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Multinational firms and FDI destinations: what explains the productivity gap?

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Abstract

This paper deals with the issue of the heterogeneity of productivity among three different groups of multinational firms according to where they invest. We use the procedure developed by Di Nardo et al (1996) and Melly (2005) to decompose the productivity gap across the entire productivity distribution in order to account for the relative importance of observed characteristics versus different returns. We find that the productivity gap suffered by firms that invest only in less developed countries is due to lower efficiency, not to worse characteristics. The most productive firms are those able to invest in both developed and less developed countries. They outperform firms investing only in one geographical area because of their better characteristics.

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1. Introduction

Several studies have documented the growing importance of firm heterogeneity. In this regard, the main prediction of the empirical literature is that productivity differences among firms play a role in explaining the presence of domestic, exporting and investing firms (Helpman *et al.* 2004). This is consistent with the self-selection hypothesis suggesting that firms engaged in some kind of foreign activity need to have some ex-ante advantages in order to deal with the costs and the complexities of international markets.[1] Yeaple (2009) shows that less productive firms invest in more attractive countries, while the more productive firms establish affiliates in even the least attractive markets.[2]. Chen and Moore (2010) predict that tougher markets, characterized by smaller market demand and higher production costs, are more likely to attract more efficient firms rather than less productive ones. Both papers show that countries' characteristics define a productivity cutoff that influences the decision of multinational firms to invest abroad. As regards Italy, Grasseni (2010) finds that the Italian firms investing in less developed countries perform worse than those investing in developed countries. In addition, both Yeaple (2009) and Tanaka (2012) show that more productive firms establish their affiliates in a larger number of foreign countries.

This paper offers additional insights into the issue of the productivity gap that may exist within Italian multinationals, and it takes a slightly different approach in order to assess whether productivity plays a role in the localization decision.

We concentrate on firms that have chosen the same internationalization modes (FDI), ruling out self-selection into FDI, and we consider localization choice only. In the previous literature (i.e. Yeaple 2009, and Chen and Moore 2010) it is not possible to disentangle market-driven (horizontal) FDI from research-driven (vertical) FDI, and countries are characterized using many different continuous variables (for example, GDP, GDP per capita, labour costs, host country's corporate tax rate). Even if we do not have better information about the type of FDI in our data-set, we prefer to group our firms into two broad homogeneous groups[3], according to the foreign locations where they invest – namely developed, less developed, or both developed and less developed countries – in order to be able to speculate on the nature of the FDI . Because the degree of development is a good proxy for the host country's wage-costs, this classification brings us closer to the literature which studies the type of investment (horizontal and vertical FDI), and it enables us to explore the existence of non-linearity in the relationship between TFP and the degree of development of the destination country. In fact, our approach is more in line with the one proposed by Head and Ries (2003), who classify destination countries according to their average wage and find that firms with lower productivity have mainly resource-driven motives, while firms with higher productivity have market-driven ones, entering both high- and low-wage countries. As predicted by the theoretical literature, our results show that the most productive firms are those that are able to invest in countries of different kinds (both developed and less developed) because multinationals of this type are more likely to overcome the productivity cut-off of a larger number of countries, and are more likely to undergo both horizontal and vertical FDI. Furthermore, we find that the firms investing only in less developed countries are the less productive ones.

Another contribution of our analysis is that it assesses whether some type of heterogeneity exists among the three groups of firms. In order to study the source of total

[1] This finding is also consistent with those of several studies on trade, which show that self-selection mechanisms differ from market to market (Serti and Tomasi 2012, and Crinò and Epifani 2010).

[2] The attractiveness of the destination country is measured using GDP and GDP per capita, as a proxy for the country's market demand and degree of development; furthermore, the effect of country destination GDP is homogeneous across firms.

[3] This classification can probably be used as a proxy for the average country wage cost, but it strictly prevents comparability with previous results.

factor productivity differentials between groups of firms, we decomposed the productivity premium related to FDI destinations across the entire productivity distribution. To this end, we followed the methodologies proposed by Di Nardo *et al*. (1996) and Melly (2005). Our approach is essentially descriptive, and it measures how much of the observed productivity gap is due to well-identified sources of inequalities among the three groups of firms. For this purpose, the decomposition method makes it possible to separate the effect due to differences in the impacts of factors' endowments (characteristics) from the effect due to differences in the impacts of these characteristics on productivity (returns). No theoretical predictions exist with respect to which part of the productivity may prevail over the other in explaining firms' localisation choices.

2. Data and Methodology

We used Italian firm-level data using the "Centro Studi Luca D'Agliano-Reprint" dataset,[4] and we considered three groups of firms: those that invest only in developed countries (DC), those that invest only in less developed countries (LDC), and those that invest in both developed and less developed countries (Both). To construct our measure of productivity we used the Levinsohn and Petrin (2005) method and we estimated the TFP by industry[5] using the balance sheet information available for every year from 1994 to 1998. Following Tanaka (2012), in order to compare the total factor productivity for different sectors, we used the relative TFP obtained by dividing the estimated TFP by the industry mean. The logarithm of the TFP was then regressed on other explanatory variables widely used in the empirical literature on firm heterogeneity, such as firm size (measured by the number of employees), innovations (a dummy if the firm has patent expenditures), intensity of outward FDI (measured by the number of employees in foreign affiliates over total employment of the multinational firm), geographical location, industry and time dummies. In the regressions we used only the information for the years 1995 and 1997 because the data on FDI are collected only every two years and we used only one year for each firm. Owing to this short time horizon and the very few firms which changed their foreign locations during this observation period, we were unable to study whether the differences in productivity are explained by self-selection of learning by investing. Table 1 reports the means of our variables of interest for each group of firms, confirming some statistical regularities in line with the findings in the empirical literature.

Table 1: Descriptive Statistics – Mean (Standard Deviation)

	LDC	DC	Both
N. of firms	221	186	89
TFP	0.877(0.210)	0.987 (0.267)	1.069 (0.238)
Firm size	4.539 (1.173)	4.947 (1.238)	6.309 (1.630)
Innovation	0.394 (0.490)	0.441 (0.498)	0.652 (0.479)
FDI	0.467 (0.270)	0.342 (0.236)	0.483 (0.247)

[4] The final database was the result of a merge between the Reprint dataset of the Politecnico of Milan with information on Italian multinationals and the AIDA database of Bureau Van Dijck, which provides balance sheet data and other economic data.

[5] We estimated TFP by nine two-digit industries, using value added as output, and total labour costs and fixed tangible assets as inputs. We grouped our firms into industry categories by aggregating the 22 two-digit NACE sectors because some industries have a small number of firms: food and beverages; textiles, clothing and leather; wood, paper, printer and publishing; chemicals, rubber and plastic; minerals and metal products; non-electrical machinery; electrical, electronic and medical instruments; vehicles and transportation; furniture.

In order to run a decomposition analysis across the entire distribution of the productivity of LDC, DC and Both, we used two different methodologies that extend the OAXACA-BLINDER decomposition: the Di Nardo Fortin and Lemiex (1996) re-weighting technique to estimate the counterfactual densities, and the Melly (2005) decomposition approach.[6] In practice, the raw productivity premium is decomposed into two parts: the first reflects differences between the characteristics of the two groups considered; the second explains differences in coefficients, which are the returns of those endowments (i.e. efficient use of inputs). The decomposition of the differences between the two groups of firms (say LDC vs DC) at each quantile can be written as:

$$X^{LDC}\beta^{\mathrm{LDC}}(\theta_i)- x^{DC}\beta^{\mathrm{DC}}(\theta_i) = \beta^{\mathrm{DC}}(\theta_i)(x^{LDC}-x^{DC})+ x^{LDC}(\beta^{\mathrm{LDC}}(\theta_i) -\beta^{\mathrm{DC}}(\theta_i)) \qquad i=1,\dots,9 \quad (1)$$

where θ_i i=1,…,9 is the decile of interest. The left-hand side of equation (1) is the raw gap in productivity. We ran three pair-wise comparisons, and thus considered in turn LDC vs DC, DC vs Both and LDC vs Both extending equation (1) at each pair.

We must acknowledge that the semiparametric decomposition of a raw productivity gap may be problematic because of two different selection processes which lead to violation of the conditional independence or ignorability assumption (Fortin *et al*, 2011). One is the sample selection arising from the type of internalization (FDI /Export) choice decision: in fact, once a firm chooses to invest directly in a foreign country, the selection into different location problem arises, and this may lead to an endogeneity problem. These two selection processes may be determined by observed as well as unobserved factors: whenever these factors affect productivity as well, the productivity gaps estimated from models that do not account for the selection process are likely to be biased. Selection into FDI is typically accounted for with an Heckman two–step procedure (or a control function approach) extended to the quantile regression framework by Buchinsky (2001). However, it is well documented in the empirical literature that identification through the functional forms may not be sufficient to correct for sample selection, and that plausible identifying restrictions (i.e. variables that affect the probability of investing in foreign countries and not TFP) are needed (Woorldridge 2002). Thus, we worked with an homogeneous sample of MNEs. The endogeneity of location dummies, instead, is typically corrected using an IV approach or a fixed effect estimation method. A valid instruments should create an exogenous variation in the probability of choosing to invest in a less developed or developed country or in countries of both kinds, which has to be uncorrelated with firms' individual unobserved characteristics (and thus should not directly affect the TFP). Panel data methods are likely to adjust for the selection when this is due to the firm-specific unobserved time invariant fixed effects. In this case, one must observe the same firm investing in different countries (DC, LDC or Both) over the years, which was extremely unlikely to happen in our data-set, which covered only a three-year time horizon. Furthermore, one possible drawback of the panel data technique is that identification of the coefficients in the decomposition relies on those firms that change their foreign localization, which of course does not happen randomly, but may depend on time-varying unobserved characteristics (i.e. different expected returns). Unfortunately, the lack of valid identifying restrictions and instruments prevented us from accounting for the potential endogenous selection of firms into the three localizations considered. Accordingly, the results of the decomposition exercise reported here are mainly descriptive and must be interpreted with caution.

[6] The rqdeco command in STATA runs a quantile regression to obtain the conditional distribution, which is then integrated out over the covariates to compute the unconditional distribution and with the same specification compute the counterfactual densities, alternatively substituting characteristics and returns.

3. Results and conclusions

Figures 1 to 3 plot the counterfactual kernel densities for the different groups of multinational firms, for each pair-wise comparison, following the procedure of Di Nardo *et al*. (1996). The solid line in Fig. 1a is the density of productivity that the firms investing only in DC would obtain if they had the returns of LDC; the dotted line is the density of productivity of firms investing only in DC with their returns. Therefore, this graph reflects the contribution of returns to explaining the TFP raw gap between DC and LDC. The solid line in Fig. 1b is the density of productivity that firms investing only in LDC would obtain if they had the characteristics of those investing only in DC; while the dotted line is the density of productivity of LDC. Thus, this graph shows the role of firms' characteristics in explaining the raw gap. Overall, the estimated densities reported in Fig. 1 show that the returns to DC characteristics are better than those of LDC.

Figures 2a and 2b display the estimated density for DC vs Both using the same convention as for the previous comparison. Hence, as can be seen, the returns of Both are better than those of DC, and if DC had the characteristics of Both they would perform better, meaning that Both has also better characteristics.

Figure 1: Counterfactual Kernel density estimates. LDC vs DC

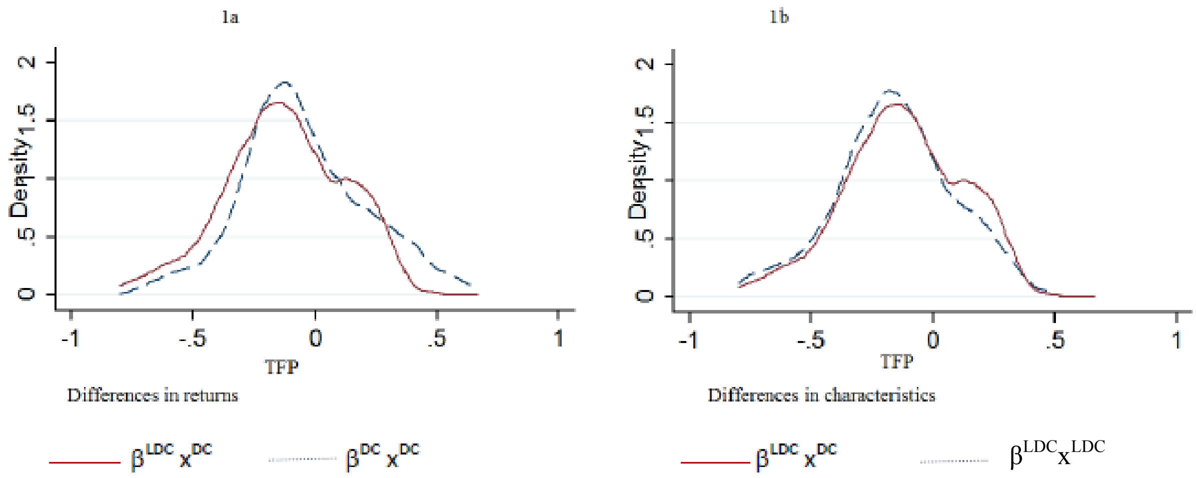


Figure 2: Counterfactual Kernel density estimates. DC vs Both

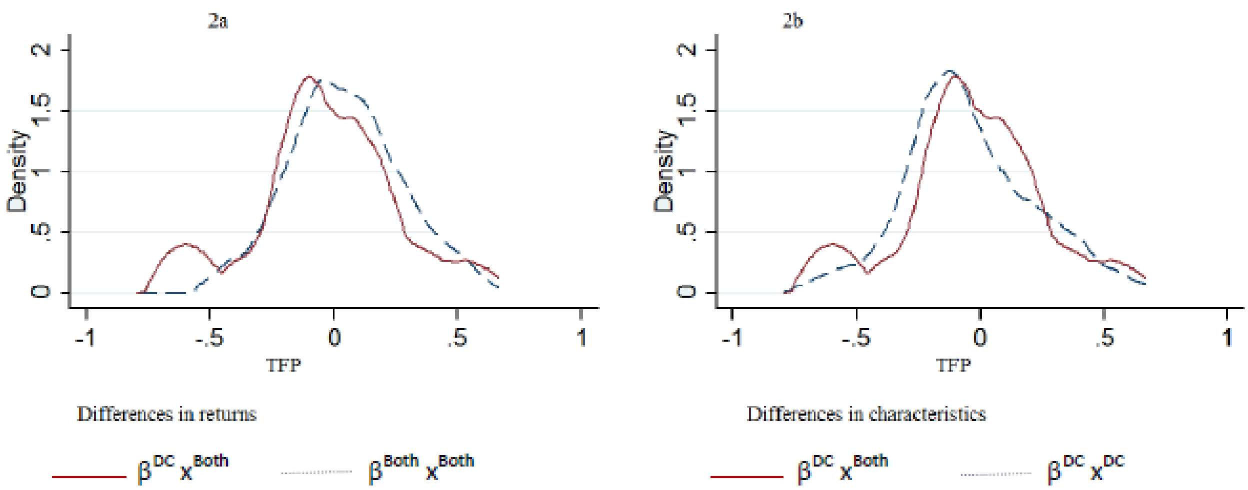
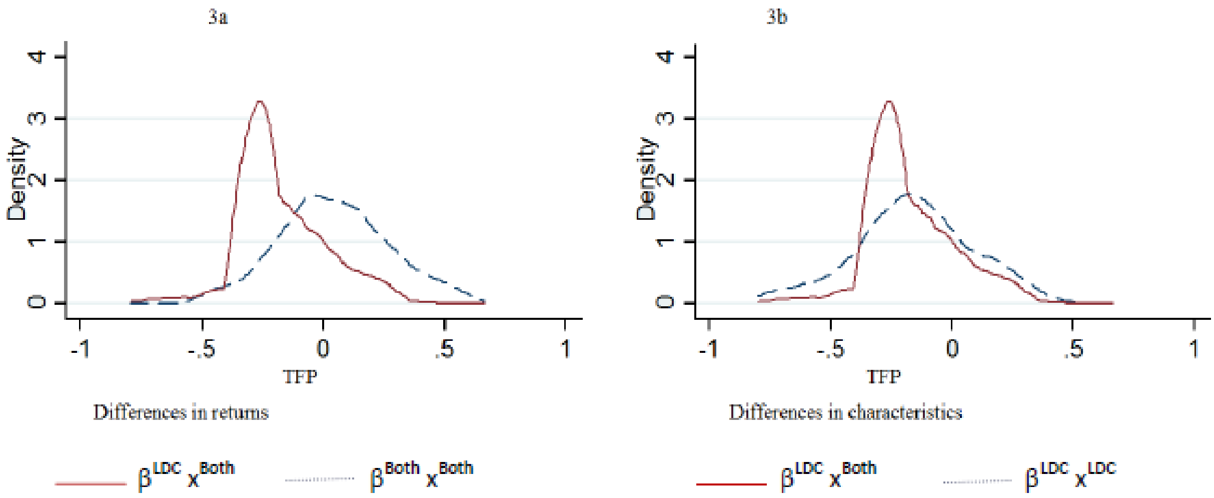


Figure 3: Counterfactual Kernel density estimates. LDC vs Both



Finally, Figures 3a and 3b plot the estimated density for LDC vs Both. Panel 3a suggests that Both returns are better than those of LDC. Panel b displays the density of productivity that LDC would obtain if they had the characteristics of Both and, given that they cross each other a couple of times, no clear dominance path seems to emerge.

To obtain a more detailed picture of the proportion of the raw productivity gap accounted for by the differences in returns to (observed) characteristics and by the differences in characteristics, we also adopted the approach proposed by Melly (2005). For each pair-wise comparison and for each quantile we report in Table 2 the raw productivity gap and its two components as indicated in the right-hand side of equation (1).

When we compare LDC and DC, we find a negative and significant raw productivity gap along the entire distribution. Without considering other observable characteristics, LDC perform worse than DC along the entire distribution, and this difference is greater at the bottom and the top of the distribution. The decomposition shows that the gap between LDC and DC is only and entirely attributable to the differences in returns, which are negative and statistically significant, suggesting a lesser ability of LDC to use their characteristics.

Comparing DC and Both, we find that DC exhibit a lower TFP than Both. The raw gap decreases in the upper part of the distribution, although it is not statistically significant at the very top. In this case, the lower TFP of DC is mainly attributable to the differences in the characteristics between the two groups of firms, while the role of returns is negligible.

Finally, on comparing LDC and Both, we find a negative and statistically significant raw gap, confirming that LDC are less productive than Both. In particular, the negative raw gap is explained by characteristics[7] as well as by returns. However, the proportion of the raw gap differential explained by differences in returns is higher and ranges between 82.5% at the second quantile and 64% at the eighth quantile. The role of characteristics in explaining the raw productivity gap is less evident, because the coefficient is not always significant.

[7] This is in line with the former results, where we found that LDC characteristics are not statistically different from those of DC.

Table 2: Decomposition of the productivity raw gap

		10	20	30	40	50	60	70	80	90
LDC vs DC	*Raw gap*	-0.143***	-0.102***	-0.083***	-0.079***	-0.072***	-0.091***	-0.113***	-0.117***	-0.165***
	Differences in characteristics	0.007	0.010	0.003	-0.002	-0.002	-0.008	-0.014	0.026	0.037
	Differences in returns	-0.149***	-0.112***	-0.086***	-0.077***	-0.070***	-0.083***	-0.099***	-0.142***	-0.201***
DC vs Both	*Raw gap*	-0.112***	-0.107***	-0.114***	-0.119***	-0.116***	-0.095***	-0.080***	-0.055	-0.016
	Differences in characteristics	-0.141***	-0.114***	-0.105***	-0.111***	-0.103***	-0.104***	-0.123***	-0.119***	-0.124**
	Differences in returns	0.029	0.007	-0.009	-0.009	-0.013	0.009	0.042	0.064	0.108**
LDC vs Both	*Raw gap*	-0.254***	-0.210***	-0.197***	-0.198***	-0.188***	-0.186***	-0.193***	-0.171***	-0.181***
	Differences in characteristics	-0.048	-0.037	-0.043*	-0.044*	-0.035	-0.033	-0.055	-0.062**	-0.106**
	Differences in returns	-0.207***	-0.173***	-0.154***	-0.154***	-0.153***	-0.153***	-0.138***	-0.110***	-0.075

Note: *, **, *** denote statistical significance at 10,5, 1 percent level

In conclusion, a clear ranking among the groups of firms emerges: Both are the most productive, DC are in the middle, and LDC perform worst. In particular, the result regarding Both is consistent with the theoretical prediction (Yeaple 2009, and Chen and Moore 2010) that the most productive firms are those able to invest in both developed and less developed countries, because multinationals of this type are more likely to overcome the productivity cut-off of a larger number of countries with uneven degrees of development. In addition, the ranking found is quite in line with Head and Ries's (2003) finding: firms with lower productivity tend to invest in less developed countries because they seek lower labour costs – vertical FDI – while firms with higher productivity, which are more likely to engage in horizontal FDI, invest in developed countries or in both developed and less developed countries. More interestingly, the decomposition analysis suggests that the main contribution to the raw gap differs among the different types of pairs. On comparing LDC with DC, and LDC with Both, we find that the differences in the raw TFP gap are due mainly to differences in returns, suggesting that, given the same level of characteristics, firms engaged in resource-driven FDI have lower returns to their size, to the presence of patent expenditure, and to their intensity of outward FDI. Consequently, they use their characteristics worse than do their counterparts. On comparing DC and Both, we find that the main contribution to the raw gap is due to different firms' characteristics. Investing in more than one macro-destination (DC and LDC) thus seems to be more closely related to better characteristics and less closely related to the returns of these characteristics. Hence, it is likely that firms investing in both developed and less developed countries need better characteristics because they have an investment strategy broader than that of other multinationals.

The previous literature does not consider that the productivity gaps among firms may be due to differences in characteristics as well as to differences in returns; but our results suggest that there exists a great deal of heterogeneity among firms, and that the sources of this inequality are not so clear and require further research. In addition, there is much scope for future research which furnishes better understanding of the role of host-country characteristics in explaining the productivity gap.

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