THE PRODUCTIVITY OF ITALIAN FIRMS: A SPATIAL ANALYSIS

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Abstract. This paper focuses on the total factor productivity (TFP) of Italian manufacturing firms over 2008-2020 and analyses the role played by different factors in determining it. Starting from the consideration that TFP in Italy presents a strong territorial component, we employ a hierarchical (multi-level) model to evaluate to what extent firms' productivity performance is influenced by location. In this context, the analysis allows to disentangle individual, firm-level, features from higher-level, provincial (NUTS-3), ones. At the firm-level, we single out the firm's age, size and the technology content of production; at the higher level, we consider a number of indicators relative to the quality of local infrastructure, services, administration and the level of social capital. The results show that territorial elements matter, especially for firms located in the South. We also detect a non-linear relation between the technology content of production and productivity: moving away from "low-technology" sectors, TFP becomes higher for "middle-low technology" sectors, but gets lower as technology improves.

1. Introduction

Starting from the mid-1990s, the growth of total factor productivity (TFP, or productivity) has known a long phase of decline in most EU-15 countries. Several authors link the phenomenon to structural changes, especially to the shift of activity from manufacturing to services, which traditionally has lower productivity (Van Ark et al., 2008). However, productivity growth remained far higher in the United States, where tertiarization followed different paths compared to those of European countries (Van Ark et al., 2008, D'Adamo et al., 2021, Bauer et al., 2021) and was accompanied by the massive introduction of information and communication technologies not only in advanced sectors -like finance- but also in traditional ones such as commerce, transportation, and accommodation. By contrast, this occurred to a far lower extent in European countries. For the EU-15 members, the main causes of productivity stagnation are generally found to lie in: partial -or incomplete-

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adoption of the ICT revolution; low investment in innovation, infrastructure, and human capital (cfr. Rodriguez-Pose, Ganau, 2022); market rigidities preventing the reallocation of resources to more productive units; limited knowledge and information diffusion (cfr. Corrado et al., 2009); and small business size.

While these features are seemingly common to all old EU members, it can be easily argued that they are all the more prominent for Italy and represent important determinants of the country's productivity stagnation (among others, cfr. Barra, Ruggiero, 2022 and Fabiani et al., 2005). In addition, Italy's well-known economic dualism, characterized by productivity differences between an efficient North and a less developed South, represents an additional drawback.

This study aims at analysing the evolution of TFP in the manufacturing sector across Italian provinces from 2008 to 2020. The provincial dimension of TFP is relatively underexplored, in favour of regions. However, these can be overly aggregated and limit the ability to fully understand the impact of different territorial characteristics on productivity. Hence, TFP is explored at the provincial level, with particular attention for the well-known geographical disparities of the Italian economy. The focus of the research lies on the territorial and structural features within which firms operate. Based on a typical hypothesis of economic geography, which posits that territorial characteristics influence firm performance, various external elements related to the territory, such as infrastructure availability and local administration efficiency, are analysed. Alongside, some internal firm characteristics, such as age, size, and specialization, are also considered. By using information both at the individual (firm) and province level, we develop a multilevel approach that allows firms' performance to be influenced by the context within which it operates.

The structure of the study is as follows: in the following paragraph, we present the data and the chosen methodology. In paragraph three we show and comment the results of our estimates, followed by a brief concluding discussion (paragraph four).

2. Data and methodology

Data comes from the "Aida" database, provided by Bureau Van Dijk. Over a ten-year frame, "Aida" reports economic and financial information for more than one million Italian companies. Data are extracted from firms' balance sheets and financial statements, whether consolidated or not, filed with the Chambers of Commerce. For each company, "Aida" also provides a wide range of indicators, including demographic and commodity data (year of establishment, industry sector, administrative procedures, number of employees, and so on).

For each active company in the 2-digit ATECO sectors ranging from 10 to 33 (manufacturing), the following variables are selected: value-added, wage costs (as a

proxy for the number of employees, which has many missing data), costs for raw materials (as a proxy for the cost of intermediate goods), and the nominal value of total tangible assets. The time-period goes from 2008 to 2020. The data is deflated using the annual average calculated from the monthly producer price index for each 2-digit ATECO sector between 10 and 33 provided by the Italian National Institute for Statistics (ISTAT). Salaries, instead, are deflated using the annual average of ISTAT's sector-specific deflators defined by collective bargaining. The sample is then cleaned of outliers by eliminating the 1st and 99th percentiles from each deflated variable. This results in an unbalanced panel of 132,486 year-observations.

TFP is estimated using the dynamic, multi-stage semi-parametric method by Olley, Pakes, 1996, that proxies a firm's (unknown) productivity by its (known) investment decisions[2]. The model has the advantage of accounting explicitly for firms' entry or exit decisions, allowing not to drop the firms that do not operate over the entire time-period. Moreover, compared to traditional methods (pooled OLS, fixed effect estimation), it helps reduce potential distortions due to endogeneity and selection issues. The first arise because productivity -which is known to the firm, but not externally- contributes to determining the demand for inputs. Instead a selection bias occurs because a firm's decision to enter/exit the market is linked to its expected productivity. In other words, assuming that a firm's profits are positively linked to its capital stock, for a given level of productivity, firms with bigger capital stocks are more likely to remain in activity than firms with smaller ones.

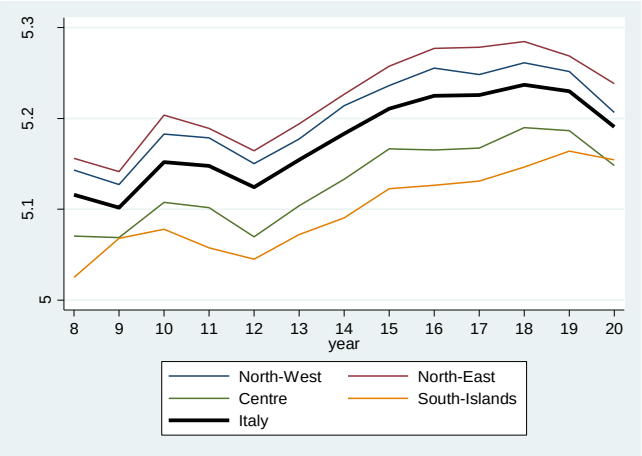
At the beginning of each period the incumbent firm decides whether to remain/exit the market. If it exits, it receives a sell-off payment and does not reappear. Instead, if the expected discounted value of profits is higher than the liquidation payment, it remains in activity. Conditional on the decision to remain and on its beginning-of-period state variables (age, capital stock and TFP), in the first step the firm selects optimal inputs, including investment. This allows to estimate the variable inputs' coefficients and the joint effect of all state variables on inputs. The second step separates the effects of age and capital on investment from those on output. This is done by estimating (*via* probit regression) the firm's probability of survival conditional on its state variables. In the final step TFP is estimated via a production function that includes a second order polynomial term accounting for the survival probability. This leads to the identification of all inputs' coefficients.

TFP levels (in logarithms) are obtained by running Stata's *opreg* command within the STATA software. Between 2008-2020, average TFP in the manufacturing sector in Italy generally grows, at least until 2019, with some fluctuation in 2008-2013, due to adjustments following the Great Recession. At the same time, the variance falls,

[2] A full discussion of the features and methodological issues related to this method is beyond the scope of the present paper. References can be found, among others, in Olley, Pakes, 1996 and in Van Biesebroeck, 2007. A good description is in Yasar et al., 2008.

indicating greater homogeneity among firms. The distribution of productivity is moderately skewed; the skewness index is positive and grows over time, indicating a concentration of observations below the mean. This, combined with the high kurtosis (leptokurtic distribution), indicates a significant presence of outliers, especially on the lower end. Both the skewness index and kurtosis reject the hypothesis of a normal distribution.

Figure 1 – *Average TFP (in log) by Italian macro-regions, 2008-20.*



Source: Authors' elaboration on BvD data, 2008-20

Figure 1 shows the trend of TFP in Italy's four (NUTS-1) macro-regions: North-West, North-East, Centre, and South-Islands. The graph confirms Italy's well-known territorial differences and highlights a general pro-cyclical pattern of TFP, which declines during crisis years (2008-09 and 2010-12) and grows during recovery. In fact, an exogenous shock, such as the one that occurred in 2009, instantly reduces demand and production, while adjustments on the input side (labour and raw materials) may be slower. The evolution of productivity during the period in exam is quite similar in the four areas, which differ for their levels. The two Northern groupings show almost identical trends. They are followed, at some distance, by the Centre, that also shows a rather similar evolution. Instead, the South follows a partially different trend, especially during crisis years 2008-10 and 2018-20, indicating a different impact of these periods on the region. Finally, it is worth noting that, due to higher average productivity growth in the North, the difference in TFP levels between the four areas is larger in 2018 than in 2008; however, the difference falls in 2019 (and even more so in 2020).

2.1 The econometric model

Fig.1 shows a seemingly strong territorial component of firm-level TFP. The possibility that firms' performance may depend also on context-specific features is now analysed. This is done by means of a hierarchical, or multi-level, model. As known, the fundamental assumption of these models is that individual performance depends on the context in which individuals operate. In other words, it is assumed that individual decisions (level 1) are influenced by the socio-economic environment in which they are taken (level 2), thus surpassing the rather restrictive assumption of traditional approaches, according to which there is no correlation among observations in different subgroups (Fazio and Piacentino, 2010; Aiello et al., 2014).

The model is expressed as follows:

$$y = X\beta + u + \varepsilon \tag{1}$$

where $\boldsymbol{y}$ is an n x 1 vector of responses, $\boldsymbol{X}$ is an n x p matrix containing the fixed effects regressors, $\boldsymbol{\beta}$ is a p x 1 vector of fixed-effects parameters, $\boldsymbol{u}$ is a q x 1 vector of random effects distributed according to a normal distribution with expected values $(0, \tau_{00})$, and $\boldsymbol{\varepsilon}$ is an n x 1 vector of errors distributed according to a normal distribution with expected values $(0, \sigma^2)$.

The first term in equation (1) constitutes the fixed part of the model, while the remaining part is the random component. The model is evaluated using two statistics. The first one is the inter-class correlation index (ICC), which measures the portion of total variance explained by the variance between the groups:

$$ICC = \frac{\tau_{00}}{\tau_{00} + \sigma^2} \tag{2}$$

The second statistic is given by the log-likelihood ratio *log-LR* which compares different specifications of the model. Under the null hypothesis, this statistic is distributed according to a chi-square (χ^2) distribution with degrees of freedom determined by the differences in the number of parameters among the specifications (Fazio and Piacentino, 2010).

The specification of equation (1) estimated in this study is:

$$TFP_{ipt} = \gamma_{00} + \sum_{i}^{3} \beta_{i} X_{ipt} + \sum_{h}^{6} \lambda_{h} Z_{hpt} + u_{0pt} + \varepsilon_{ipt} \tag{3}$$

where *TFP* is the logarithm of the total productivity of the *i-th* company located in province *p* in year *t*; γ_{00} is the average intercept of the regression lines; ***X*** is a vector of three variables that measure specific firms' characteristics; ***Z*** is a vector of six provincial variables that measure territorial features.

In particular, vector ***X*** includes:

- ✓ "*Years of activity*".
- ✓ "*Firm size*", measured by the number of employees.
- ✓ *"Technology intensity*", according to the OECD classification (2011):
  - High technology (HIT)
  - Medium-high technology (MHT)
  - Medium-low technology (MLT)
  - Low technology (LOT).

Vector ***Z*** (specific to each province) includes:

- ✓ "*Quality of local roads*" measured by the number of accidents. The hypothesis is that road accidents are a proxy for infrastructure quality: all else being equal, a better road network reduces the likelihood of accidents.
- ✓ "*Quality of personal services*" measured by the intensity of hospital migrations. The hypothesis is that hospital migrations is a proxy for the quality of the personal services available locally, a high availability reducing the likelihood of seeking treatment elsewhere.
- ✓ "*Local innovative capacity*" measured by the provincial propensity for patenting. The hypothesis is that patents are a proxy for creating a dynamic and innovative environment within the territory.
- ✓ "*Efficiency of local administration*" measured through the capacity to collect local taxes. The hypothesis is that collection capacity proxies administrative efficiency and hence the quantity and quality of the services potentially provided by local administrators. Greater collection capacity means more funds, resulting in more expenditure and hence more services.
- ✓ "*Gender equity in local administration*" measured by the number of women in local administration. The hypothesis is that women's involvement in politics acts as a proxy for social capital.
- ✓ "*Social security*" measured by the number of thefts in the territory. The hypothesis is that the number of thefts is a proxy for the quality of the social context, particularly for the perceived level of security.

All estimations are carried out using the "mixed" command of STATA software. The model is fitted by restricted maximum likelihood (REML).

3. Results

Results are reported in Table 2. As is common practice, we first estimate a null (or "empty") model with no regressors, to serve as a benchmark for the other models. “Model one" includes a subset of the firm-related ***X*** vector of variables that describe individual firms’ characteristics, i.e. "years of activity" and "firm size". "Model two" adds "Technology intensity". Finally, "Model three" introduces the entire ***Z*** vector containing all the indicators related to the territorial context.

Table 2 – *Estimations.*

VARIABLES	model 0	model 1	model 2	model 3
Time	0.00806***	0.0127***	0.0127***	0.0101***
	(0.000100)	*(0.000128)*	*(0.000128)*	*(0.000306)*
Years of activity		0.0306***	0.0368***	0.0354***
		(0.00190)	*(0.00185)*	*(0.00203)*
Firm size		-0.00471***	-0.00233***	-0.000853
		(0.000895)	*(0.000884)*	*(0.000943)*
HIT			-0.0731***	-0.0848***
			(0.00445)	*(0.00461)*
MHT			-0.0366***	-0.0506***
			(0.00685)	*(0.00709)*
MLT			0.257***	0.253***
			(0.00357)	*(0.00371)*
Quality of road infrastructure				-0.00416***
				(0.00127)
Quality of personal services				-0.0154***
				(0.00276)
Local innovative capacity				0.0184***
				(0.00124)
Efficiency of local administration				0.0245***
				(0.00724)
Gender equity in local adm.				0.0428***
				(0.00321)
Social security				-0.0134***
				(0.00201)
Constant	5.114***	5.011***	4.905***	4.713***
	(0.00173)	*(0.00550)*	*(0.00564)*	*(0.0325)*
ICC	*0.362*	*0.375*	*0.367*	*0.370*
Log-LR	*-500011****	*-357894****	*-353962****	*-314718****
Akaike criterion	*1000032*	*715802.7*	*707944.3*	*629469.2*
Observations	1,027,017	789,733	789,733	686,425
Number of groups	132,486	118,770	118,770	113,410

All variables are in logarithms. Standard errors are reported in parentheses. ***p<0.01, ** p<0.05, * p<0.1

All the statistics indicate an improvement in the model’s goodness of fit following the introduction of different groups of regressors. The highly significant log-

likelihood ratio test (log-LR), as well as the Akaike criterion, fall with the introduction of the various groups of regressors, showing that the goodness of fit improves. Moreover, the LR test (not reported in the table) indicates the presence of significant differences in the intercepts, which fall with the introduction of the regressors, confirming that each subsequent version of the model is nested within the previous one and justifying the use of a hierarchical model.

Coming to the estimation of the coefficients, they are generally highly significant and have the expected sign. Since data is in panel form, each firm represents a cluster with multiple observations over time; therefore, the first coefficient ("*Time*") estimates how much TFP within the firm is correlated over time.

"Years of activity" has a positive and statistically significant effect. In other words, the experience gained by companies helps improve their productivity. This can be seen as evidence of an ongoing process of formal and informal knowledge accumulation. "Firm size" has a negative and statistically significant coefficient in models 1 and 2, where we do not consider the provincial variables; it becomes no longer statistically significant when territorial features are introduced (model 3).

The introduction of "*Technology intensity*" (model 2) opens new scenarios. The three technology levels (HIT, MHT, and MLT) show highly significant coefficients. (Results should be read with reference to LOT, omitted to avoid multicollinearity). Results show that firms belonging to "medium-low technology" sectors (MLT) achieve higher levels of TFP compared to firms in "low-technology" ones (LOT). Instead, firms operating in "high" (HIT) or in "medium-high technology" (MHT) sectors obtain TFP performance below that of "low-technology" firms. This could be explained by Italy's traditional specialisation in the so-called "made in Italy" sectors (medium-low technology textiles, clothing, leather, footwear), all heavily contributing to the country's strong position in international markets and all showing relatively high average TFP levels.

The introduction of the $\boldsymbol{Z}$ vector of socio-economic local features (model 3), does not alter the overall picture described above. All territorial variables' coefficients are highly significant and have the expected signs, although they have very low values[3].

In conclusion, the hierarchical model adopted seems to account for TFP adequately; in particular, provinces account for over one third of the total variability.

Model 3 is then estimated separately for each macro-region Results are reported in Table 3.

[3] The coefficients of the territorial variables shown in the Table should be interpreted bearing in mind that, for three of them -namely "Quality of road infrastructure", "Quality of personal services" and "Social security"- higher values imply worse territorial features.

Table 3 – *Estimations by Italian macro-regions.*

VARIABLES	North-West	North-East	Central	South
Time	0.00614***	0.0116***	0.00924***	0.0109***
	(0.000634)	*(0.000633)*	*(0.000826)*	*(0.00130)*
Years of activity	0.0306***	0.0532***	0.0208***	0.0267***
	(0.00373)	*(0.00401)*	*(0.00420)*	*(0.00481)*
Firm size	-0.00715***	0.00213	-0.00188	0.0105***
	(0.00165)	*(0.00174)*	*(0.00216)*	*(0.00243)*
HIT	-0.102***	-0.0539***	-0.0980***	-0.0982***
	(0.00826)	*(0.00858)*	*(0.0104)*	*(0.0126)*
MHT	-0.122***	-0.0280**	0.00719	0.00143
	(0.0127)	*(0.0131)*	*(0.0155)*	*(0.0193)*
MLT	0.246***	0.327***	0.204***	0.187***
	(0.00723)	*(0.00730)*	*(0.00763)*	*(0.00830)*
Quality of road infrastructure	0.00190	0.000850	-0.0123***	-0.0118***
	(0.00186)	*(0.00285)*	*(0.00348)*	*(0.00376)*
Quality of personal services	0.0186***	0.00298	-0.0411***	-0.0269***
	(0.00466)	*(0.00683)*	*(0.00739)*	*(0.00780)*
Local innovative capacity	0.0203***	0.0186***	-0.00259	0.00340
	(0.00380)	*(0.00354)*	*(0.00329)*	*(0.00287)*
Efficiency of local administration	0.172***	-0.00992	-0.0207	0.0402***
	(0.0174)	*(0.0183)*	*(0.0152)*	*(0.0146)*
Gender equity in local adm.	0.0688***	0.0726***	0.0561***	0.0205**
	(0.00911)	*(0.00670)*	*(0.00890)*	*(0.00871)*
Social security	-0.0112***	-0.0287***	-0.00723	-0.0421***
	(0.00394)	*(0.00344)*	*(0.00523)*	*(0.00688)*
Constant	3.980***	4.736***	5.016***	4.948***
	(0.0809)	*(0.0860)*	*(0.0747)*	*(0.0726)*
ICC	*0.390*	*0.385*	*0.342*	*0.313*
Log-LR	*-106690****	*-84049****	*-60747****	*-46551****
Akaike criterion	*213412.2*	*168129.2*	*121525.9*	*93134.2*
Observations	250,134	205,907	124,390	84,013
Number of groups	38,378	31,793	22,154	16,564

All variables are in logarithms. Standard errors are reported in parentheses. ***″p<0.01, ** p<0.05, * p<0.1

A first, unexpected indication concerns the model's goodness of fit: the Log-LR likelihood index, although highly significant for all macro-regions, shows a better fit for the South, followed closely by the Centre and, quite at a distance, by North-East and by North-West; the Akaike information criterion confirms. At the same time, the ICC index shows lower residual variability among provinces in the South compared to other macro-regions, especially the two northern groupings. In other words, the territorial regressors explain a greater component of TFP variability in the South than elsewhere. This confirms that location has a different impact on productivity depending on the area to which provinces belong (cfr. Chapman, Pipitone, 2022).

Coming to the coefficients, they are in general significant and follow those for Italy as a whole. Over time, TFP improves within companies, especially in the North-East and in the South (much less so in the North-West). The "*Years of activity*" have a positive impact on TFP in all macro-regions. Instead "*Firm size*" is statistically significant only in the North-West and South, but with an opposite effect: negative in the first case, positive in the second one. In the former, the presence of large-scale companies is often linked to mature, heavy industry sectors; the South instead is characterized by smaller firms, for which an increase in firm size yields positive effects on TFP. As for the coefficients of "*Technology intensity*", they are generally significant and have the same sign as the ones highlighted for Italy. Companies in MLT sectors present higher levels of TFP in all macro-regions, particularly in the North-East. On the other hand, both HIT and MHT companies record lower TFP (with respect to LOT sectors), especially in the North-West. In the Centre and South, the coefficients for MLT firms are not statistically significant.

Also the coefficients of territorial indicators are generally in line with those for Italy as a whole, even if with some difference across macro-regions. The coefficient for the "*Quality of road infrastructure*" (measured by the number of road accidents) is negative and statistically significant only in the central and southern areas, where infrastructure is historically lower than elsewhere. This highlights the importance of infrastructure both in terms of firm efficiency and of regional development. A similar argument applies to the "*Quality of personal services*" (measured by hospital migration), that also shows a negative and statistically significant effect on TFP only for the Centre and South. The low quality of local services affects all those operating in a region, by raising costs and reducing efficiency.

Instead, "*Local innovative capacity*" (proxied by the propensity for patenting) has a positive and statistically significant effect only in the two northern, economically more advanced, macro-regions. This implies that patenting may produce positive effects on TFP only if associated with a local production system that is able to capture the positive effects of research and innovation.

The impact of "*Efficiency of local administration*" on TFP is less clear and less pronounced than that of the other variables. It has positive and statistically significant effects in the North-west and South, but loses significance in the other two.

On the other hand, "*Gender equity in local administration*" and "*Social security*" play a statistically significant role in all macro-regions. Although with different intensities, women involved in local administration give an important contribution to the efficiency of territories, generating positive effects on firms' TFP. Finally, lower social security reduces TFP everywhere, but more in the South.

4. Conclusion

The study examines the TFP of Italian manufacturing firms, clustered by provinces and by the technology content of their specialization, during 2008-2020.

The estimation of a multilevel econometric model confirms, that the choice of a hierarchical model is appropriate. This indicates that, in general, a company's performance in terms of TFP is related to the territorial context in which it operates (in our case, provinces). Second, contrary to expectations, the model shows that "medium-low technology" (MLT) sectors are associated with higher levels of efficiency, while TFP is lower in higher technology sectors. This implies a non-linear relation between the technology content of production and productivity: moving away from "low-technology" (LOT -our reference sector), TFP is initially higher but becomes lower as technology improves. This is an interesting result that deserves further inspection; we leave it to future research. Finally, when considering macro-regions individually, the model shows a better fit for the South (and even more so for the Islands) suggesting that territorial elements count differently across the country. In particular, it is the quality of local administration, of infrastructure, and the level of social security that matter most for southern firms, generally more than what occurs for firms located elsewhere. Another result is that, among all the territorial features that were considered, only the number of women involved in local administration cuts across all macro-regions with a positive and significant impact on TFP. We leave also this result to further research.

From the perspective of economic policy implications, these results suggest that there remains -potentially substantial- room for public intervention aimed at addressing Italy's dualism. One possible area of intervention lies in the traditional approach focused on tackling the diseconomies generated by deficiencies in infrastructure and public administration, even with reference to the considerable availability of European funds aimed at recovery and resilience. Last, as the literature acknowledges a significant lack of territorial connections among provinces in the South, implying a lower diffusion of spillovers and networks across firms (cfr. Chapman, Pipitone, 2022), intervention should be targeted at removing the obstacles that hinder the formation of clusters allowing the higher-productivity territories to act as drivers for neighbours.

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