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The Heterogeneity of Foreign Direct Investors: Linking Affiliates to Parent Productivity

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Abstract

We investigate the heterogeneity within the group of foreign direct investors and the relation between affiliates characteristics and parent productivity. Using data on Italian firms, we show that foreign direct investors differ in their productivity level according to their characteristics and their investment decisions. Larger parents by employment or sales tend to be more productive, to have more affiliates and to invest in a higher number of destinations. Focusing on manufacturing firms, we show econometrically that having more and larger affiliates in rich countries leads to higher ex-post productivity. In particular, investing in high income countries or both in high and low income countries is associated with a subsequent productivity premium *vis-à-vis* low income countries investors, especially for larger parents. Low income countries investors are found to be relatively more productive when operating in low technology sectors, while the opposite applies to high income countries investors.

Keywords: foreign direct investment, heterogeneous firms, total factor productivity, multinationals, affiliates.

JEL Classification: F12; F14; F21.

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1 Introduction

In the last decade there has been a growing empirical and theoretical literature in international economics on the role of heterogeneity among firms (for a review of the literature see Melitz & Redding, 2012). The new theoretical approach has been motivated by firm-level empirical findings (highlighted in the late '90s) inconsistent with New Trade Theory models. In particular, firms appear to be heterogeneous in productivity, factor inputs, and trade behavior. Only a small fraction of firms export, the so-called "Happy Few" (Mayer & Ottaviano, 2008); and exporters appear to be systematically different from non-exporters: larger, more productive, more skill intensive. The most export oriented firms sell only to few markets and the extensive margin of trade plays a significant role in shaping the cross-sectional variation in aggregate exports. Finally, trade liberalization leads to market share reallocations towards more productive firms, thereby increasing aggregate productivity.

Standard New Trade Theory models, based on the representative firm framework (such as the model by Krugman, 1980), are not suited to explain these evidences. In his seminal paper, Melitz (2003) relaxes the homogeneity assumption, allowing for different productivity levels among firms.[1] In that model, the existence of a structure of entry fixed/sunk cost implies the self-selection of exporters. Before entering the market, potential firms are all equal, and have to decide whether it is worth paying the entry cost. After entry, each firm discovers its productivity, drawing it from a common distribution. Then, given the level of productivity, firms choose to produce or exit the market. Eventually, the most productive firms, paying an additional export cost, end up producing also for foreign markets.

Subsequent theoretical developments are based on the Melitz (2003) model.[2] The core mechanisms is extended to different internationalization modes, such as FDI, in Helpman, Melitz, and Yeaple (2004). Antràs and Helpman (2004) analyze incomplete contracts and their effects on trade. Melitz and Ottaviano (2008) introduce a quadratic linear demand, to study how trade and market size affect the average markups. Chaney (2013) models exogenous liquidity constraint to explain both export behavior of firms and the effects of exchange rate fluctuations.

All these papers have in common the assumption of heterogeneity in productivity. However, productivity remains unexplained, being a *lottery* outcome. Similar considerations apply to the empirical analyses, in which productivity is typically calculated as total factor productivity (TFP), which is a residual term that captures the unexplained output variability.

Empirical firm-level tests of the Melitz (2003) model, typically including TFP among the regressors, confirm the prediction of self-selection. Evidence on causality in the opposite direction tends to support the so-called learning-by-exporting (or by-internationalizing, in the more general case) effect, but results are less robust.

Recent surveys and evidence, such as Gattai (2015) and Borin and Mancini (2015), confirm common findings about productivity sorting by internationalization mode and self-selection, while results on ex-post effects are mixed depending on the country and, related to our work, mostly supportive of learning-by-internationalizing for Italian firms.

In applied works, scholars have mainly focused their attention on heterogeneity between groups by internationalization mode: domestic firms vs. exporters vs. firms involved in inward and outward foreign direct investments (FDI). Heterogeneity *within*

[1] The closed economy of Melitz (2003) represents a continuum version of Krugman (1980) model.

[2] Neary (2010) abandons the monopolistic competition framework to develop a model with heterogeneous firms in an oligopoly framework. Parenti (2013) develops a model in which large oligopolistic firms coexist with small monopolistically competitive firms. Later in the paper, we discuss how our work relates to those contributions.

groups received less attention. However, available evidence suggests that heterogeneity matters also among firms with the same mode of internationalization, and this is worth analyzing.

As Redding (2011) pointed out, we believe that "one area for further research is gaining a deeper understanding of the origins of firms' heterogeneity and the role of internal firm organization" (p. 30).

One contribution of this paper is to shed light on the sources of heterogeneity in productivity among foreign direct investors. This group of firms is of primary interest as it includes the largest and top performing firms: multinationals and foreign direct investors are among the most technologically advanced firms and they pursue the most complex strategies involving decisions on whether, where, when and how to import, export, outsource and invest abroad.[3]

Recent findings show that even foreign direct investors that operate within the same sector adopt different strategies of internationalization: some firms that invest abroad (horizontal FDI) using middle large countries as productive platform to export in neighboring countries through commercial affiliates; others are global players (vertical FDI) and their production is carried out for cost-saving reasons and/or in search of professional skills; finally, most foreign activities seem to be linked to commercial purposes, in the attempt to promote exports. Heterogeneity in investors' network also matters, i.e., number of markets where they invest, number of affiliates (and affiliates of affiliates), destinations' income, affiliates certifications and involvement in global value chains etc. (De Masi, Giovannetti, & Ricchiuti, 2013).

Specifically, we investigate the link between parent productivity and affiliates characteristics such as their number, location, turnover and sectoral characteristics. Investments can affect parent productivity in several ways through cost-saving decisions, technological spillovers and internal reorganization of production. Understanding whether and how investments abroad contribute to parent's productivity is both theoretically and policy relevant. Investors can acquire new knowledge and resources (resource-seeking) or can gain access to a larger international market (market-seeking), thus improving productivity through spillovers and/or economies of scale. Productivity gains, however, are likely to depend on the characteristic of the specific investment pursued.

Our aim is to identify the main sources of heterogeneity in parents productivity with respect to their investment decisions. Thus, a second contribution of the paper is to asses the relation between affiliates characteristics and parent productivity.

For the empirical analysis, we rely on an original longitudinal firm level data-set of Italian firms, focusing on outward FDI for the period 2002-2011.

The descriptive analysis confirms our hypothesis that there is a strong heterogeneity among foreign investors; larger investors tend to have a higher number of larger affiliates in more countries and tend to be significantly more productive. Controlling for sector characteristics, not surprisingly, we find that manufacturing firms significantly differ from non-manufacturing ones, and that the technological level of the sector is a source of heterogeneity. Larger and more productive investors tend to have complex networks: they have more affiliates and invest in a higher number of countries, often both developed and developing, while also having larger affiliates. Investor-level sales are positively associated with geographical distance and with the GDP per capita of the destination market, even controlling for a number of both investor and affiliates characteristics.

[3] For instance, for a cross-section of European firms, Gattai and Sali (2015) document how those involved in both inward and outward FDI outperform outward FDI firms only, which in turn perform better than inward FDI firms only.

2 Data

We built an original longitudinal database, matching and merging three different firm level data-set over the period 2002-2011: the MET 2011 survey (our primary source), the AIDA-BvD on Italian balance sheet data, and the yearly ICE-Reprint on outward FDI. To complete the database, we have also added geographical information, such as the distance between destination countries and Italy, using data from CEPII, and both GDP and GDP per capita taken from the World Development Indicators of the World Bank. Finally, the producer price indexes from Eurostat are used as 2-digit sector deflators.

The MET 2011 survey covers 25,090 Italian firms belonging to manufacturing and service sectors, with some information also referring to the period 2009-2011. The information contained in the survey is mostly qualitative, it includes detailed information on employment, input, sales, investments, internationalization modes, innovation, as well as participation and the role of firms within networks and supply chains over the period 2009-2011. This sample of firms has been built using a stratification procedure by size, sector and region of the firms, to ensure representativeness at the national level. Firms in the data-set belong to different sectors of manufacturing and services and are located in all Italian regions.

AIDA contains comprehensive information on firms in Italy through theirs balance sheets, and we use it to have additional information on the investors: value added, cost of labor, capital equipment, sales, the value of raw materials and energy, legal form (corporate vs. other legal form), the age of the firm, and sector identified by the 2-digit ATECO code (the Italian equivalent of the NACE rev. 2, adopted by the Italian Institute of Statistics).

The ICE-Reprint database represents one of the main source of information on the foreign affiliates of Italian firms (it represents the census for the affiliates with a turnover higher than 2.5 millions euros) in manufacturing and services other than financial sectors. The database concerns only equity (joint venture, participation with affiliates) and has relevant information both on Italian investors and affiliates and for both M&A and greenfield investments. Specifically, the unit of observation is the foreign affiliate. It is worth noting that data on the Italian foreign direct investments are collected yearly: each wave is independent from the previous and not meant to represent a panel.

Based on the ICE-Reprint yearly waves, we did an extensive work on the data in order to be able to follow each parent company over time and build the panel of Italian foreign direct investors. Starting from the database firm identifier, we checked consistency of the yearly databases using the investor fiscal code and the firm's name and location. This operation required us to deal with possible inconsistencies in the variables and measurement errors.[4] After building the panel, we computed several indicators regarding affiliates activities: the number of affiliates, the average and median turnover, the average distance from Italy and the income of country of destination etc. The final data-set is at the investor-level and parents are the unit of observation.[5]

In what follows, we explain how we match and merge the three databases. Our primary source is MET 2011. To have quantitative information and to switch to a panel dimension, we added both the AIDA balance sheet information and the ICE-Reprint data. After matching the information for each firm, we are left with 11,026

[4]Detailed technical explanations are available upon request.

[5]Additionally, there is no available data on affiliates for the years 2009, 2010 and 2012. In order to avoid a loss of information, we interpolated the investor-level affiliates indicators for the missing years. Note that interpolating the missing years implies assuming that the firm did not temporarily stop being a foreign direct investor. However, given our focus on investors' characteristics rather then on entry and exit, we are unlikely to introduce any significant bias in the analysis.

firms. The total number of foreign investors is 840, representing 7.6% of our final sample.[6]

Using this final consolidated data-set, we have estimated the TFP for all firms: domestic, exporters and foreign investors. In line with the literature, before estimating the TFP, we performed some data cleaning by trimming out observations with extreme values or inconsistencies in the balance sheet data (see for instance Benfratello and Sembenelli (2006). In particular, we dropped firms with missing or negative values for the key variables employed, or with a rate of growth below the $1st$ or above the $99th$ percentile. Our TFP estimates are calculated as in Levinsohn and Petrin (2003) as explained in the next section.

3 Methodology

In our analysis we proceed in two stages. First, we calculate the TFP for the entire set of firms including domestic and internationalized firms. Second, we focus on foreign direct investors only, analyzing the determinants of their TFP controlling for both affiliates' and parents' characteristics and other variables related to investment decisions.

TFP estimation. Our main variable of interest is the parents' total factor productivity. We start from a firm-level Cobb-Douglas production function:

$$Y_{it} = A_{it} L_{it}^{\beta_l} K_{it}^{\beta_k} \qquad \beta_l, \beta_k > 0, \tag{1}$$

where i and t are firms and year subscripts respectively; Y is output (value added); L is labor; K is capital and A is a Hicksian neutral technology multiplier (unobservable).

One of the advantages of the econometric approach is that the production function is not required to exhibit constant returns to scale (i.e. $\beta_l + \beta_k = 1$), as it is often necessary under non-econometric approaches. However, in order to perform the estimation, we must assume that firms share the same technology, except than for the neutral parameter A, that is β_l and β_k are the same for all firms. Taking the logarithm (denoted by small case letters), the baseline econometric specification takes the following form:

$$y_{it} = \beta_0 + \beta_l l_{it} + \beta_k k_{it} + \varepsilon_{it} \tag{2}$$

In the above equation, the sum of the constant and the error term gives the Hicksian technology:

$$a_{it} = \beta_0 + \varepsilon_{it} \tag{3}$$

Theoretically, we can further model the unobservable firm-level error term so to decompose it into a predictable and an unpredictable component such that $\epsilon_{it} = v_{it} + u_{it}$. Since both terms are unobservable, additional assumptions need to be made on the v_{it} terms; while the u_{it} terms are usually assumed to be i.i.d. and uncorrelated with inputs choices, being due to measurement errors and other unpredictable factors.

After the estimation of the production function parameters, the estimated productivity can be calculated as:

$$\hat{a}_{it} = y_{it} - \hat{\beta}_l l_{it} - \hat{\beta}_k k_{it} \tag{4}$$

Equation (4) represents the objective of the TFP estimation. Note that applying the above model directly or performing an OLS estimation gives biased estimates for several reasons, mainly due to the endogeneity of labor and capital and to the fact that we cannot disentangle the predictable and unpredictable component of the error term

[6]This share, as well as the main descriptive figures, are in line with existing evidence on Italian FDI; see Gattai (2015) for a survey.

without additional data and/or assumptions (Arnold, 2005; Del Gatto, Di Liberto, & Petraglia, 2011; Van Beveren, 2012).

We now discuss the empirical approach that we employ, namely Levinsohn and Petrin (2003; LP). The LP estimation uses intermediate inputs as an instrument for unobservable productivity shocks. In particular, the LP estimation assumes that the firm demand for intermediate inputs depends on firms state variables, namely capital and the predictable component of the error term, $m_{it} = m(k_{it}, v_{it})$. Under the assumption of monotonicity, the latter function can be inverted and we can write $v_{it} = v(k_{it}, m_{it})$, so that the unobservable productivity is a function of two observable variables. However, the functional form is unknown. Following Olley and Pakes (1996), LP take a semi-parametric approach by approximating the function $\varphi(k_{it}, m_{it}) = \beta_0 + \beta_k k_{it} + v(k_{it}, m_{it})$ with a third-order polynomial. The production function to be estimated can now be written as:

$$y_{it} = \beta_l l_{it} + \varphi(k_{it}, m_{it}) + u_{it} \tag{5}$$

The first stage of the LP estimation involves equation (5) so to get $\hat{\beta}_l$, while $\hat{\beta}_k$ is obtained in the second stage under some additional assumptions about the v_{it} terms, e.g. that they follow a first order Markov process.

Parent's TFP and investment indicators. The second stage of the analysis is to study the sources of heterogeneity of foreign direct investors. We perform an econometric analysis at the investor level, based on the following baseline panel model with (year and sector) fixed effects:

$$TFP_{i,t} = \alpha + X_{i,t-1}\beta_x + Z_{i,t-1}\beta_z + \gamma_j + \delta_t + \varepsilon_{i,t} \tag{6}$$

where $TFP_{i,t}$ is the productivity of the parent company (in logarithm), $X_{i,t-1}$ is a set investors' characteristics, $Z_{i,t-1}$ are the variables related to the affiliates, γ_j are the fixed effects for the 2-digit sector of investors, δ_t are the time effects and $\varepsilon_{i,t}$ are usual i.i.d. errors. The possible simultaneity bias is avoided by the use of lagged regressors.

In the baseline specification of equation (6), sector characteristics are absorbed by 2-digit sector dummies. Alternatively, we include in the model also the technological level (based on the EUROSTAT classification) and a measure of competition, namely profit elasticity (PE). The latter measures the percentage decrease in profits due to a 1% increase in (marginal) costs, i.e. $PE \equiv |d \ln \Pi / d \ln C|$, and is estimated as in Boone (2008), in Boone, Van Ours, and Van der Wiel (2013), and in Boone, Brouwer, Filistrucchi, and Van der Wiel (2015) with the idea that a higher PE signals a higher degree of competition. In particular, for each 2-digit sector, PE is estimated econometrically from the following model:

$$\pi_{i,t} = \alpha_i - \beta c_{i,t} + \delta_t + \varepsilon_{i,t} \tag{7}$$

where $\pi_{i,t}$ are (operating) profits and $c_{i,t}$ are unit costs, α_i is a firm fixed effect, δ_t is a time effect and $\varepsilon_{i,t}$ is the usual i.i.d. error (profits and costs are in logarithm). The estimated $\hat{\beta}$ is our parameter of interest as it represents a sectoral measure of PE.

PE elasticity is preferred to other measures for its robustness. In particular, PE is found to be robust also when industries become relatively concentrated and is particularly suited when firm-level data is available. Moreover, in estimating PE no assumptions are required about the functional form of demand nor on the market structure.

4 Descriptive Statistics

In figure 1, we show the distribution of TFP by mode of internationalization (figure 1.a), and by quartile-based employment class of foreign direct investor (figure 1.b):

large foreign direct investors tend to be more productive than exporters and domestic firms. This evidence to some extent mirrors what is usually found in the heterogeneous firms literature when comparing different groups of firms such as non-exporters, exporters and foreign direct investors. A productivity sorting seems to exist both between and within the groups, in our case within foreign direct investors.

The productivity sorting by size of investors is mainly due to manufacturing firms (figure 2.a). A very similar pattern emerges also if we consider the number of affiliates and income of the destination markets. In figure 2.b, we compare the average TFP of firms investing only in low income countries, only in high income countries and in both of them.[7] For manufacturing firms there is a clear sorting such that the most productive firms tend to invest in high income countries rather than in low income countries, or invest in both at the same time, thus pursuing complex internationalization strategies. Investors with larger affiliates are also found to be more productive, however the productivity sorting is less clear in this case.

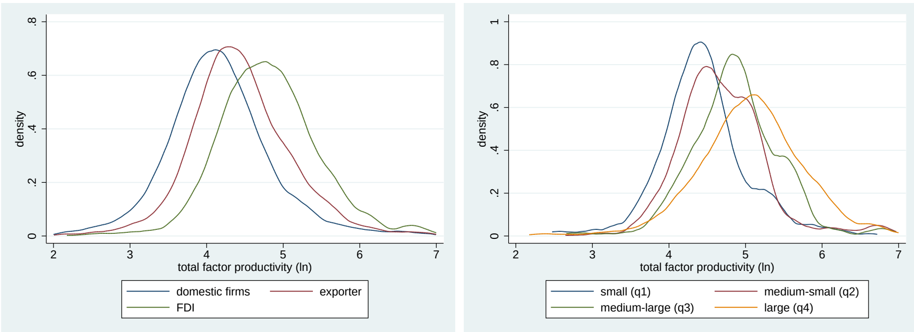
The main descriptive findings regarding productivity of foreign direct investors can be summarized as follows. Larger investors tend to be more productive, thus having generally more affiliates in more countries. They also tend to invest in developed countries or follow complex strategies, such as investing in both developing and developed countries.

In Table 1 we report some pooled descriptive statistics. On average, foreign direct investors are large firms whose sales account for 209 millions of euros (against 34.62 for the whole sample) and they are considerably larger than their affiliates (roughly 7 millions of euros). The average investor has less than 6 affiliates in roughly 4 different countries with a medium-high GDP per capita (on average $25,000$ of dollars). Note that investors, affiliates sales and number of affiliates have large standard deviations and highly skewed distributions, implying that looking a the simple average values may be misleading.

Let us separate manufacturing and services (mainly commercial). As expected, they have different characteristics as far as sales, the average distance between investor and affiliates and the GDP of the countries where the affiliates are located. Manufacturing firms are significantly smaller in terms of sales, but tend to go to larger and more distant markets. Additional evidence emerges when we consider firms of different size (based on quartiles of employment). Relatively large firms tend to have more and larger affiliates in more countries; they also tend to reach more distant and richer markets. Figures 3 and 4.a show the average number and average sales of affiliates by size of investor (based on sales quartiles) for manufacturing and services. The relationship between average number and average sales of affiliates is generally positive (figure 4.b).

[7] We divide low income and high income countries at 15,000 dollars, which is slightly less than half of the Italian GDP per capita.

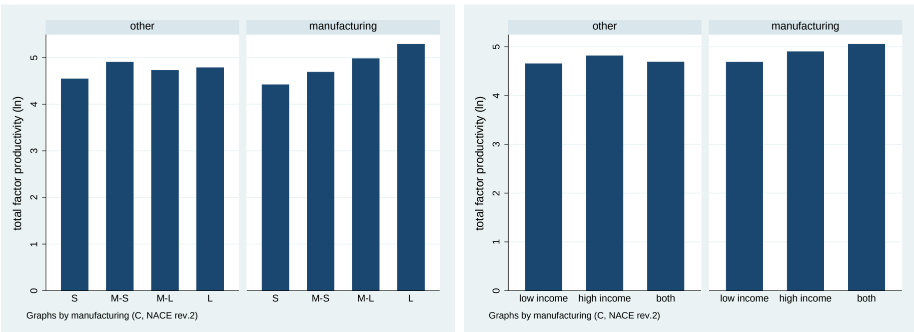
Figure 1: TFP distributions



(a) by mode of internationalization

(b) by size of investors

Figure 2: Average TFP



(a) by size of investors

(b) by destination income

Table 1: Summary statistics

Variable	Mean	Std. Dev.	Min.	Max.	N
n. workers (all)	120.77	1690.82	1	195404	64454
n. workers (fdi)	776.21	6112.8	1	195404	4025
sales_mln (all)	34.62	580.67	0.02	59324	64454
sales_mln (fdi)	209.9	1892.6	0.04	59324	4025
sales_affiliates	6.66	11.43	1	188.97	4025
n_affifliates	5.67	16.94	1	553	4025
n_countries	3.68	4.67	1	59	4025
distance_aff	3743.4	2828.81	230.02	11923.97	4025
gdppc_aff	24435.43	13974.01	304.2	87716.73	3971
gdp_aff_mln	2586.5	3256.12	2.26	13846.8	3993

Figure 3: Number of affiliates by size of investors

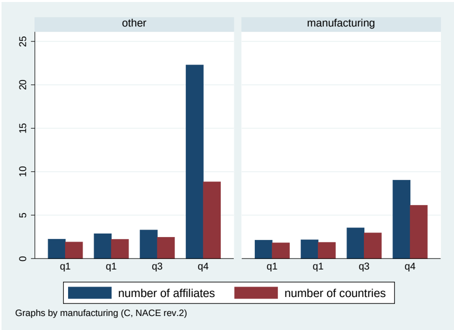
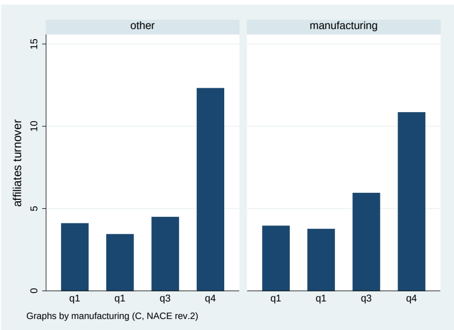
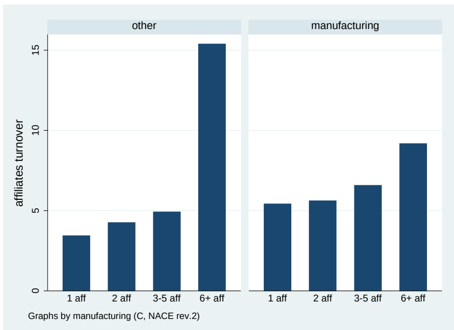


Figure 4: Average affiliate sales



(a) by size of investors



(b) by number of affiliates

5 Econometric analysis

As discussed above we investigate the relation between parent's productivity and the investment strategy. In table 4, we report the results of our baseline model, described by equation (6). We distinguish regressions (1)-(3) from (4)-(6) because in the latter we consider sector's dummies. In table 5, we analyse the baseline model separating firms into three subgroups as described in the previous section: low income countries investors only, high income countries investors only and, finally, firms that invest in both.

From the above mentioned literature on heterogeneous firms we expect TFP to be positively correlated with firm's size, either measured by employment and sales, and with value added and value added per employee, the latter being an alternative measure of productivity. Our expectations are confirmed also for foreign direct investors as shown in table 2. Given the high level of correlation between productivity and other size measures and, as shown by the descriptive statistics, between size and many investor-level affiliate indicators, we decided to control for size of investors including 4 dummy variables for the four quartile-based employment classes rather then the actual level of employment. In this way, we allow for a greater degree of variability in our model.

Table 2: Correlation matrix of size and productivity measures

Variables	tfp_LP	ln_size	ln_sales	ln_va	ln_va_emp
tfp_LP	1.000				
ln_size	0.393	1.000			
	(0.000)				
ln_sales	0.564	0.896	1.000		
	(0.000)	(0.000)			
ln_va	0.609	0.927	0.952	1.000	
	(0.000)	(0.000)	(0.000)		
ln_va_emp	0.652	-0.001	0.324	0.374	1.000
	(0.000)	(0.955)	(0.000)	(0.000)	

Model (1), in table 4, shows that TFP is positively correlated with lagged values of affiliate sales, number of affiliates and destination income. These results are confirmed in model (2) in which we add quantile-based employment dummies and replace destination income with two dummies: one for firms investing only in high income countries and one for firms investing simultaneously in both low and high income countries. Being a larger investor in the previous period is correlated with a premium in terms of productivity. The same applies to firms investing in high income countries only. Therofre, model (1) and (2) confirm the main findings of the descriptive analysis. In model (3) we introduce a set of interactions. There is a positive interaction between income destination and size of the investor: investments in either high or both high and low income countries are associated with a higher TFP, on top of the premium due to size only.

The pattern described above is robust also when we introduce both year and 2-digit sector fixed effects, as shown in models (4)-(6).

The evidence from table 4 suggests that, not surprisingly, destination income and the geographical distribution of affiliates is an important source of heterogeneity. Building on this evidence, in table 5 we extend our model in two directions: first, we separate investors by average income of the destination country; second we introduce two variables in order to determine how sector characteristics are related to productivity.

The first sector characteristic that we include in the analysis is technology. This variable is based on the official EUROSTAT classification which groups manufacturing sectors into 4 categories: low tech, medium-low tech, medium-high tech and high tech. The second variable is a measure of profit elasticity, as explained in methodology. We estimate PE according to equation (7) for the whole MET sample and define the variables as follows. Profits are calculated as the difference between sales and total variable costs. Total variable costs are based on the wage bill and inputs, such as materials and energy. Unit costs are obtained dividing total variable costs by real output (sales deflated by sector PPI).[8]

In the Table 3 we report the average values of PE by different levels of technology. It is worth noting that there a clear inverse relation between the two variables: the high tech sectors are those with lower profit elasticity (that is lower competition).

Table 3: Profit elasticity by technological level

Tech	Mean	Median	Std. Dev.
Low	1.58	1.44	0.69
Medium-low	1.39	1.15	0.52
Medium-high	0.83	0.74	0.31
High	0.46	0.69	0.28
Total	1.15	1.10	0.62

Table 5 uncovers an interesting source of heterogeneity with respect to affiliate productivity. Firms investing in high income countries tend to be more productive when their affiliates are larger, while no significant association is found for firms investing in poorer countries. As long as investing in low income countries represents a cost-saving strategy, it seems reasonable to interpret this finding as a sign of the fact that less productive firms have a greater incentive to find ways to reduce their costs. This is also in line with the negative coefficient on technology: high-tech firms investing in low income countries tend have low productivity levels.

PE provides similar results: its coefficient is negative for investors in low-income countries and positive for global investors. Note also that introduction of PE does not significantly affect the regressions, except for the technology variable, which becomes non-significant. The interpretation of this result is similar to that of the technology coefficients and complements it: our data in fact show that high technology sectors tend to have a lower profit elasticity. For investors operating in sectors with a high PE (in absolute value) profits tend to decrease rapidly when costs raise, thus high PE firms investing in low income countries (a cost-saving strategy) tend to be more productive; on the contrary, for low PE firms reducing costs is perhaps a less stringent requirement and can more easily invest in high income countries as well.

[8] As in equation (7), the regression is run for each sector separately and also includes year fixed effects. Variables used in the regression are in logarithms and demeaned.

Table 4: TFP regression, baseline

	(1)	(2)	(3)	(4)	(5)	(6)
	basic	dummies	interac.	basic	dummies	interac.
ln_fatt_aff_lag	0.011***	0.005***	0.005***	0.009***	0.004***	0.003***
	(7.12)	(3.41)	(3.35)	(8.09)	(3.85)	(3.40)
n_aff_lag	0.021***	0.011***	0.009**	0.020***	0.010***	0.009***
	(8.17)	(3.66)	(3.07)	(11.77)	(5.40)	(4.65)
ln_dist_aff_lag	0.017	-0.021	-0.017	0.037**	0.004	0.004
	(0.83)	(-1.09)	(-0.90)	(2.67)	(0.35)	(0.34)
ln_gdppc_aff_lag	0.030+			0.033**		
	(1.67)			(2.77)		
highonly_lag		0.130**			0.071**	
		(3.24)			(2.82)	
highlow_lag		-0.013			0.000	
		(-0.30)			(0.01)	
2.Dsize_lag		0.271***	0.315***		0.296***	0.289***
		(5.38)	(3.72)		(9.32)	(5.42)
3.Dsize_lag		0.576***	0.541***		0.478***	0.409***
		(11.51)	(6.07)		(15.01)	(7.26)
4.Dsize_lag		0.816***	0.605***		0.713***	0.382***
		(15.20)	(5.53)		(20.75)	(5.49)
size1Xhigh_lag			0.130			-0.013
			(1.48)			(-0.24)
size2Xhigh_lag			0.053			-0.016
			(0.78)			(-0.38)
size3Xhigh_lag			0.151*			0.075
			(2.01)			(1.60)
size4Xhigh_lag			0.315**			0.413***
			(3.08)			(6.37)
size1Xhighlow_lag			-0.148			-0.117
			(-1.17)			(-1.48)
size2Xhighlow_lag			-0.167*			-0.092+
			(-1.97)			(-1.74)
size3Xhighlow_lag			0.010			0.014
			(0.15)			(0.31)
size4Xhighlow_lag			0.225*			0.297***
			(2.32)			(4.82)
_cons	4.219***	4.365***	4.360***	4.102***	4.289***	4.358***
	(16.77)	(27.57)	(26.12)	(24.50)	(41.47)	(40.73)
N	2395	2433	2433	2395	2433	2433
R^2	0.067	0.165	0.169	0.119	0.262	0.273
Year FE	YES	YES	YES	YES	YES	YES
Sector FE	NO	NO	NO	YES	YES	YES

t statistics in parentheses

Models (1)-(3) have year f.e.; models (4)-(6) have year and 2-digit sector f.e.

$^+$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 5: TFP regression, destination income and sector characteristics

	(1) low inc.	(2) low inc.	(3) high inc.	(4) high inc.	(5) both	(6) both
ln_fatt_aff_lag	-0.001	-0.001	0.006**	0.005*	0.006^{+}	0.008**
	(-0.34)	(-0.33)	(2.75)	(2.42)	(1.90)	(2.60)
n_aff_lag	0.008	0.036	0.026**	0.024*	0.006^{+}	0.005
	(0.25)	(1.08)	(2.66)	(2.41)	(1.79)	(1.39)
ln_dist_aff_lag	0.056*	0.032	-0.102**	-0.110***	-0.004	-0.006
	(2.21)	(1.22)	(-3.18)	(-3.34)	(-0.09)	(-0.14)
2.Dsize_lag	0.319***	0.383***	0.229**	0.236**	0.249^{+}	0.273*
	(4.49)	(5.29)	(3.09)	(3.09)	(1.84)	(1.99)
3.Dsize_lag	0.521***	0.626***	0.580***	0.586***	0.638***	0.640***
	(7.01)	(8.26)	(7.56)	(7.49)	(5.18)	(5.14)
4.Dsize_lag	0.607***	0.672***	0.742***	0.801***	0.953***	0.979***
	(6.63)	(6.94)	(8.52)	(8.87)	(7.86)	(7.98)
tech	-0.057^{+}	0.039	0.027	0.014	0.100***	0.056
	(-1.94)	(1.06)	(0.98)	(0.41)	(3.47)	(1.53)
PE		0.226***		-0.056		-0.129*
		(4.25)		(-1.07)		(-2.40)
_cons	4.031***	3.631***	4.922***	5.085***	4.036***	4.290***
	(18.59)	(14.91)	(18.25)	(16.65)	(10.95)	(11.12)
N	592	552	851	827	990	960
R^2	0.120	0.180	0.192	0.199	0.155	0.165
Year FE	YES	YES	YES	YES	YES	YES

t statistics in parentheses

All models have year f.e.

$^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

6 Conclusions

Recent empirical literature has confirmed the existence of a significant degree of heterogeneity in firms' performance. This literature has highlighted heterogeneity with a specific focus on different group by mode of internationalization (exports vs. FDI): the average productivity of exporters is lower than that of foreign investors. However, the related kernel density distributions show a strong heterogeneity also within groups and the distributions of different groups partially overlap (for instance, some exporters are more productive than some foreign investors). In this paper, focusing on the former issue, we analyze the determinants of heterogeneous productivity among firms that invest abroad.

Our results show that parents' productivity depends on: i) the investments strategy; ii) sectoral characteristics. In the first case, the relevant dimensions are the average size of affiliates, the number of investment projects, and the countries of destination. In the second case, sectoral characteristics have different effects depending on the destination country income: high tech investors show an higher productivity when they invest in both low and high income countries; while low tech investors gain a productivity premium when they invest in low income countries. Related to sectoral characteristics, the degree of competition also matters: parents operating in highly competitive domestic sectors have a higher productivity when investing in low income countries; the opposite applies to parents investing in both low and high income countries. These two sectoral characteristics (technology and competition) are probably capturing the same phenomenon: firms in high tech sectors tend to be characterized by a higher degree of market power.

Our findings, highlighting a key role for large firms and complex heterogeneous investment decisions, suggest that market power and strategic behaviors are relevant, at least for foreign direct investors. This idea is in line with the theoretical analysis developed by Neary (2010) and Parenti (2013), who argue that the international trade literature should pay more attention to oligopolistic competition, especially when dealing with superstar firms such as foreign direct investors.

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