The impact of Outward FDI on the performance of Chinese Multinationals

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Abstract

Using a new firm-level database, EMENDATA, this paper investigates the effects on Chinese multinational enterprises of Outward FDI (OFDI) into advanced European countries. Propensity score matching is combined with a difference-in-difference estimator to reduce the problems of self-selection of treated firms in foreign markets and to eliminate time-invariant and unobservable differences between those firms and the controls. The results provide robust evidence in support of the view that China's OFDI had so far a positive impact on domestic activities in enhancing firms' productivity and scales of operation, measured by sales and employment. When we distinguish among such investments on the basis of entry mode, and account for the endogeneity in the selection process, we show that acquisitions facilitate early access to intangible assets but are detrimental to financial performance, while greenfield investments have a stronger impact on the scale and productivity of Chinese investors.

Keywords: Outward FDI; Reverse Spillovers; Performance; Chinese Multinationals

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1. Introduction

Outward Foreign Direct Investment (OFDI) from China has become a popular topic in the academic literature because of its rapid increase and unconventional patterns (among many others, see Child and Rodrigues, 2005; Buckley et al, 2007). The rise of Chinese investments follows the provisions of the "Going Out" strategy, launched with the 10th Five-year Plan in 2000 and later reinforced in subsequent plans that fostered the internationalization of domestic firms. The aim was to promote industrialization and technological upgrading to support growth of the domestic economy (Gu and Reed, 2013). But so far there is only a limited amount of empirical research available regarding the effect of OFDI on the performance of Chinese investor companies. The related empirical literature has, in fact, mainly focused on analysing the drivers of internationalization and on location choices, at both country level (Buckley et al., 2007; Deng, 2009) and firm level (Amighini et al, 2013; Ramasamy et al, 2013). Some recent notable exceptions include a paper by Chen and Tang (2014) analysing the impact of Chinese OFDI on firms' performance on the basis of data from the Chinese Ministry of Commerce and another paper by Edamura et al (2014) that deals with the impacts of acquisitions and uses a Chinese-based financial database (ChinaVenture).

In this paper, we investigate whether and how OFDI has a positive impact on the performance of Chinese investing companies, using a sample of 368 Chinese firms, each having an affiliate in Europe, and covering the period 2003-2011. The empirical analysis takes advantage of the availability of a new database, EMENDATA (see Amighini et al., 2014, for a complete description), which merges FDI (both greenfield and M&A) information with firm financial data from *Orbis* Bureau van Dijk's (BvD).

We measure the impact of OFDI on the investing companies covering different dimensions of firms' performance, including productivity, scale, sales, and profitability. In addition, we disaggregate OFDIs according to the mode of entry - Mergers and Acquisitions (M&As) or greenfield investments - and we assess whether there is any difference in impact on investors. To the best of our knowledge, this is the first study examining the impact of Chinese OFDI (a) into advanced economies and (b) accounting for specific effects of the different modes of entry.

Europe is an interesting destination because Chinese OFDI into EU countries is mainly motivated by the search of new markets, with the aim of creating overseas platforms for sales and distribution, and of strategic assets, aimed at acquiring foreign technologies, knowledge and brands that are not fully available at home (Amighini et al, 2013). Therefore, it is of particular interest to investigate whether these investments - by introducing more efficient production techniques and improving overall performance in terms of scale, sales and profitability – generate positive effects on the performance of the investing firms.

We use the propensity score matching (PSM) technique to investigate the impact of OFDI on treated firms, each having an affiliate in Europe, by comparing them with a closely matched control group, selected from the subgroup of all the Chinese companies included in BvD *Orbis* with no investments abroad. Propensity score matching is then combined with difference-in-difference estimators to further eliminate time-invariant and unobservable differences between the treated and control firms.

Our results confirm that OFDI does affect Chinese investing firms' performance. We find a positive effect on firms' efficiency and performance, which materialize at different points in time: while the productivity enhancement takes some time (Mansfield, 1985; Chen et al., 2012), there is an immediate impact on company size, as indicated by increases in the number of employees. Total sales also show an upsurge as a result of the investment, showing the importance of market-seeking motives. Some interesting differences in the above results occur when we distinguish among investments on the basis of their entry mode, while taking into account the potential endogeneity of the choice. While both contribute to increases in productivity, acquisitions favour early access to intangible assets, but result in negative financial performance. On the other hand, it is via greenfield investments that Chinese firms are more likely to increase their size and sales.

Our analysis has important implications, since it adds to the existing knowledge of Chinese OFDI, in that we shed light on the kinds of spillovers that result from asset-exploring strategies in the more advanced markets and on which modes of entry enable Chinese companies to gain competitive advantages.

The remainder of the paper is structured as follows. Section 2 reviews the existing literature on the effects of OFDI on the investing firms' performance. Section 3 presents the original data used for the analysis and discusses the methodology. Results are discussed in Section 4, and Section 5 concludes.

2. The effect of Outward FDI on investor firms' performance

The nexus between OFDI and the investors' performance has been mainly investigated in the context of advanced economies, and the results have not been clear-cut. Firms exploring foreign markets through FDI can expect high returns, but they come together with large costs related to complexity, coordination and resource trade offs (Bertrand and Capron, 2014). The empirical literature on heterogeneous firms typically shows that MNEs enjoy a productivity advantage over other types of firms (Helpman et al., 2004), but the evidence on other dimensions of performance, including employment and profitability, is less straightforward. Several studies have shown that both horizontal and vertical OFDI generally have positive effects on productivity as well as on the size of domestic activities (Barba Navaretti et al., 2010; Desai et al., 2009), but the effects of vertical FDI on employment are not as obvious (Castellani and Barba Navaretti, 2004; Hijzen et al., 2011).

On emerging and developing countries, the empirical evidence on the impact of OFDIs on the investing firms is more limited. In contrast to the traditional MNEs, firms from emerging economies invest abroad in order to gain new competitive advantages and strategic resources they do not possess (Ramamurti, 2012; Luo and Tung, 2007). In light of this, it is not uncommon for EMNEs to undertake OFDIs as a deliberate strategy to grow larger and increase the overall scale of their activities (Luo and Tung, 2007).

Furthermore, both the motivation of the investments and their final destination have an important influence on performance. This is a relevant aspect for the purposes of this study, which focuses on the emerging economies' OFDI into advanced economies, characterized by a prevalence of *market*- and *strategic asset-seeking* motivations (Amighini et al., 2013).

In the case of *market-seeking* FDI, the resulting increase in the scope of operations of MNEs may stimulate the exploitation of economies of scale, at the level of both the parent company and the affiliate. This might happen as a consequence of sharing sunk costs, information, or learning by doing (Hijzen et al., 2011). In addition, economies of scale may significantly impact the performance of the parent company, which provides specialized services to the affiliates as well as intermediate goods, if the latter are involved in overseas production activities serving foreign markets. In this context, not only do MNEs increase their overall size; they also combine domestic and foreign production to enhance their productivity and competitiveness in both the home and host country (Herzer, 2012; Desai et al., 2009).

The effect is potentially stronger in the case of *asset- or technology-seeking* FDI, which are usually directed to advanced economies[1], and are common for EMNEs. Foreign affiliates can be seen as a vehicle to acquire knowledge, technologies, know-how, and management capabilities, all assets that are then transferred back to the parent company in the form of reverse technology and knowledge transfers (Chen et al., 2012). It should be noted that in some circumstances the potential benefits of such investments might be offset because of a lack of international experience of EMNEs and a lack of knowledge of foreign markets, especially those with a larger cultural distance (Bertrand and Capron, 2014), as recently shown by Buckley et al. (2014).

Among the few studies investigating the effects of OFDIs on the performance of EMNEs, some have looked specifically at the effect of asset-seeking motivation on the technological performance of investor firms (Chen et al., 2012; Pradhan and Singh, 2009). Only a few other studies focus on the effects of OFDIs on other aspects of firms' performance in the context of emerging economies. Among them, a paper by Debaere et al. (2010) combines propensity score matching with difference-in-difference estimators to study the effect of FDI on employment growth in a group of Korean MNEs and shows significant reductions for firms investing in developing countries but non-significant effects for investments into advanced economies. Two other studies focus on Taiwan and show that foreign operations generally: a) promote an increase in domestic production and employment, conditional on the size of the investment (Liu and Nunnenkamp, 2011); and b) raise firms' productivity, as they affect both technological endowments and the firms' technical efficiency (Yang et al., 2013).

A recent work by Chen and Tang (2014) investigates the effect of OFDI on different dimensions of performance of Chinese firms. The paper is based on MOFCOM approved investments[2] and finds positive effects of OFDIs on productivity, employment and on various dimensions of export performance. With respect to this analysis, we focus here on

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[1] Indeed, extant literature on MNEs has showed that the investment destination matters, with increases in productivity being associated with investments in higher technology intensive countries (de la Potterie and Lichenberg, 2001; Barba Navaretti et al., 2010).

[2] As recognized by the same authors, MOFCOM data are biased towards financial centers, like Hong Kong, and in some cases this hides the real final destination of the investments (for a comparison of the database used in our empirical analysis versus MOFCOM data, see Amighini et al., 2014).

Chinese investments into advanced economies and we include information on the entry modes of the investments. As a matter of principle, efficiency gains and learning from FDI could be equally captured by means of both M&As and greenfield, though in practice it is more likely that the former entry mode contributes mainly to learning and knowledge transfer while the latter is more likely to enhance complementarities and the exploitation of existing resources (Bertrand and Capron, 2014).

To our knowledge no studies have examined the effect of greenfield FDI on firms' performance, at least in the context of EMNEs, while there are a few evaluating the impact of M&As. Using a sample of public listed firms, Edamura et al. (2014) have empirically shown the existence of a positive effect on sales, productivity, and assets of M&As for Chinese acquiring firms. But there is also evidence suggesting that EMNEs may lack the internal capability needed for completing well performing M&A deals (Nair et al., 2015). This is consistent with the findings of Bertrand and Bertschinger (2012) based on a sample of Russian MNEs, which look at the effects of acquisitions on profitability and find that a lack of international experience, together with the limited ownership advantages, have undermined the capacity to leverage values from foreign acquisitions.

There is also some evidence from case studies on Chinese EMNEs confirming that the expected positive outcomes of M&As in advanced countries are often delayed or reduced because of a lack of experience and competitive advantages, especially in contexts characterized by wide cultural differences (Nolan, 2012; Spigarelli et al., 2013; Hansen et al., 2014).

3. Data and Methodology

3.1. The database

Our analysis is based on a novel database – the Emerging Multinationals' Events and Networks DATAbase (EMENDATA) – which includes greenfield investments, mergers and acquisitions (M&A), and other minority investments (Amighini et al., 2014). EMENDATA matches different international data sources: *fDiMarkets* from the Financial Times Group providing information on greenfield investments; *Zephyr* from Bureau van Dijk (BvD) and *SDC Platinum* from Thomson Reuter offering information on M&A and other minority investments (corresponding to a share of less than 50% of ownership). EMENDATA covers all FDI from emerging multinationals (EMNEs) in Europe between

2003 and 2011. In addition, EMENDATA provides information on investor companies and their Global Ultimate Owners (GUO) from *Orbis* (BvD).

For the specific purposes of this work, we look at all the deals undertaken by Chinese investor firms within the EU27. According to EMENDATA, the EU27 is the most attractive region for Chinese OFDI, followed by Asia (Amighini et al, 2014).[3] The total number of Chinese companies with one or more investments in Europe is 521 (423 with one investment and 98 with more than one deal). The sample shrinks to 368 companies (70% of the initial sample) because of the limited availability of firm level information. The information has been extracted at the parent company level, consolidating all the deals of the same business group, even when undertaken through different subsidiaries.[4]

As far as the main descriptive statistics are concerned, our data show that the list of destinations of the first investment in Europe is quite concentrated, as the top five locations (in order of relevance: Germany, UK, France, Netherlands and Italy) represent together the 77.7% of the total. Sectorally, on the other hand, there is a larger diversification, with a slight prevalence of industrial machineries (15% of total projects) and electronics (12%), but it is not surprising to observe that all the main sectors of specialization of the different European markets have been targeted by Chinese investors.

Distinguishing by entry mode, our data show that a large majority (more than three quarter) of Chinese OFDI are greenfield investments, the half of which is directed towards Germany. Also in the case of M&As the top 5 target countries are the same, although with a slightly different ranking (Netherlands more attractive than France) and less distance among them (M&As towards Germany are just a few more than to other top destinations). Other specificities appear when looking at sectors of investment: the industrial machinery sector is clearly the top one both for greenfield and M&As (with 14% and 19% on total, respectively); then investments are quite distributed across all other sectors, with textile and transports more attractive for M&As, while electronics and consumer products more for greenfield. Finally, two thirds of M&As are represented by acquisitions of 100% of company shares.

3.2 The econometric methodology

[3] This is the case where we exclude from Asia all the investments from Mainland China into Honk Kong; if these are included, Asia becomes the main destination for Chinese OFDI.

[4] In the whole sample, only 30 Chinese investor firms have undertaken cross-border deals through multiple companies within the same business group. This implies that for all investors the matching with BvD variables has been done via the consolidated balance sheets, except for firms that did not consolidate.

The empirical assessment of the impact of OFDI on the investor companies faces a major problem of endogeneity and reverse causality, widely recognized in the literature (Helpman et al., 2004). In fact, there is problem of self-selection because larger and more productive firms could be more likely to undertake foreign investments. In other words, the better performance of MNEs with respect to firms without foreign investments could be independent of their decision to undertake OFDI (Castellani and Barba Navaretti, 2004).

The first step of our analysis is to assess the existence of structural differences between two groups of firms: the *treated* firms corresponding to those companies that have invested in the EU27 and the *control* group of companies without foreign investments. As far as the latter are concerned, from BvD Orbis we also included 4,801 Chinese companies that control at least one subsidiary in China but do not have any foreign subsidiaries, that is, companies that have not undertaken any OFDI before 2011.

Table 1 presents their key characteristics in the year before the first investment. In order to assign counterfactual treatment dates to the firms included in the control group we follow the procedures described in Chari et al. (2012). More specifically, we adopt the approach of proportional random investment time assignment. We have first determined the number of investments that occur in each calendar year during our sample period and then assign the hypothetical treatment year to the companies in the control group in the same proportion as the investments occurred in the treated group. Thus, for instance, since about 12% of all investments occurred in 2006 in our sample of targets, then 12% all firms in the control group receive 2006 as the hypothetical treatment year.

The choice of considering the first investment in the EU27 is motivated by the fact that the decision to internationalise in an advanced market and become a multinational represents a change of status for a company.[5] In the empirical analysis we aim at investigating whether this decision has an impact on firms' productivity and structural characteristics.

Our data confirm that there are significant differences between the two considered groups: the treated companies are younger, larger, and more profitable than the companies in the control group.

<Table 1 here>

[5] In 63% of the greenfield and 82% of the M&As, the companies have not previously invested in any other country, Furthermore, in 78% of the greenfield and 95% of the M&As the companies have not carried out any other investments in other advanced countries (i.e. Australia, Canada, Japan, Switzerland and the US).

The second step of the analysis is to further investigate the existence of heterogeneity among the sample firms using a simple OLS regression to test the relationship between firms' characteristics, performance indicators and a dummy variable (*OFDI*) taking the value of 1 in the year of the first investment and at the following years and 0 otherwise (i.e. if a firm has first invested in Europe in 2006, this variable takes the value of zero for the years 2003-2005 and 1 for 2006-2011)[6]. The model is:

$$Y_{i,j,x,t} = \beta OFDI_{i,j,x,t} + \gamma_j + \delta_x + \rho_t + \varepsilon_{i,j,x,t} \quad (1)$$

where *Y* indicates firms' characteristics and measures of productivity (see Appendix A for details) in firm *i* in province *j*, sector *x* and year *t*, and γ_j, δ_x, and ρ_t, are respectively province, industry (2 digit codes of the ISIC Rev. 3 classification), and year effects.

Table 2 shows that the effects of the investments are positive and significant with respect to productivity, sales and employment, while there is a negative effect on financial performance, especially on the return on assets[7].

<Table 2 here>

In the third step of the empirical analysis we follow a well-established strand of empirical literature (Castellani and Barba Navaretti, 2004; Debaere et al., 2010) and, using propensity score matching technique (PSM), we build a counterfactual by selecting a group of non-investors whose characteristics closely match the Chinese investing companies. Therefore, the control group includes Chinese companies without any foreign affiliates but with the same ex-ante probability to undertake an OFDI.

We then estimate the probability of investing in Europe as a function of observable characteristics by means of a Probit model:

$$Prob\ (OFDI_{i,t} = 1 | X_{i,t-1}) \quad (2)$$

Our vector of observable characteristics, *X*, includes a number of standard variables that can affect the probability of investing overseas (see Debaere et al., 2010; Chari et al., 2012;

6 As suggested by Bertrand and Capron (2014), the construction of the OFDI variable in this way allows to take into account as well firms that make multiple investments. We also introduce specific robustness checks in section 4.2 to better account for these occurences. Still, there is a limitation in our approach, i.e. that in the treated group the variable OFDI takes the value of 0 even if the company has made an investment before 2003. This is due to the lack of availability of information on firms deals in EMENDATA before that year. This notwithstanding, we are confident that this does not affect significantly our results since the larger wave of foreign investments from China started only by the second half of the 2000s.

7 Summary statistics and the correlation matrix for all the variables included in the different models are reported in Tables B1-B2 in the Appendix.

Chen and Tang, 2014), including age and age squared, as a proxy for the experience of the firm, size (measured by the number of employees), capital intensity, financial performance (measured by the return on assets)[8], and a dummy variable equal to 1 if the firm is listed on the stock exchange or 0 otherwise as a proxy for the capacity to access financial capital.[9] The specification also includes 2-digit industry dummies, to control for industry-specific performance and to take into account specific incentives and policies targeted to specific sectors; and provincial dummies based on the geographic distribution of firms within provinces and autonomous municipalities, to control for the heterogeneity of local policies which might affect the decision of the firms to invest. Finally, we also include year dummies to control for common shocks and business cycle fluctuations.

The results for the Probit model, reported in Table B3 in the Appendix, show that larger firms, in terms of employment, those more capital intensive, as well as those with higher returns on assets are more likely to invest in Europe. Age appears to have a negative effect, as in Edamura et al (2014), which is explained by the high propensity of Chinese MNEs to undertake early internationalization strategies and thus leapfrog the traditional stages of development. However, the relation between age and the propensity to invest in advanced countries is non-linear, indicating that the most recently established firms have lower probabilities to go abroad.

Propensity scores are then computed based on the output of the Probit analysis. We select those firms that are as similar as possible to the investing companies in terms of propensity scores, using the Kernel matching estimator with common support by means of the Leuven-Sianesi (2003) algorithm.[10]

Figure 1 provides an illustration of the matching procedure. The graph on the left shows the predicted probability, i.e. the propensity score, of investing abroad for the entire control group before matching *vis-à-vis* the treated firms, while the right graph presents the same

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[8] For the variables representing firm structure, capital intensity and financial performance we use the average values for the last three years before the investment. Two main reasons for this: first we are able to increase the number of observations given the large number of missing values in our sample; second the decision to invest abroad might not necessarily be taken the year before investing (on this see Hijzen et al., 2011), especially when – as in the case of China – approval procedures take time.

[9] The choice of the control variables for the probit model has been affected by the limitation of the data. It would have been of interest, for instance, to include other variables measuring the internationalization status of the companies, their R&D and additional information on their financial accounts. In addition, we could not add a variable to identifying State Owned Enterprises, given that this information is not directly available either in our database or in Orbis.

[10] A total of 139 firms are included in the final group of the treated, while the firms in the control group are 1,096. Alternative matching algorithms, including the nearest neighbour and the Mahalanobis one, were also tested, but their performance was worse in terms of the balancing test.

probability for the groups of the matched controls and the treated, showing that the two distributions almost overlap after the matching procedure.

<Figure 1 here>

Another way to evaluate the results of the matching procedures is to test the so-called balancing hypothesis, which means that observations with the same score have the same distribution of observable characteristics independently of the treatment. This hypothesis is tested both before and after the matching. Table 3 shows that the two samples can be considered well-balanced given that the standardized percentage bias falls well below the standard 5% threshold, and that the t-tests on the selected variables are not significant (Rosenbaum and Rubin, 1985). Furthermore, following Sianesi (2004), we compare the *pseudo* R^2 before and after the matching finding a sensible reduction.[11]

<Table 3 here>

Finally, in the fourth step of our empirical analysis, we use the propensity scores to calculate a difference-in-difference (DID) estimator to further rule out time-invariant and unobservable differences between treated firms and the controls, using the following genral specification:

$$Y_i = \beta_0 + \beta_1 t_i + \beta_2 treated_i + \beta_3 treated_i * t_i + \gamma_j + \delta_x + \rho_t + \varepsilon_i \qquad (3)$$

where firms in the control group are weighted on the basis the propensity score difference between treated and control firms, obtained via the matching procedure described earlier. The DID allows to compare the change in the average outcomes for the two groups of firms in our sample during a time period including the year before the investment took place (t= -*1*) and a time period (t=n) following the investment. Given the availability of a relatively long time series, we are able to test the effects on performance from the year of the investment (t=0) up to five years after (t=5).

4. Results

[11] As the *pseudo* R^2 is an indicator of how well the regressors explain the probability of selection, after matching, its value should decrease considerably compared to that prior to the procedures (Sianesi, 2004).

Table 4 provides the results of our difference-in-difference estimator including a number of indicators over a period covering from the year of the investment (t=0) up to five years (t= 1,…,5) after it.

<Table 4 here>

Columns I-III present the effects of the investment on firms' efficiency, showing that investments hardly induce a significant immediate increase in productivity. The sign of the coefficient (although still not significant) switches from positive at t=0 to negative for the following two years. The positive sign at t=0 can be considered a further indicator for the existence of a productivity premium for foreign investors, as already pointed out in the previous section. On the other hand, the switch to a negative sign from t=1 can be interpreted as an initial effect of the investment, which implies high costs linked to greater complexity and adaptation, this being especially true for firms from emerging economies, starting with a less developed set of resources and competitive advantages (Sanfilippo, 2014; Nair et al., 2015). Then, after four years from the investment, Chinese firms investing in Europe experience a significant increase in their productivity, which is estimated at some 20 to 58 percentage points higher than for non-treated firms, depending on the indicator used. There are two possible explanations for this positive and significant difference in productivity. It could be the result of reorganization of production activities, leading to a more efficient division of labour between parent and affiliates. Moreover, we can expect intra-firm transfer of knowledge, technologies and managerial best practices, which would provide evidence of learning and reverse spillovers. The latter mechanisms depend on the existence of a knowledge gap between the host and the home market, which is likely in the China-EU case, as well as on the existence of absorptive capacities and a domestic environment conducive to knowledge transfer (Bertand and Capron, 2014). As the latter may still be weak in the case of China, we show that productivity gains take on average four years to be absorbed by firms (Mansfield, 1985; Chen et al., 2012).

Related to this, in Column IV, we control for intangible assets, as a proxy for the asset-seeking motivation (Deng, 2009; Buckley et al., 2014). In fact, one of the reasons why EMNEs invest abroad, especially in advanced markets, is to complement their resources with new assets hardly available in the home country (Ramamurti, 2012). Nevertheless, we do not find any significant improvements relative to non-investors in the share of intangible over total assets, which actually show a small relative decrease in years three and four, possibly due to more rapid accumulation of fixed assets, as recently shown by the industry level analysis conduced by You and Solomon (2015).

Another key implication of OFDI is represented by the capacity to expand the overall scale of investors' activities. Though such an investment itself represents an expansion of the investor's scale, this can also be due to a number of different factors, including, for instance, the need to serve new markets or to extend and coordinate existing activities across borders. We test this hypothesis using two main variables.

In Column V, we measure the impact of investments in Europe on the employment of Chinese EMNEs finding a positive and significant effect. This result is consistent with the existing evidence on the employment effect of OFDI in Chinese firms (Chen and Tang, 2014) as well as in firms in other emerging economies, such as Korea (Debaere et al., 2010) and Taiwan (Liu and Nunnenkamp, 2011). In the case of China, this result does not come as a surprise. As the country is still in its process of building up its domestic capacities, it is very likely that efficiency seeking investments can be excluded and that OFDI is generally oriented to increasing the scale of the investor companies rather than substituting domestic employment with the establishment of foreign affiliates.

In a similar vein, we find that investments lead to a significantly larger increase in total sales as compared to the control group (Column VI). Unfortunately, due to data limitations, we cannot determine whether exports, intra-company trade or domestic sales explain this increase. Consistently, based on the literature on the determinants of Chinese FDI (Buckley et al., 2007), we assume that such an increase could be explained by market seeking investments aimed at strengthening the market position in advanced countries through the establishment of trade offices and/or the acquisition of distribution networks. The importance of market seeking as motivation for investments is also confirmed by surveys undertaken on Chinese investors in Europe (European Chamber of Commerce, 2013). Moreover, Chinese investments in advanced economies are also aimed at responding to the increasing sophistication of domestic demand, as documented in the case of the investments of Haier, an Italian white goods company, by Pietrobelli et al (2011). This helps to explain the rise in domestic sales compared to national firms. Finally, in the case of production related vertical investments there could also be an increase in intra-firm trade (Barba Navaretti and Venables, 2004).

Finally, columns VII-VIII report the impact of the investments on certain financial indicators for investigating how the profitability of the investors is affected by OFDI. The results are always not significant, but the situation changes in the next section, where we take into account the different modes of entry of the investments - greenfield versus M&As – given the different financial efforts involved (Norback and Persson, 2002).

4.1 Does the entry mode influence domestic performance?

In this section, we replicate the empirical analysis presented in the previous section introducing a distinction between the two entry modes – greenfield and M&As – to explore whether there is any difference in their impact on investors. Treated and control samples have been selected following similar procedures as those described in Section 3.1. Methodologically, however, following the same approach would have hindered a potential bias in the following results due to endogeneity of the entry mode choice by the firms, considering that the decision to invest and the decision on the mode are not likely to be taken separately (Javorcik, 2004). To overcome such limitation, we estimate the decision regarding the entry mode of the investment project conditional on investment taking place using a sample selection model. More precisely, we first adopt a bivariate probit model with sample selection in which there are two dependent variables: *OFDI* taking the value of 1 if the firm undertook an investment and 0 otherwise (as in equation 2), and *OFDI_MA* taking the value of 1 if the firm undertook a M&A and 0 if it opted for a greenfield investment:

$$OFDI\_MA_{it} = \begin{cases} 1 & if \quad OFDI_{it} > 0 \\ 0 & otherwise \end{cases} \qquad (4)$$

To estimate (4) we use the same set of characteristics affecting the choice of investing abroad (as in 2), with the exclusion of the years' dummy, less likely to influence the entry mode[12].

[12] An additional reason for this is that for the model to be correctly identified, the selection equation should have at least one variable that is not in the probit equation. We estimate the model in two steps, computing the inverse mill's ratio after running the first probit model, and including its coefficient in the second equation. Due to the large number of dummies, which prevented convergence, we could not estimate the two equations simultaneously by means of the "heckprob" routine in STATA. For robustness, we have however run a restricted model, including only industry and provincial dummies, getting very similar results (such results, for comparison, are reported in column 2 of Table B3).

Results of the bivariate probit model are reported in Table B4, and are broadly in line with those reported in Table B3. Firms undertaking M&As are younger, smaller in size and less capital intensive compared to those involved in greenfield FDI. Interestingly, the effect of public listing on the probability to choose M&A is positive and significant. M&As usually require larger capital commitments, and public listed firms are more likely to have access to financial resources. This is even more likely in the case of China, where access to credit is considered a binding constraint to potential (non-listed) investors (Sutherland and Ning, 2011).

Once the selection model has been correctly specified, we apply similar procedures to those described in section 3.2 to retrieve propensity scores and weights, which are then used in the DID regressions.

Tables 5 and 6 present the results of this analysis.

<Table 5 here>

<Table 6 here>

Considering Columns I-III in the two tables, we notice that it is both through greenfield FDI and M&As that Chinese EMNEs can increase their productivity. This result provides new evidence with respect to the analysis presented in Edamura et al. (2014), which is only focused on M&As. Greenfield investments can result in early and higher gains in productivity compared to M&As, and this can be the results of stronger complementarities with foreign affiliates. On the one hand, strategic acquisitions are more likely to be undertaken by Chinese firms with the objective of getting access to resources, which are mainly oriented to increasing the value added of production rather than its efficiency. It is also true that – especially in more distant contexts such as the EU27 – M&As are more complex operations to manage than greenfield investments, and this can result in underperforming deals. Indeed, in some cases, the lack of prior international experience of many Chinese firms and their cultural distance from western companies cast doubts on their ability to successfully take advantage from foreign operations. This has been documented by case studies on several acquisitions made in Europe, showing the difficulty to obtain the expected gains through the production efficiency of the acquired company (Spigarelli et al., 2013) as well as the obstacles encountered in the transfer of knowledge and technology from the target to the acquirer (Hansen et al., 2014).

With regard to employment and sales, there are significant and positive effects of greenfield investments, which can be much larger than those of domestic firms. Such a result does not come as a surprise considering that setting up a new affiliate necessarily involves a duplication of existing activities. But given that the vast majority of greenfield investments in Europe are of small size[13], we would also expect that the large increase relative to domestic firms goes beyond the new activities created abroad and positively affects the sizes of investors. Taking into account sales, given that some greenfield investments in Europe consist of the establishment of market-oriented and trade-related activities, their rise can be considered a confirmation of the positive impact of internationalization strategies.

Taking into account M&As (Table 6), the impact on size is also generally positive and significant, but it is smaller than in the case of greenfield investments. Given that M&As generally require higher cash flows and a more complex *ex ante* structure, firms investing via acquisitions are in general better established companies in their home country and this can explain this relatively more limited impact on scale. In addition, considering that existing analyses linking the motivation of the investment to the entry mode consistently show that M&As are mainly used by Chinese firms to gain access to strategic assets for upgrading their operations (Deng, 2009), while greenfield investments are used for expansion purposes (Quer et al., 2012), one could argue that acquisitions should contribute mainly (and earlier) to a qualitative, rather than quantitative, improvement of the firm.

Indeed, considering intangible assets, we observe that Chinese firms increase their relative endowments as an immediate consequence of M&As in Europe, confirming a finding by Edamura et al. (2014) that it is mainly through acquisitions that Chinese firms tap into foreign technologies and knowledge for accelerating their upgrading (Deng, 2009).

Finally, the indicators of financial profitability weaken steadily as a consequence of M&As. This result is consistent with the literature on the effects of M&As. On the one hand, in line with Norback and Persson (2002), we confirm that negative profitability is more likely to be caused by M&As, rather than greenfield investments. On the other hand, in accordance with the findings of Bertrand and Betschinger (2012) on M&As undertaken by Russian MNEs, we show that also Chinese MNEs (in most cases at their first foreign M&A) are unable to leverage value from their foreign acquisitions.

[13] According to our data, about 75% of affiliates established through greenfield investments in Europe has less than 50 employees.

4.2 Robustness checks

A number of robustness checks have been run to confirm the overall validity of our main findings. First of all, we have verified that the results are robust to changes in the set of explanatory variables used in the probit model. This has been done either by replacing the control variables averaged for the last three years with their equivalents at time t and t-1, and by adding a larger set of controls, including assets, turnover, returns on efficiency (ROE)[14]. In both cases results of the probit model (Table B3, columns II-IV) and of the DID remains largely unchanged[15], leaving us quite confident on their relevance and overall robustness.

Moving to the results of the DID (Table 4), one could argue that other firm-specific characteristics can have an influence on the performance of the firms, together with OFDI. This is especially true for the estimates of productivity, considering the large literature pointing out that variables such as experience, size, the internationalization status and the innovative capacity have a strong influence on firms' heterogeneous performance (Helpman et al., 2004). In order to address such potential concern, we also ran the DID model on the main measures of productivity reported in Columns I-III of Table 4, including age, size and capital intensity among the independent variables in the regressions. Results, summarized in Table B5 in the Appendix, are robust to the introduction of the additional controls. It is interesting to notice, however, that there is a reduction in the size of the effect of FDI on the different measures of productivity, which can indeed be attributed to the moderating effect of the covariates.

4.2.1 Dealing with multiple treatments

As remarked in section 3.2, the propensity score matching estimator has several advantages over standard procedures, and it allows to get more clarity about the direction of causality between OFDI and performance, while taking in due account the issues related to endogeneity. This approach is nonetheless not immune to criticism. One point of contention that may be quite relevant to our case is related to the issue of multiple treatments, i.e. the

[14] The introduction of these additional variables reduces the explanatory power of the model, and the balancing test run after the selection has a worst performance compared to our preferred specification. In addition, the introduction of total assets drops out the capital per employees due to collinearity.
[15] Results of the DID are not included for reasons of space, but are available upon request to the authors.

presence of firms performing multiple investments over the period considered. This may introduce biases into our estimations. While, as suggested by Bertrand and Capron (2014), the way we constructed the treatment indicator (OFDI) allows to take into account firms that have invested in more than one year, one should not overlook the fact that the large size of the coefficients reported in Table 4 some years after the initial investment could be attributable to the effect of additional investments.

As remarked in section 3.1, our sample is partially affected by such issue, considering that investors with more than one deal represent 18.8% of the initial sample of 521 firms, and raise up to about 26% of the usable sample of 368 investors.

In what follows, we try to account for such potential bias in the results by adopting two different strategies. First, we ran our PSM-DID model on a sample of treated firms composed of individual investors only, i.e. excluding all firms that have undertaken more than one investment in the period considered. Table B6 in the Appendix shows that our concerns are not necessarily supported by the results since the relations examined remain significant. Interestingly, however, we notice that the size of the scale-related coefficients (employees and sales) tends to reduce as we move to later years. In such cases, this can be explained by the exclusion of multiple investors in the sample.

Second, following the empirical strategy adopted by Bertrand and Betschinger (2012), we check the overall robustness of our approach by adopting an alternative estimator, based on a dynamic GMM. In order to account for the presence of multiple investors, we replace our OFDI dummy with a new variable (N_OFDI) counting the number of investments undertaken by each firm. In our settings, the GMM is a good alternative to the PSM approach, given that it allows to take into account the endogeneity of OFDI. Moreover, it also controls for the possibility of omitted variables. This enables us to overcome the potential limitations due the assumptions of conditional independence in PSM (Imbens and Wooldridge, 2009). Finally, adopting a dynamic panel approach has the additional advantage of controlling for persistence, i.e. the dependence of performance indicators on their past values.

We control for factors affecting the performance of both investors and non-investors to isolate the effect of FDI using a system GMM approach (Roodman, 2009) to test the effects of FDI on productivity.[16] It is possible to infer from Table 7 that both the Hansen test of over-identification and the Arellano-Bond test of first- and second- order autocorrelation confirm the adequateness of the GMM specification adopted here. These results point once again to the positive relation between investment and productivity, proven by the positive and significant coefficient of the N_OFDI variable. Compared to previous results (e.g. Table 2) the coefficient of the FDI variable is higher since we explicitly account for the presence of multiple investors in the sample of treated firms.

<Table 7 here>

5. Conclusions

This paper has analysed the effects of OFDI into the EU-27countries on the performance of Chinese MNEs. Our results robustly show that Chinese OFDIs have so far affected different dimensions of MNEs performance. We find that Chinese investors register an increase in productivity and capital endowments, but these effects only materialize some years after the initial investment. In line with the existing literature on EMNEs, we also show that firms may speed up the process of gaining access to new resources and intangible assets via M&As, even if this seems to happen at the cost of a lower profitability. We show that M&As are not so frequently aimed at the quantitative growth *per se*, but rather at a qualitative improvement in the firm. Indeed, firms engaging in M&As are expected to be relatively larger ex ante but to grow more slowly after the acquisition, as their efforts concentrate on the assimilation of technological advantages. Conversely, Chinese firms undertaking internationalization via greenfield investments see larger complementarities between domestic and foreign activities, the former benefitting from significant increases in scale, sales and assets.

Taken together, these results provide new evidence that the recent rise of Chinese investments, spurred by the Government's strategy of promoting the internationalization of domestic firms, is leading to improved performance by the domestic sector. However, it is still difficult to say whether the improvements in performance can contribute to the upgrading of the productive structure of the country. We find only weak evidence that M&As are leading to the transfer of more valuable resources in the form of intangible

[16] This choice is justified by the presence of a number of standard control variables (size, capital intensity and age), whose inclusion in the models used to estimate other performance indicators such as size, sales and profitability could be hardly motivated.

assets to the parent companies making the investments, and this effect even disappears a few years after the deal is concluded. In addition, due to the lack of information on value added, we are unable to investigate whether the gains in productivity lead to any process or product upgrading.

An implication of our work for the study of China's upgrading is that Chinese MNEs are still in the process of learning from their internationalization process and, especially in the case of M&As, they are gaining experience by accessing geographic and culturally distant markets. On the basis of our results, we can reasonably affirm that the stock of accumulated experience in overseas investments is directly related to an increase in the size of the gains accruing to domestic firms. This can be interpreted as an encouraging sign for Chinese investors, whose relative inexperience and lack of key competitive advantages have so far constrained their capacity to fully exploit the potential of overseas activities, as well as for the Chinese economy as a whole, which could well expect large returns from its increasing OFDI activities.

This study has some limitations, which needs to be addressed in future research. The main one has to do with the availability of balance sheet information for Chinese firms. Not only this information is missing for a number of firms in our sample. For firms for which it is available, we have found many missing information, thing that did not allow us to explore some important dimensions, such as exports and innovation, or that forced us to rely on proxies for many indicators, such as TFP, due to the lack of information on value added and intermediate inputs, among the others. Accessing new sources of firm level information will make possible to provide a more comprehensive evaluation on whether and through which mechanisms Chinese firms upgrade through OFDI.

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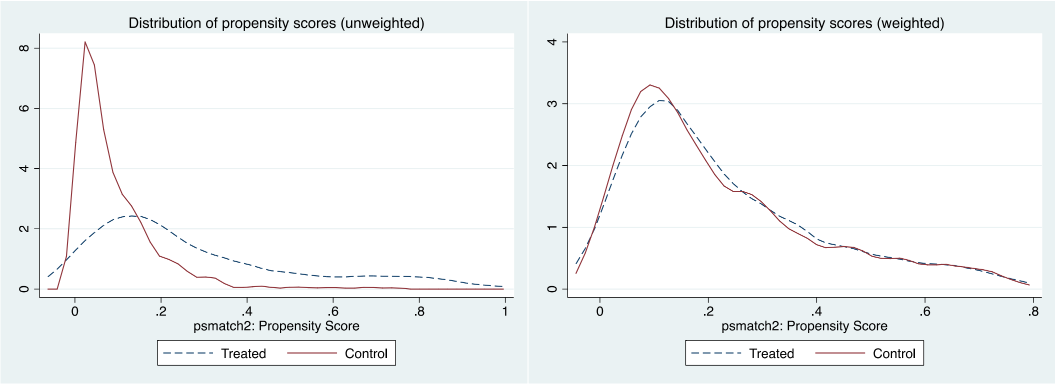
Figures

Figure 1. Distribution of propensity scores before (left panel) and after (right panel) matching



Source: Authors' elaboration

Tables

Table 1. Structural characteristics of sample firms (year before investment)

	Treated	**#**	**Control**	**#**	t-stat
Year of establishment	1997	212	1995	1868	-2.5136*
Employees (#)	23097.4	134	2202.96	1295	-10.2274**
Total assets (USD million)	29,300	152	749	1395	-7.8857**
Sales (USD million)	1530	140	234	1384	-6.8162**
Turnover (USD million)	2350	150	251	1394	-9.8151**
Profit margin (%)	12.711	138	8.084	1250	-2.9728**

Source: Authors' elaboration on EMENDATA and Bvd Orbis

**p<0.01 , *p<0.05

Table 2. Determinants of firms' performance

	(I) LAB PROD	(II) TFP	(III) TFP_GMM	(VI) SALES	(VII) EMP	(VIII) PROF	(IX) ROA
OFDI	0.160***	0.129***	0.0242	1.501***	1.428***	-0.00871	-0.663*
	(0.0497)	(0.0405)	(0.0356)	(0.0895)	(0.0782)	(0.00597)	(0.372)
Constant	11.15***	7.325***	8.006***	18.64***	7.583***	0.0349**	2.641**
	(0.116)	(0.0828)	(0.0559)	(0.103)	(0.144)	(0.0153)	(1.198)
Province effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	11,982	11,982	11,975	13,422	12,200	12,589	12,821
R^2	0.200	0.165	0.941	0.212	0.229	0.131	0.064

Table 3. Balancing test, before and after matching

	Unmatched	**Mean**		**%reduct**		**t-test**	
Variable	**Matched**	**Treated**	**Control**	**%bias**	**|bias|**	**t p>t**	**p>|t|**
AGE	Unmatched	2.1409	2.3528	-27.8	81.9	-12.50	0.000
	Matched	2.12	2.0808	5		0.43	0.669
AGE2	Unmatched	5.3061	6.0581	-21.4	78.9	-9.39	0.000
	Matched	5.0265	4.8679	4.5		0.39	0.697
EMPL	Unmatched	7.3231	6.7263	30	63.9	13.35	0.000
	Matched	7.0673	6.8521	10.8		0.88	0.378
K_E	Unmatched	11.718	11.547	11.7	36.2	4.81	0.000
	Matched	11.699	11.589	7.5		0.58	0.563

ROA	Unmatched	7.8838	5.9605	19.6	97.1	7.06	0.000
	Matched	8.0526	7.9969	0.6		0.05	0.963
PUBLIC	Unmatched	0.49861	0.56104	-12.5	66.4	-5.52	0.000
	Matched	0.58594	0.56499	4.2		0.34	

Sample	Pseudo R2	LR chi2	p>chi2	Mean bias	Median bias
Raw	0.183	1382.49	0.000	8.3	6.3
Matched	0.022	7.76	1.000	2	0.5

Table 4. Propensity score matching difference-in-difference estimator

	(I)		(II)		(III)	
t	**LAB PROD**	**N**	**TFP**	**N**	**TFP_GMM**	**N**
0	0.0468	2,122	0.0748	2,122	0.0793	2,122
1	-0.0328	1,991	-0.00888	1,991	-0.0397	1,991
2	-0.0324	1,707	-0.0261	1,707	-0.127	1,707
3	0.154	1,506	0.15	1,506	0.0642	1,506
4	0.379**	1,349	0.307**	1,349	0.201*	1,349
5	0.582**	1,259	0.469***	1,259	0.292**	1,259

	(IV)		(V)		(VI)	
t	**INT/TOT**	**N**	**EMP**	**N**	**SALES**	**N**
0	0.00498	1,410	0.549***	2,155	0.429***	2,233
1	1.31E-05	1,393	0.714***	2,024	0.607***	2,082
2	-0.00157	1,208	1.094***	1,735	0.962***	1,816
3	-0.0103*	1,071	0.901***	1,533	0.875***	1,599
4	-0.0183**	952	0.853***	1,373	1.025***	1,414
5	-0.0126	858	1.019***	1,282	1.600***	1,272

	(VII)		(VIII)	
t	**PROF**	**N**	**ROA**	**N**
0	-0.00921	1,995	-0.0623	2,033
1	-0.0295	1,862	-1.025	1,903
2	0.00114	1,605	-0.226	1,646
3	-0.0167	1,418	-0.182	1,452
4	-0.0212	1,285	0.0379	1,312
5	-0.00574	1,156	-0.147	1,185

Note: This table reports difference-in-difference estimates for the post-investment performance between treated and control firms on different outcomes. All equations include province, sector and years fixed effects. t={0,5} denotes the post-investment year.

Robust standard errors in parentheses;

*** p<0.01, ** p<0.05, * p<0.1

Table 5. Results for propensity score matching difference-in-difference estimator (Greenfield)

	(I)		(II)		(III)	
t	**LAB PROD**	**N**	**TFP**	**N**	**TFP_GMM**	**N**
0	0.329*	1,615	0.234	1,615	0.0792	1,615
1	0.148	1,601	0.0595	1,601	-0.144	1,601
2	0.0784	1,466	0.0204	1,466	-0.126	1,466
3	0.201	1,293	0.0941	1,293	-0.0955	1,293
4	0.572**	1,160	0.441**	1,160	0.183	1,160
5	0.507**	1,060	0.384**	1,060	0.153	1,060

	(IV)		(V)		(VI)	
t	**INT/TOT**	**N**	**EMP**	**N**	**SALES**	**N**
0	-0.0125	1,134	0.352	1,643	0.487*	1,742
1	0.00226	1,168	0.609**	1,628	0.709**	1,704
2	-0.0167	1,056	0.383	1,493	0.369	1,561
3	-0.0151	923	0.839**	1,318	1.008**	1,376
4	-0.0148	825	1.205***	1,181	1.776***	1,234
5	-0.0208	750	1.053**	1,080	1.560***	1,113

	(VII)		(VIII)	
t	**PROF**	**N**	**ROA**	**N**
0	-0.0081	1,563	-2.982	1,593
1	0.0166	1,532	-2.508	1,562
2	0.0285	1,414	-5.788	1,439
3	0.0563**	1,246	-1.568	1,272
4	0.00958	1,119	-3.407	1,133
5	0.0625	995	0.587	1,011

Note: This table documents difference-in-difference estimates for the post-investment performance between treated and control firms on a different set of outcomes. All equations include province, sector and years fixed effects. t={0,5} denotes the post-investment year.
Robust standard errors in parentheses;
*** p<0.01, ** p<0.05, * p<0.1

Table 6. Results for propensity score matching difference-in-difference estimator (M&As)

	(I)		(II)		(III)	
t	**LAB PROD**	**N**	**TFP**	**N**	**TFP_GMM**	**N**
0	-0.0233	1,558	-0.0155	1,558	-0.048	1,558

1	0.16	1,542	0.129	1,542	0.0749	1,542
2	0.0982	1,416	0.0477	1,416	-0.0222	1,416
3	0.0779	1,284	0.0591	1,284	0.0942	1,284
4	0.341*	1,178	0.261*	1,178	0.272**	1,178
5	0.223	1,052	0.237	1,052	0.315*	1,052

	(IV)		(V)		(VI)	
t	**INT/TOT**	**N**	**EMP**	**N**	**SALES**	**N**
0	0.0215*	1,134	0.615**	1,576	0.684*	1,703
1	0.0157*	1,183	0.702**	1,558	0.673**	1,634
2	0.0049	1,020	0.678**	1,430	0.817***	1,506
3	-0.00562	938	0.517*	1,299	0.632*	1,400
4	0.00694	861	0.258	1,191	0.649*	1,261
5	-0.0102	752	-0.233	1,065	0.203	1,108

	(VI)		(VII)	
t	**PROF**	**N**	**ROA**	**N**
0	-0.0476**	1,538	-1.844	1,568
1	-0.0894***	1,470	-2.493*	1,498
2	-0.0780**	1,333	-2.858*	1,355
3	-0.0243	1,254	-1.711	1,279
4	-0.0651*	1,138	-1.229	1,153
5	-0.0407	972	-1.422	987

Note: This table reports difference-in-difference estimates for post-investment performance between treated and control firms on a different set of outcomes. All equations include province, sector and years fixed effects. t={0,5} denotes the post-investment year.
Robust standard errors in parentheses;
*** p<0.01, ** p<0.05, * p<0.1

Table 7. System GMM Estimator

	(I) Lab prod	(II) TFP	(III) TFP_GMM
L1.	0.4478***	0.5493***	0.5688***
	[0.045]	[0.042]	[0.043]
N_OFDI	0.1901***	0.1549***	0.0841**
	[0.037]	[0.033]	[0.042]
AGE	-0.0196	-0.0162	-0.0313
	[0.016]	[0.014]	[0.107]
EMPL	-0.1046***	-0.0816***	-0.0368**
	[0.022]	[0.021]	[0.018]
K/E	0.3632***	0.1392***	-0.1421**
	[0.030]	[0.017]	[0.069]
Constant	2.8787***	2.4034***	5.5438***
	[0.430]	[0.387]	[1.161]
Province effects	Yes	Yes	Yes
Industry effects	Yes	Yes	Yes
Year effects	Yes	Yes	Yes
Observations	9,705	9,705	9,701
N. of panels	2,071	2,071	2,069
Hansen	0.100	0.144	0.0439
AR2	0.229	0.346	0.512

Robust standard errors in parentheses;
*** p<0.01, ** p<0.05, * p<0.1

Note: This table reports the results of the System GMM estimator on the full sample of controls and treated firms on different measures of productivity. The variable L1 is the first lag of the dependent variable; N_OFDI is the number of investments for firms-years; AGE is the log of a firm's age; EMPL is the log of the number of employees; K/E is the capital labour ratio. In each model, only variables L1, OFDI and N_OFDI are treated as endogenous and instrumented by the other dependent variables, including fixed effects.

Appendix A

The following indicators of productivity are used in the empirical analysis.

1) A standard indicator of firms' efficiency in terms of labour productivity, measured by the ratio between sales and number of employees (LAB PROD).

2) An indicator of total factor productivity (TFP):

$$Y_{it} = A_{it} L_{it}^{\alpha_L} K_{it}^{\alpha_K} \qquad (1)$$

in which A_{it} is the Hicks-neutral efficiency level that represents the TFP of firms. Total sales is used as a proxy for output (Y), while the number of employees is used as the labour component (L) and total assets[17] to measure capital (K). All the variables reported in monetary terms are deflated by their respective industry price indexes. We calculate TFP with a constant return to scale Cobb-Douglas production function, assuming a conventional share of 2/3 for the labour component and 1/3 for capital (for a discussion on this, see Hulten and Isaksson, 2007).

The lack of a number of sufficient observations to proxy intermediate inputs does not allow us to calculate more robust semi-parametric estimators using proxies to correct for the unobservable productivity shocks and input levels, such as the Olley-Pakes or Levinshon-Petrin methods (Petrin et al., 2004). Therefore, we also estimate TFP (1) using the GMM approach (TFP_GMM) (Arellano and Bond, 1991), albeit with full awareness of concerns raised in the existing literature concerning these methodologies (Van Beveren, 2012).

[17] Total assets are used instead of fixed assets, given the presence of firms operating in the service sector, where intangibles are usually relevant.

Appendix B

Table B1. Summary Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
LAB_PROD	11991	11.2401	1.1719	3.2050	20.2823
TFP	11991	7.3224	0.9301	-0.4101	13.8726
prod_GMM	11984	2.0879	3.1555	-16.3051	23.9412
K/L	12172	11.7933	1.2678	7.0540	20.4665
TOT_ASSETS	13656	18.7257	1.8320	8.7566	28.3503
INTANGIBLES	10232	0.0503	0.0685	-0.0013	0.8396
EMPL	12209	6.9931	1.6071	0	13.1010
SALES	13431	18.1672	1.7816	7.2226	26.3514
ROA	12830	5.6443	10.7362	-97.9000	97.2200
PROFIT	12598	0.0879	0.1707	-0.9972	1
AGE	19417	2.3369	0.7233	0	5.0106
PUBLIC	20586	0.5545	0.4970	0	1

Table B2. Correlation Matrix

	LAB_PROD	TFP	prod_GMM	K/L	TOT_ASSETS	INTANG	EMPL	SALES	ROA	PROFIT	AGE	PUBLIC
_PROD	1											
	0.9605	1										
_GMM	0.1206	0.1854	1									
	0.7782	0.5726	-0.0633	1								
_ASSETS	0.3368	0.2777	0.0283	0.3655	1							
ANGIBLES	-0.1454	-0.1456	-0.0298	-0.0998	-0.0809	1						
PL	-0.2963	-0.1893	0.0776	-0.4455	0.6705	0.0017	1					
ES	0.4537	0.5246	0.1604	0.1525	0.8716	-0.1046	0.7167	1				
A	0.1089	0.1557	0.0841	-0.0307	-0.065	-0.018	-0.0381	0.044	1			
FIT	0.0688	0.0176	-0.0079	0.163	0.0331	-0.0118	-0.0981	-0.0413	0.7363	1		
	0.0492	0.029	-0.0496	0.0794	0.1083	0.053	0.0409	0.0741	-0.1164	-0.0674	1	
LIC	-0.0331	-0.0764	-0.0767	0.0748	0.2102	0.065	0.1426	0.1088	-0.0172	0.0556	0.0742	

Table B3. Results, probit estimator

	(I)	(II)	(III)	(IV)
AGE	-1.361***	-1.296***	-2.101***	-1.359***
	(0.288)	(0.308)	(0.402)	(0.288)
AGE^2	.199***	0.200***	0.345***	0.198***
	(.0617)	(0.0672)	(0.0811)	(0.0618)
EMPL	.126***	0.187***	0.0959**	0.0435

	(.0399)	(0.0432)	(0.0456)	(0.0606)
K/L	.082	0.110*	-0.00809	
	(.05344)	(0.0602)	(0.0664)	
ROA	.0134**	0.0134**	0.0124*	0.0144*
	(.0061)	(0.00646)	(0.00633)	(0.00773)
PUBLIC	-.062	-0.0275	-0.0199	-0.0646
	(.1319)	(0.152)	(0.156)	(0.133)
ASSETS				0.0834
				(0.0786)
TURNOVER				-0.00233
				(0.0792)
ROE				-0.000688
				(0.00192)
Province effects	Yes	Yes	Yes	Yes
Industry effects	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes
Constant	-6.332***	-6.013	-2.678	-5.129
Observations	1,235	1,049	957	1,213
Pseudo R^2	.2005	.2145	.2105	.1967

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table B3. Results, bivariate probit model with sample selection

	(I) OFDI_MA	(II) OFDI_MA
AGE	0.956***	0.360**
	(0.365)	(0.160)
AGE^2	-0.101	-0.0511
	(0.0744)	(0.0367)
EMPL	-0.408***	-0.111***
	(0.0893)	(0.0254)
K_E	-0.374***	-0.0793**
	(0.0990)	(0.0319)
ROA	0.00476	-0.0231***
	(0.0139)	(0.00521)
PUBLIC	3.224***	1.179***
	(0.402)	(0.151)
Constant	1.871	1.058
	(165.1)	(0.647)
Observations	814	1,095
LR test (p-value)		14.89 (0.0000)

Standard errors in parenthesis
*** p<0.01, ** p<0.05, * p<0.1
Note: OFDI_MA, the dependent variable of the latent model, takes the value of 1 if the firm undertook a M&A, and 0 if it undertook a greenfield FDI. Column I includes results obtained using the two stages Heckman selection model. Column II reports estimates of the two equations run simultaneously. The selection model in column I does not include year dummies, while no dummies are included in the model reported in column II.

Table B4. Propensity score matching difference-in-difference estimator, with additional controls

t	LAB PROD	N	TFP	N	TFP_GMM	N
0	0.0949	2,122	0.0949	2,122	0.108*	2,122
1	-0.0211	1,991	-0.0211	1,991	-0.0277	1,991
2	-0.0342	1,707	-0.0342	1,707	-0.0648	1,707
3	0.114	1,506	0.114	1,506	0.0906	1,506
4	0.229**	1,349	0.229**	1,349	0.247**	1,349
5	0.362***	1,259	0.362***	1,259	0.372***	1,259

Note: This table reports difference-in-difference estimates for the post-investment performance between treated and control firms on a different set of outcomes. All equations include capital labour ratio (K/L), the log of firms' age and the log of firms' employees as additional controls, together with province, sector and years fixed effects. t={0,5} denotes the post-investment year.
Robust standard errors in parentheses;
*** p<0.01, ** p<0.05, * p<0.1

Table B5. Results, propensity score matching difference-in-difference estimator – Individual investors only

t	Lab_prod	N	TFP	N	prod_GMM	N
0	0.109	1,696	0.142*	1,696	0.127	1,696
1	0.0423	1,652	0.0393	1,652	-0.0307	1,652
2	0.0574	1,458	0.0182	1,458	-0.0794	1,458
3	0.0562	1,286	0.0379	1,286	0.00317	1,286
4	0.312**	1,149	0.223*	1,149	0.139	1,149
5	0.477***	1,052	0.424***	1,052	0.431***	1,052

t	Intangible assets/tot. assets	N	Employees	N	Sales	N
0	0.00345	1,189	0.493***	1,720	0.484***	1,834
1	0.00242	1,206	0.639***	1,677	0.679***	1,761
2	-0.000566	1,045	0.898***	1,479	0.774***	1,554
3	-0.0122	920	0.657***	1,310	0.524*	1,359
4	-0.0061	813	0.736**	1,168	0.726**	1,211
5	-0.0152	738	0.709*	1,069	0.649**	1,099

t	Profit	N	ROA	N
0	0.00224	1,617	-0.358	1,650
1	-0.0206	1,570	-0.436	1,608
2	0.00679	1,400	-2.156	1,425
3	-0.00618	1,214	-1.177	1,241
4	0.00353	1,084	1.103	1,104
5	-0.00498	971	1.244	989

Note: This table reports difference-in-difference estimates for the post-investment performance between treated and control firms on a different set of outcomes. All equations include province, sector and years fixed effects. t={0,5} denotes the post-investment year.

Robust standard errors in parentheses;

*** p<0.01, ** p<0.05, * p<0.1