD. 2008. "OECD Benchmark Definition of Foreign Direct Investment." (4th ed.) Paris: OECD.
- Pandit, K. 2012. "The Indian Landscape after Two Decades of Liberalization: An Introduction." *Eurasian Geography and Economics* 53: 1-6.
- Pavcnik, N. 2002. "Trade Liberalization, Exit, and Productivity Improvements: Evidence from Chilean Plants." *The Review of Economic Studies* 69: 245-276.
- Petkova, N. 2013. "The Real Effects of Foreign Investment: Productivity and Growth." *SSRN Electronic Journal* 5: 1-55.
- Pradhan, J. P. 2004. "The Determinants of Outward Foreign Direct Investment: A Firm-Level Analysis of Indian Manufacturing." *Oxford Development Studies* 32: 619-639.
- Pradhan, J. P. 2017. "Guest Editor's Introduction to the Special Issue: Indian Outward FDI and MNEs." *Transnational Corporations* 24: 1-7.

- Prime, P. B. 2009. "China and India Enter Global Markets: A Review of Comparative Economic Development and Future Prospects." *Eurasian Geography and Economics* 50: 621-642.
- Raff, H., M. Ryan, and F. Stähler. 2012. "Firm Productivity and the Foreign-Market Entry Decision." *Journal of Economics & Management Strategy* 21: 849-871.
- Ramamurti, R. 2008. *What Have We Learned about Emerging Market MNEs?*. Cambridge, U.K: Cambridge University Press.
- Ramamurti, R. 2012. "What is Really Different about Emerging Market Multinationals?" *Global Strategy Journal* 2: 41-47.
- Ramamurti, R. and J. Singh. 2008. *Emerging Multinationals from Emerging Markets*. Cambridge, U.K: Cambridge University Press.
- Ribeiro, S. P., S. Menghinello, and K. De Backer. 2010. "The OECD Orbis Database" *OECD Statistics Working Paper*: 1.
- Roberts, M. J., and J. R. Tybout. 1997. "The Decision to Export in Colombia: An Empirical Models of Entry with Sunk Costs" *American Economic Review* 87:545-564.
- Rosenbaum, P., and D. B. Rubin. 1985. "Constructing A Control Group Using Multivariate Matched Sampling Methods that Incorporate the Propensity Score." *The American Statistician* 39: 33-38.
- Salis, S. 2008. "Foreign Acquisitions and Firm Productivity: Evidence from Slovenia." *The World Economy* 31: 1030-1048.
- Sanghamitra, D., M. J. Roberts, and J. R. Tybout. 2007. "Market Entry Costs, Producer Heterogeneity, and Export Dynamics." *Econometrica* 75: 837-873.
- Sauvant, K. P. 2008. *The rise of transnational corporations from emerging markets – Threats or opportunity?*. Cheltenham: Edward Elgar.
- Sharma, C. 2010. "Does Productivity Differ in Domestic and Foreign Firms? Evidence from Indian Machinery Industry." *Indian Economics Review* 45: 87-110.
- Sharma, C. 2011. "R&D and Productivity in the Indian Pharmaceutical Firms." *MPRA Working Paper* 31681.
- Shaw, A. 2012. "Metropolitan City Growth and Management in Post-Liberalized India." *Eurasian Geography and Economics* 53: 44-62.
- Singh, T. 2010. "Does International Trade Cause Economic Growth? A Survey." *The World Economy* 33: 1517-1564.
- Thomas, R., and K. Narayanan. 2017. "Determinants of Outward Foreign Direct Investment: A Study of Indian Manufacturing Firms." *Transnational Corporations* 24: 9-26.
- UNCTAD. 2018. *World Investment Report 2018: Investment and New Industrial Policies*. UNCTAD.

Van Biesebroeck, J. 2005. "Exporting Raises Productivity in Sub-Saharan African Manufacturing Firms." *Journal of International Economics* 67: 373-391.

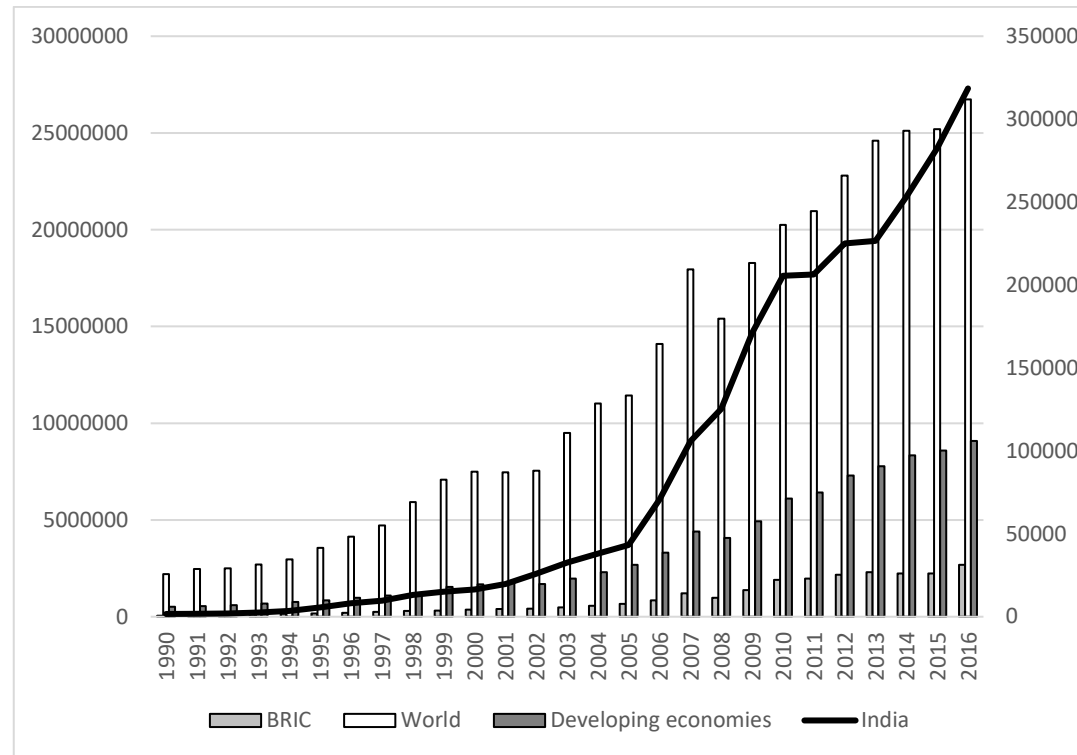
Yang, C. H., and Y. H. Chen. 2012. "R&D, Productivity, and Export: Plant-Level Evidence from Indonesia." *Economic Modelling* 29: 208-216.

Yang, Y., and S. Mallick. 2010. "Export Premium, Self-selection and Learning-by-Exporting: Evidence from Chinese Matched Firms." *The World Economy* 33: 1218-1240.

Wagner, J. 2016. "A Survey of Empirical Studies Using Transaction Level Data on Exports and Imports." *Review of World Economics* 152: 215.

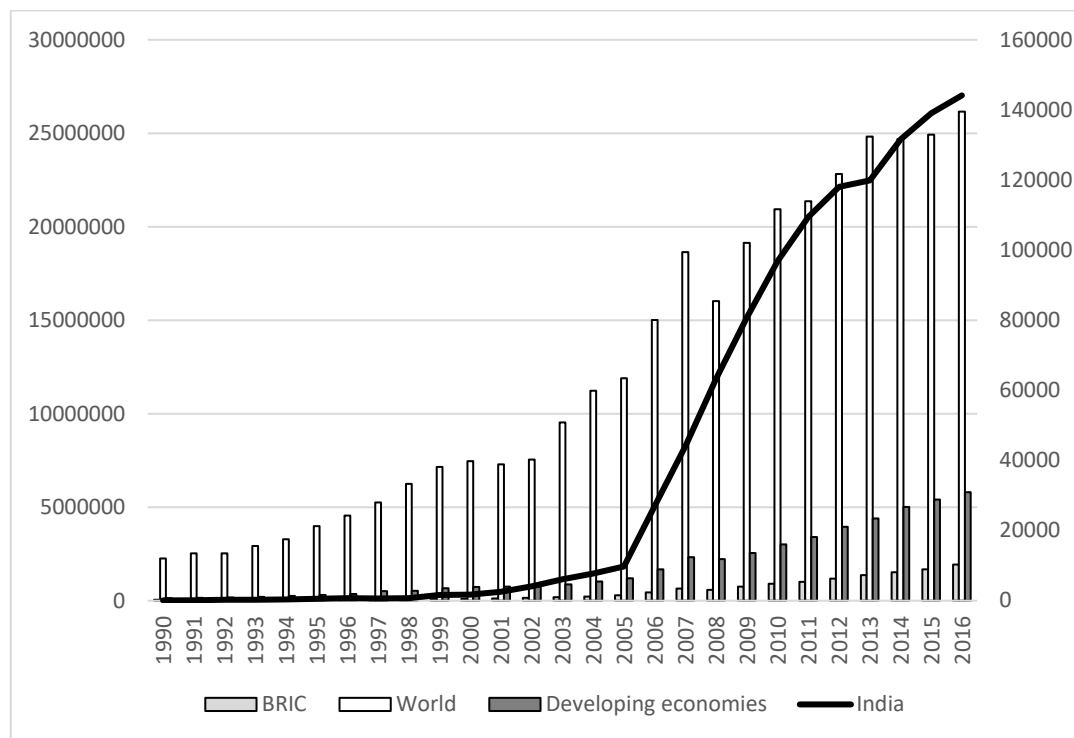
Figures and Tables

Fig. 1: Stocks of inward FDI, selected economies, 1990–2016 (USD mn at current prices). Global data, developing countries, and BRIC countries are presented on the left vertical axis; India is presented on the right vertical axis



Source: Authors' elaborations from UNCTAD (2018)

Fig. 2: Stocks of outward FDI, selected economies, 1990–2016 (USD mn at current prices). Global data, developing countries, and BRIC countries are presented on the left vertical axis; India is presented on the right vertical axis



Source: Authors' elaborations from UNCTAD (2018)

Table 1: Definition of FDI involvement

		variable	definition	years	
FDI status	current involvement	general	<i>FDI</i>	dummy =1 if firm i has at least one foreign subsidiary or one foreign shareholder at t; =0 otherwise	2015, 2016
		mutually exclusive classes	<i>only_inwardFDI</i>	dummy =1 if firm i has at least one foreign shareholder but no foreign subsidiaries at t; =0 otherwise	2015, 2016
			<i>only_outwardFDI</i>	dummy =1 if firm i has at least one foreign subsidiary but no foreign shareholders at t; =0 otherwise	2015, 2016
			<i>twoways_FDI</i>	dummy =1 if firm i has at least one foreign subsidiary and one foreign shareholder at t; =0 otherwise	2015, 2016
FDI start	first involvement	general	<i>start_FDI</i>	dummy =1 if firm i has at least one foreign subsidiary or one foreign shareholder at t and neither foreign subsidiaries nor foreign shareholders at t-1; =0 otherwise	2016
		mutually exclusive classes	<i>start_only_inwardFDI</i>	dummy =1 if firm i has at least one foreign shareholder but no foreign subsidiaries at t and neither foreign subsidiaries nor foreign shareholders at t-1; =0 otherwise	2016
			<i>start_only_outwardFDI</i>	dummy =1 if firm i has at least one foreign subsidiary but no foreign shareholders at t and neither foreign subsidiaries nor foreign shareholders at t-1; =0 otherwise	2016
			<i>start_twoways_FDI</i>	dummy =1 if firm i has at least one foreign subsidiary and one foreign shareholder at t and neither foreign subsidiaries nor foreign shareholders at t-1; =0 otherwise	2016

Table 2: FDI involvement of Indian firms in our sample

FDI status current involvement						FDI start first involvement						
general FDI status			mutually exclusive classes of FDI status			general FDI start			mutually exclusive classes of FDI start			
variable	2015		2016		variable	2015		2016		variable	2016	
	number	%	number	%		number	%	number	%		number	%
<i>non FDI</i>	796	29%	1316	50%	<i>non FDI</i>	796	29%	1316	50%	<i>non FDI start</i>	618	87%
<i>FDI</i>	1954	71%	1321	50%	<i>only_inwardFDI</i>	1176	43%	417	16%	<i>start_FDI</i>	95	13%
					<i>only_outwardFDI</i>	37	1%	211	8%			
					<i>twoways_FDI</i>	741	27%	693	26%			
total	2750		2637		total	2750	100%	2637	100%	total	713	100%

Source: Authors' elaborations from Orbis (2016, 2017)

Table 3: Panel OLS estimates of Equation 1

	TFP				SALES				VALUE-ADDED			
	(a)	(b)	(c)	(d)	(a)	(b)	(c)	(d)	(a)	(b)	(c)	(d)
start_FDI	.6468 (0.094)*	.6641 (0.077)*	.9088 (0.040)**	.8340 (0.59)*	1.4026 (0.000)***	1.5951 (0.000)***	.9398 (0.000)***	.5059 (0.027)**	1.5913 (0.000)***	1.7401 (0.000)***	1.1648 (0.000)***	.7023 (0.001)***
IA				.0319 (0.509)				.2150 (0.000)***				.2292 (0.000)***
age		-.0067 (0.167)	-.0061 (0.325)	-.0061 (0.322)		.0026 (0.506)	.0030 (0.605)	.0032 (0.504)		.0136 (0.000)***	.0075 (0.179)	.0077 (0.102)
city	no	yes	yes	yes	no	yes	yes	yes	no	yes	yes	yes
industry	no	yes	yes	yes	no	yes	yes	yes	no	yes	yes	yes
Obs.	1,068	1,068	469	469	1,509	1,509	583	583	1,509	1,509	583	583
R2	0.0024	0.0660	0.2107	0.2121	0.0197	0.1886	0.2823	0.3814	0.0318	0.1665	0.2380	0.3582
	WAGES				ROE				ROCE			
	(a)	(b)	(c)	(d)	(a)	(b)	(c)	(d)	(a)	(b)	(c)	(d)
start_FDI	1.5620 (0.000)***	1.6867 (0.000)***	1.0761 (0.000)***	.6145 (0.004)***	.4291 (0.003)***	.4936 (0.001)***	.2837 (0.114)	.3329 (0.059)*	.3782 (0.001)***	.4224 (0.000)***	.2504 (0.076)*	.2922 (0.031)**
IA				.2287 (0.000)***				-.0289 (0.227)				-.0246 (0.190)
age		.0202 (0.000)***	.0137 (0.012)**	.0139 (0.002)***		.0021 (0.409)	.00002 (0.996)	-.00002 (0.995)		.0007 (0.750)	-.0011 (0.738)	-.0011 (0.729)
city	no	yes	yes	yes	no	yes	yes	yes	no	yes	yes	yes
industry	no	yes	yes	yes	no	yes	yes	yes	no	yes	yes	yes
Obs.	1,509	1,509	583	583	1,043	1,043	415	415	1,043	1,043	415	415
R2	0.0320	0.1800	0.2419	0.3681	0.0078	0.1481	0.2347	0.2389	0.0084	0.1628	0.2382	0.2435

P-value in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Standard errors are clustered at the firm level. Year (2016) fixed effect is included.

Source: Authors' elaborations from Orbis (2016, 2017)

Table 4: Panel OLS estimates of Equation 2

	TFP				SALES				VALUE-ADDED			
	(a)	(b)	(c)	(d)	(a)	(b)	(c)	(d)	(a)	(b)	(c)	(d)
<i>start_only_inwardFDI</i>	.8183 (0.235)	.9311 (0.157)	1.3738 (0.078)*	1.3025 (0.092)*	1.4440 (0.000)***	1.4822 (0.000)***	.6818 (0.052)*	.2715 (0.425)	1.6738 (0.000)***	1.6656 (0.000)***	.9325 (0.013)**	.4950 (0.174)
<i>start_only_outwardFDI</i>	.5730 (0.214)	.6040 (0.128)	.5742 (0.079)*	.4948 (0.148)	1.2187 (0.000)***	1.5555 (0.000)***	.94864 (0.007)***	.6058 (0.044)**	1.3911 (0.000)***	1.6861 (0.000)***	1.1465 (0.000)***	.7809 (0.004)***
<i>start_twoways_FDI</i>	.2810 (0.588)	-.2770 (0.627)	-.0459 (0.928)	-.1912 (0.721)	2.1587 (0.000)***	2.3476 (0.000)***	1.9861 (0.000)***	1.1295 (0.017)**	2.2487 (0.000)***	2.3880 (0.000)***	2.2074 (0.000)***	1.2939 (0.002)***
<i>IA</i>				.0347 (0.476)				.2136 (0.000)***				.2278 (0.000)***
<i>age</i>		-.0069 (0.151)	-.0068 (0.260)	-.0069 (0.255)		.0027 (0.490)	.0034 (0.564)	.0034 (0.474)		.0137 (0.000)***	.0079 (0.162)	.0079 (0.095)*
<i>city</i>	no	yes	yes	yes	no	yes	yes	yes	no	yes	yes	yes
<i>industry</i>	no	yes	yes	yes	no	yes	yes	yes	no	yes	yes	yes
Obs.	1,068	1,068	469	469	1,509	1,509	583	583	1,509	1,509	583	583
R2	0.0026	0.0667	0.2150	0.2166	0.0205	0.1893	0.2859	0.3831	0.0327	0.1670	0.2417	0.3597
	WAGES				ROE				ROCE			
	(a)	(b)	(c)	(d)	(a)	(b)	(c)	(d)	(a)	(b)	(c)	(d)
<i>start_only_inwardFDI</i>	1.6008 (0.000)***	1.6321 (0.000)***	.8242 (0.020)**	.3893 (0.248)	.5668 (0.025)**	.6076 (0.005)***	.3080 (0.291)	.3512 (0.222)	.4168 (0.022)**	.4923 (0.002)***	.2186 (0.341)	.2565 (0.252)
<i>start_only_outwardFDI</i>	1.3704 (0.000)***	1.5763 (0.000)***	.9940 (0.002)***	.6306 (0.015)**	.3349 (0.055)*	.4705 (0.013)**	.2908 (0.215)	.3266 (0.155)	.3463 (0.009)***	.4007 (0.004)***	.2616 (0.158)	.2931 (0.103)
<i>start_twoways_FDI</i>	2.3684 (0.000)***	2.5476 (0.001)***	2.4458 (0.000)***	1.5378 (0.000)***		.13060 (0.743)	.1459 (0.701)	.2810 (0.466)	.3957 (0.162)	.2428 (0.514)	.3331 (0.342)	.4518 (0.196)
<i>IA</i>				.2264 (0.000)***				-.0287 (0.235)				-.0252 (0.184)
<i>age</i>			.0141 (0.010)**	.0142 (0.002)***		.0020 (0.426)	-.00004 (0.992)	-.00005 (0.990)		.0006 (0.764)	-.0010 (0.750)	-.0011 (0.747)
<i>city</i>	no	yes	yes	yes	no	yes	yes	yes	no	yes	yes	yes
<i>industry</i>	no	yes	yes	yes	no	yes	yes	yes	no	yes	yes	yes
Obs.	1,509	1,509	583	583	1,043	1,043	415	415	1,043	1,043	415	415
R2	0.0332	0.1809	0.2483	0.3712	0.0084	0.1488	0.2349	0.2389	0.0085	0.1631	0.2383	0.2438

P-value in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Standard errors are clustered at the firm level. Year (2016) fixed effect is included.

Source: Authors' elaborations from Orbis (2016, 2017)

Table 5: Average treatment effects on treated (treatment: start_FDI)

Nearest neighbor matching					
variable	n. treated	n. controls	ATT	Std. Err.	t
TFP	74	223	0.633**	0.309	2.049
SALES	95	286	1.793***	0.323	5.556
VALUE-ADDED	95	286	1.964***	0.299	6.568
WAGES	95	286	1.835***	0.267	6.874
ROE	75	206	0.559***	0.182	3.076
ROCE	75	206	0.534***	0.190	2.817
Kernel matching					
variable	n. treated	n. controls	ATT	Std. Err.	t
TFP	74	445	0.470	0.307	1.533
SALES	95	590	1.444***	0.231	6.258
VALUE-ADDED	95	590	1.643***	0.201	8.165
WAGES	95	590	1.616***	0.219	7.378
ROE	75	396	0.504***	0.217	3.970
ROCE	75	396	0.460***	0.106	4.341

Common support and bootstrapped standard errors. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Source: Authors' elaborations from Orbis (2016, 2017)

Table 6: Average treatment effects on treated (treatment: start_only_inwardFDI)

Nearest neighbor matching					
variable	n. treated	n. controls	ATT	Std. Err.	t
TFP	31	102	1.199*	0.676	1.774
SALES	40	123	1.707***	0.609	2.803
VALUE-ADDED	40	123	1.661***	0.463	3.591
WAGES	40	123	1.595***	0.484	3.294
ROE	29	77	0.583*	0.306	1.901
ROCE	29	77	0.531**	0.253	2.094
Kernel matching					
variable	n. treated	n. controls	ATT	Std. Err.	t
TFP	31	451	0.527	0.472	1.116
SALES	40	563	1.349***	0.324	4.162
VALUE-ADDED	40	563	1.577***	0.284	5.545
WAGES	40	563	1.508***	0.312	4.834
ROE	29	396	0.561**	0.266	2.107
ROCE	29	396	0.410**	0.186	2.204

Common support and bootstrapped standard errors. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Source: Authors' elaborations from Orbis (2016, 2017)

Table 7: Average treatment effects on treated (treatment: start_only_outwardFDI)

Nearest neighbor matching					
variable	n. treated	n. controls	ATT	Std. Err.	t
TFP	36	167	0.354	0.462	0.767
SALES	46	207	1.475***	0.509	2.901
VALUE-ADDED	46	207	1.496***	0.435	3.441
WAGES	46	207	1.426***	0.391	3.650
ROE	39	157	0.560**	0.241	2.323
ROCE	39	157	0.402**	0.195	2.062
Kernel matching					
variable	n. treated	n. controls	ATT	Std. Err.	t
TFP	36	475	0.379	0.375	1.012
SALES	46	625	1.075***	0.351	3.063
VALUE-ADDED	46	625	1.252***	0.276	4.530
WAGES	46	625	1.241***	0.241	5.147
ROE	39	404	0.308	0.204	1.506
ROCE	39	404	0.315**	0.126	2.502

Common support and bootstrapped standard errors. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Source: Authors' elaborations from Orbis (2016, 2017)

Table 8: Average treatment effects on treated (treatment: start_twoways_FDI)

Nearest neighbor matching					
variable	n. treated	n. controls	ATT	Std. Err.	t
TFP	7	34	0.407	0.435	0.936
SALES	9	46	2.805***	0.842	3.333
VALUE-ADDED	9	46	2.928***	0.687	4.083
WAGES	9	46	3.216***	0.851	3.778
ROE	7	32	0.456	0.580	0.787
ROCE	7	32	0.518	0.597	0.868
Kernel matching					
variable	n. treated	n. controls	ATT	Std. Err.	t
TFP	7	220	0.205	0.536	0.383
SALES	9	360	2.040***	0.452	4.511
VALUE-ADDED	9	360	2.270***	0.507	4.479
WAGES	9	360	2.436***	0.561	4.340
ROE	7	272	0.309	0.384	0.805
ROCE	7	272	0.281	0.291	0.968

Common support and bootstrapped standard errors. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Source: Authors' elaborations from Orbis (2016, 2017)

Table 9: DID estimates of Equation 3

	<i>TFP</i>		<i>SALES</i>		<i>VALUE-ADDED</i>		<i>WAGES</i>		<i>ROE</i>		<i>ROCE</i>	
	(i)	(ii)	(i)	(ii)	(i)	(ii)	(i)	(ii)	(i)	(ii)	(i)	(ii)
<i>start_FDI</i>	1.5619		.2130		.3070		.0290		.3121		.1052	
	(0.036)**		(0.101)		(0.019)**		(0.711)		(0.77)*		(0.305)	
<i>start_only_inwardFDI</i>		1.8206		.2362		.3287		.0527		.3457		.1344
		(0.032)**		(0.143)		(0.087)*		(0.531)		(0.102)		(0.264)
<i>start_only_outwardFDI</i>		1.5954		.1853		.3422		-.0043		.4278		.1921
		(0.033)**		(0.160)		(0.010)**		(0.968)		(0.052)*		(0.120)
<i>start_twoways_FDI</i>		.4429		.2575		.0609		.0978		-.4033		-.4462
		(0.656)		(0.039)**		(0.770)		(0.283)		(0.381)		(0.253)
Obs.	232	232	232	232	232	232	232	232	192	192	192	192
R2	0.0554	0.0626	0.3552	0.3634	0.3781	0.2956	0.4241	0.1430	0.0362	0.0878	0.0143	0.0992

P-value in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Standard errors are clustered at the firm level. Year (2016) and firm fixed effects are included.

Source: Authors' elaborations from Orbis (2016, 2017)

Table 10: Standardized mean bias

	<i>Before match</i>			<i>After match</i>		
	treated	control	SMB	treated	control	SMB
<i>agriculture, forestry and fishing</i>	.0541	.0279	.1313	.0597	.08	-.0790
<i>mining and quarrying</i>	.0135	.0279	-.1011	.0149	.02	-.0384
<i>manufacturing</i>	.7162	.7467	-.0686	.7164	.62	.2040
<i>construction</i>	.0541	.0204	.1770	.0448	.10	-.2124
<i>wholesale and retail trade</i>	.0405	.0577	-.0793	.0448	.06	-.0678
<i>information and communication</i>	.0405	.0242	.0919	.0448	.02	.1391
<i>professionale, scientific and technical activities</i>	.0405	.0204	.1162	.0448	.02	.1391
<i>human health and social work activities</i>	.0135	.0093	.0394	.0000	.02	-.2000
<i>city</i>	.3108	.2756	.0771	.3134	.30	.0289
<i>age</i>	30.15	32.70	-.1358	30.94	29.44	.0900

Source: Authors' elaborations from Orbis (2016, 2017)

ⁱ FDI is denoted as an investment in a foreign company in which the investor owns at least 10% of the ordinary shares and the investor undertakes the company with the objective of establishing a lasting interest in the country, a long-term relationship, and a significant influence on the firm's management (OECD 2008).

ⁱⁱ WORLDBOX AG is the data source for India.

ⁱⁱⁱ The Statistical Classification of Economic Activities in the European Community, commonly referred to as NACE (for the French term "nomenclature statistique des activités économiques dans la Communauté européenne"), is the industry standard classification system used in the European Union. The current version is revision 2 and was established by Regulation (EC) No 1893/2006. Information regarding the conversion from the Indian National Industry Classification (NIC) to NACE are available from the Orbis database upon request.

^{iv} Companies in Orbis are considered "very large" when they match at least one of the following conditions: a) operating revenues are larger than or equal 130 million USD; b) total assets are larger than or equal 260 million USD; c) employees are larger than or equal 1000; d) they are listed.

^v According to the OECD (1996) definition, FDI implies an equity participation above 10%. Therefore, when we downloaded the data, we used the 10% threshold as a filter. This means that all subsidiaries and shareholders in our dataset are characterized by an equity participation above 10%. Then, we distinguished between domestic versus foreign subsidiaries and shareholders by comparing their country ISO code with that of the Indian parent company.

^{vi} The small number of FDI starters compared with the overall number of FDI firms is consistent with previous results from Goldar and Banga (2020).

^{vii} A better proxy would be the number of employees. Unfortunately, our database is missing many values in this variable, therefore, we follow Goldar, Banga, and Renganathan (2004), Petkova (2013), and Goldar and Banga (2020) and measure labor with the cost of employees.

^{viii} In this paper, we pool firms belonging to the manufacturing and the service industry together and account for potential differences through industry controls. An alternative approach would be to split the overall sample in two sub-samples by manufacturing versus service industry.

^{ix} The results from the first stage logit model are available from the authors upon request.

^x NACE 1-digit industry dummies are considered at this stage. *IA* is not considered depending on the limited number of observations.

^{xi} If a treated unit forward and backward matches happen to be equally good, the routine randomly draws either the forward or backward matches. The ATT is computed by averaging over the unit-level treatment effects of the treated where the control(s) matched to a treated observation is/are those observations in the control group that have the closest propensity score. If there are multiple nearest neighbors, the average outcome of those controls is used.

^{xii} NNM1 is performed. Based on the distance of propensity scores between the treated and control units, one control unit with the smallest distance to its matched treated unit is selected. For treated units that are matched to multiple controls, we use weights to balance the sample. Our choice of NNM1 is intended to keep the sample as balanced as possible in terms of the number of treated and control units, considering the limited number of treated units.

^{xiii} The list of NACE 1-digit industries is not complete in Table 10. Our firms in the treated group belong only to the reported industries.