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INTERNAL VS. EXTERNAL FIRM PRODUCTIVITY DRIVERS. A STUDY OF THE ITALIAN COUNTIES

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Internal vs. External Firm Productivity Drivers. A Study of the Italian Counties[◊]

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Abstract

We analyse productivity growth differentials across 68.000 Italian manufacturing firms over 2001-2010, in order to disentangle internal and external productivity drivers. A two-stage procedure is implemented for extracting fixed effects for 103 home counties of the firms (stage one), and regressing them upon a number of external factors that could affect productivity dynamics (stage two). We find that the local environment matters for firm performance with external drivers, such as financial conditions, social capital and market potential, explaining about two-thirds of the cross-county productivity dispersion.

[JEL Classification: R11, R15, L60]

Keywords: total factor productivity; external effects, local manufacturing dynamics.

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1. Introduction

Italy is the EU country where regional differences in per capita income are the largest, according to the estimates of EU Commission. Interestingly, this is not only reflected in the well-known North-South divide, but it is also true at a more disaggregated level. Very deep differentials persist also in the level and dynamics of productivity across Italian regions, as well as counties i.e. at a smaller territorial level. An interesting and policy sensitive question is to investigate if and to what extent these differentials can be accounted for by local external factors such as human and social capital, infrastructures, financial development, and to assess which of these drivers are actually significant. The more these variables can be shown to account for local productivity gaps, the more policymakers can target instruments to address such gaps.

In this paper, we focus on productivity growth differentials across 68.000 Italian manufacturing firms over 2001-2010, in order to disentangle internal from external productivity drivers. A two-stage procedure is implemented for extracting fixed-effects for 103 counties where the firms of our sample are located (stage one), and regressing them upon a number of external factors that could affect productivity dynamics (stage two). We find that the quality of local environment, proxied by a rather limited set of external drivers, accounts for about two thirds of the variability of the county specific fixed effects. Among the statistically significant variables, social capital (trust and crime incidence), financial proxies and market potential seem to be the most important determinants of local competitiveness. We test the robustness of our estimate with respect to dummy meant to capture the structural difference between Northern and Southern Italian regions, and find that our findings are not driven by the North-South gap.

The paper is organized as follows. In section 2, we provide a selected review of the recent empirical literature on internal and external productivity drivers. In section 3 we describe our empirical methodology while in section 4 our variables and their sources. In section 5, we provide econometric results and discuss them. Section 6 concludes.

2. A selected review of the empirical literature

Firm efficiency and competitiveness depend both on internal and external drivers. Internal drivers include aspects regarding both the strategy and the structure of the firm itself, such as a centralized or decentralized organization, the quality of human and physical resource, investments in innovation, and others. External drivers encompass various aspects of the environmental context in which a firm operates, such as the standard and efficiency of the public administration, national or regional credit conditions, physical infrastructures and intangible capital. Most of these external factors may affect the productivity performance of rather similar firms if they are located in different areas of the same country.

Differences in the level and the dynamics of productivity of similar firms across regions, can be then also the result of differences in quality and efficiency of the various factors available at local level. Several studies have analyzed the evolution of spatial disparities at regional level over time (for a survey see Brailinch et al. (2014)). One of the main findings of the literature (see Caselli 2005, Hsieh and Klenow 2010) is that international output differences are only partially explained by physical and human capital accumulation, while most of the variability is accounted for by total factor productivity, measured by a residual term.

In turn this implies that local institutions can be a determinant of the comparative advantage of regions, in the same way as national institutions appear to shape the comparative advantage of countries. Also cultural features can influence economic development, either directly or indirectly through the functioning of institutions. Using regional data for Europe, Tabellini (2010) analyzes the relationship between regional incomes (and their evolution) and proxies of cultural environment, such as trust, respect, etc.[1]

An interesting branch of the empirical research has focused on the distinction between tangible and intangible external drivers of firm performance. Eickelpasch, Lejpras and Stephan (2007) estimate the effects of different factors on a sample of 2.500 firms

[1] *Tabellini (2010) suggests, for example, that the judicial system performs differently in Southern and Northern Italy with judges taking much longer to complete investigations and to rule on civil cases in the South than in the North, even though the formal framework is similar.*

from West Germany. They consider different measures of firm performance such as turnover growth, profits, and the increase in market shares. Two categories of external drivers are considered: "hard factors" such as skilled labour, proximity to university and research centres, backward and forward linkages, physical infrastructures, and "soft factors", such as support from local institutions and credit conditions. Their results point out to some key elements that positively affect performance in their sample of German firms, namely skilled labour, geographical proximity to other firms and institutions, and cooperation with research centres and universities.

Firm competitiveness is also affected by the financial system. For instance, the amount and the conditions of banking finance can influence firm performance over time. These conditions are subject to high geographical variability, depending on the development of the local financial system and on the risk level associated to local firms. Castelli, Dwyer and Hasan (2009) study a sample of Italian firm looking at bank-firm relations based on geographical proximity. They find that firm performance (proxied by return on assets or equity) is negatively correlated to the number of firm-bank relationships. A possible explanation is that firms relying on only few banks are able to build a sounder credit relationship and to limit the asymmetric information bias.

Adopting a more general framework, Escribano, Guasch, de Orte e Pena (2008) study the effect of five sets of variables on TFP in a sample of Turkish firms. These five categories include: physical infrastructures, institutions and crime incidence, finance and economic governance, labour market, and the innovation environment. They find that productivity is more deeply related to social and institutional environment than to other sets of variables. Aiello and Scoppa (2000) try to explain why factor productivity differs so widely across Italian regions. They underline that the main cause of the development gaps lies in differences in TFP rather than in differences in factor accumulation, and analyze to what extent the differences in TFP across Italian regions depend on a number of specific local aspects. The main conclusion is that regional differences in productivity depend on TFP that, in turn, is affected by socio-economic variables.

3. The econometric set-up

The first step in order to empirically study the relationship among external factors and firm competitiveness is to identify a proxy for economic performance at the firm level. We use Total Factor Productivity (TFP) which reflects a complex set of phenomena, most of them not always directly observables, such as innovation, labour organization, managerial ability, increasing experience of the labour force, changes in the quality of machinery, input reallocation, and others.

Two distinctive features of TFP are widely recognised by the literature: first, the existence of a remarkable dispersion of productivity within sectors; and second, that the most productive firms (those located in the upper tail of the distribution) are more likely to survive and grow in the market. TFP dispersion within sectors is persistent suggesting that this is not simply the cumulated effect of firm specific shocks, but a more systematic feature. According to Syverson (2011) a portion of such dispersion is related to heterogeneity due to both internal and external factors. Internal factors are under the control of the firm, while external factors are outside direct firm influence.

Among internal factors that may generate TFP dispersion, Ilmakunnas et al. (2004) underline the role of managerial skills as well as human capital accumulation and workforce experience, although they are not enough to explain TFP persistent variability within industries. Another fundamental internal factor for productivity dynamics in recent years is Information Technology (IT). Jorgenson et al. (2005, 2008), as well as Oliner et al. (2007), suggest that productivity growth in IT industries explains most of the aggregate productivity growth in US over the last two decades. At the same time, the slowdown in TFP across Europe at the beginning of this century seems to be partly due to lower rates of IT investment.

It is worth noting, however, that even when most of the internal factors are taken into account, the unexplained within-industry dispersion of TFP remains relatively high. For instance, Fox and Smeets (2011) use a matched employer-employee data for Danish firms and are able to control for several characteristics of the labour force: education, gender, experience and tenure. Even if such factors are highly significant in estimating the production function, the resulting TFP distribution still shows a huge dispersion within sectors. This suggests that part of such variability could be due to external factors such as agglomeration externalities, specialized input markets, physical infrastructures, access to business services, regulation, and others.

In order to disentangle internal and external productivity drivers, we use a two-stage econometric approach. In the first stage, firm-level TFP is regressed on a series of firm covariates. Then, we extract from the first-stage regression the county fixed effects that in the second stage are regressed on local structural variables. More formally, we start from the following equation:

$$y_{imt} = \alpha_m + \mathrm{Z}_{\mathrm{it}}^{'}\beta_{\mathrm{k}} + X_{mt}^{'}\beta_k + \varepsilon_{imt} \quad (1)$$

where y_{imt} represents the TFP computed as described in Section 3.1, of firm *i* locate in county *m*, at time *t*. The vector $\mathrm{Z}_{\mathrm{it}}^{'}$ contains all firm level controls, in the estimated equation we include: the log of age, and the log of age squared, plus a control on firm production size. Our preferred specification for production scale employs quintiles dummies that guarantee a larger deal of flexibility.[2] Finally, the vector $\mathrm{Z}_{\mathrm{it}}^{'}$ contains also industry and year fixed effects.

The vector $X_{mt}^{'}$ contains indicators of the infrastructural endowment, or external factors, of county *m*. As external factors we consider several indicators of physical and social characteristics: human and social capital, criminal incidence, credit efficiency and financial development, and market potential.

Since most of those groups encompass complex phenomena we make use of different indicators for each class extracting a principal component to synthesize local endowment.[3] The use of Principal Component Analysis (PCA) in this context allows extracting the valuable information from a set of variables, in order to have a synthetic indicator of the local endowment for each infrastructural class, using in a more parsimonious way the large set of underlying variables.

In detail, we include in $X_{mt}^{'}$ as covariates: human capital (as the log of science graduate), social capital (as the log of the number of newspaper per inhabitant) and a measure of market potential (as the log of the multimodal accessibility index).

[2] We also uses the log of sales as control for production size, results are robust and available upon request from the authors.
[3] The PCA is used to extract the information for physical infrastructures, financial development, crime incidence. See Table A1 in the Appendix for a list of the variables used to identify the principal component in each class.

For other classes we include only the largest Principal Component. As underlying variables for the incidence of criminality we include: the number of beds in penal institutions, the number of convicts for 100 beds and the number of reported crimes. The principal component for credit efficiency is characterized by the value of not reimbursed credits, the number of person signaled to the bank vigilance authority for default and the ratio among the outstanding and risky credit. Financial development principal component is extracted using: the number of domestic, foreign and cooperative banks branches; the stock of credit issued to business sector; the growth rate of the ratio of business to overall credit (as a measure of financial innovation). Finally, α_m represents the province level fixed effect.

Including environmental variables (X'_{mt}) directly in Equation (1) would raise a clustering problem. Since TFP is firm specific, while infrastructural variables varies only at country level, this will generate a potential bias in the estimated standard errors (Moulton 1986) proportional to the within group (county) correlation. Given the data structure we can assume that within the county *m* between firm *i* and *j* at each time period exist the following relation: $E\left|\varepsilon_{imt}\varepsilon_{jmt}\right| = \rho\sigma_{\varepsilon}^{2} > 0$ where ρ represent the intra-county correlation coefficient, while σ_{ε}^{2} is the residual variance. The error term ε_{imt} can be modelled with an unobservable component, common to all firms in cluster m, μ_{mt}, and an idiosyncratic component (ϵ_{imt}) from which: $\varepsilon_{imt} = \mu_{mt} + \epsilon_{imt}$. Econometric literature proposes different techniques to deal with the “Moulton problem” (for a detailed discussion see Wooldrigde 2006). Available corrections depend on the number of clusters and their relative size. In our case, data structure reveals a relatively high number of clusters (*m*=103) but of an extremely variable size (number of firm per county). Given the number and the size of county clusters we prefer a two stage approach to control for cluster autocorrelation.

In the first stage we estimate the following Equation (1a) over the period 2001-2010, using only firm specific controls, leaving aside the vector of county level covariates.

$$y_{imt} = \alpha_m + \mathrm{Z}'_{\mathrm{it}}\beta_{\mathrm{k}} + \varepsilon_{imt} \qquad (1a)$$

From the first stage regression we recover the county fixed effect α_m that can be interpreted as a county average productivity (over the 2001-2010 time period), conditional on firm characteristics and sectoral composition.

In the second stage the country specific fixed effect α_{m} is regressed over the set of local infrastructures indicators $X_m^{'}$ – measured in year 2000 – that may have an impact on firm productivity. The second stage estimated equation is given then:

$$\alpha_m = \theta + X_m^{'}\beta_k + v_m \qquad (2)$$

Starting from the estimated Equation 2 it is possible to derive the expected average productivity for each country as $\widehat{\alpha}_{\mathrm{m}}$. The difference among observed and predicted values of α_{m} gives a useful metrics to evaluate the relative competitiveness of each county. Given the distribution of local endowments across counties and considering the effect that such variables have on average productivity – represented by the estimated coefficient in Eq 2 The difference among the observed and predicted values then could be interpreted as a county relative performance indicators, in fact, if $a_m > \widehat{\alpha}_{\mathrm{m}}$ for county m this means that in such county the observed average productivity if higher than the predicted – given the relative endowment of external factors (vector X_m'). On the other hand, $a_m < \widehat{\alpha}_{\mathrm{m}}$ suggests that county m has registered an average productivity below what could have expected, given their endowments, signalling a lower ability of firms to benefit from the local business environment.

4. Data and Descriptive Statistics

We use individual firm level data are from Bureau Van Dijk (AIDA dataset) which contains balance sheet data for about 68 thousand Italian manufacturing firms over the period 2001-2010, 15 thousand of which (22.6%) are included for the whole period. Table 1 shows the number of observations across years.

The geographical distribution of firms is relatively stable over the period; Table 2 reports the share of plants by macro-areas. Over 70% of the firms are located in the northern regions, while only 10% is located in south regions and islands. This feature of the dataset, correctly characterizes the spatial distribution of economic activity in

Italy. Regarding the sectoral composition of the sample, it appears to be fairly stable over time as well, in year 2010 – see Table 3 – the most relevant sector is the Machinery industry, Metal products and Textiles: those tree sectors alone covers almost half of the overall sample (48%), while petroleum and transport sectors are less represented.

Table 1: Number of firms observed by year

Year	Freq.
2001	31.916
2002	38.826
2003	38.368
2004	46.178
2005	48.817
2006	51.874
2007	54.007
2008	53.332
2009	53.724
2010	51.437

Table 2: Geographic distribution of firms for macro-regions (year 2010)

Region	Freq.	Percent.
Center	9.010	17,52
Island	1.012	1,97
North-Est	16.480	32,04
North-West	20.412	39,68
South	4.523	8,79
Total	51.437	100

Table 3: Firm distribution across industries - Nace rev.2 (year 2010)

Industries	Freq.	Percent.
Fabricated metal products	12.076	23,48
Machinery and equipment	6.863	13,34
Textiles, wearing, leather	6.126	11,91
Chemicals	4.827	9,38
Paper, Printing	4.227	8,22
Electronics	4.132	8,03
Food and Beverages	4.022	7,82
Non-metallic mineral products	2.799	5,44
Other Manufacturing	2.727	5,3
Furniture	2.210	4,3
Motor vehicles and transport equipment	1.318	2,56
Coke and refined petroleum	110	0,21
Total	51.437	100

Our measure of TFP measure is computed using the semi-parametric approach proposed by Levinshon and Petrin (2003), using material inputs and services as proxy for capital.[4] Value added, capital stock, materials inputs and services have been deflated using 2 digit indexes from Eurostat.[5] To control for outliers and measurement errors, we have excluded all the observations with negative values in the variables used to compute TFP as well as the observation with a growth rate above (below) the 99^{th} (1^{st}) percentile of the distribution.[6]

Figure 1: Firm level TFP distribution for selected years

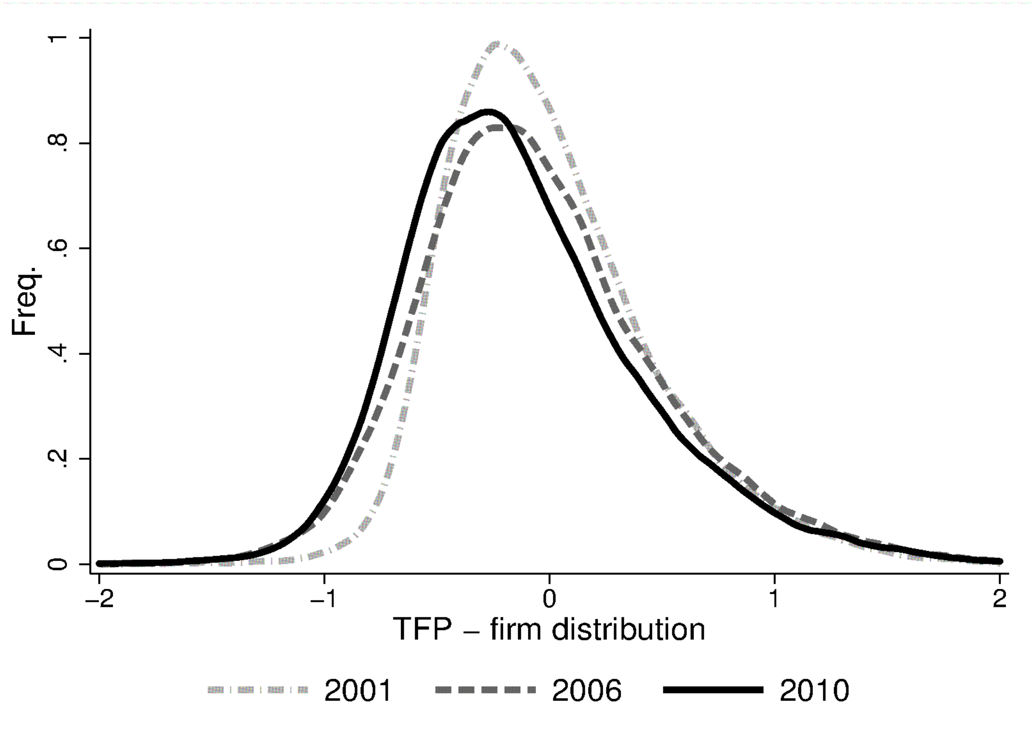


Figure 1 shows the distribution of firm-level TFP over selected years, respectively 2001, 2006 and 2010. The left shift of the distribution during the years suggests a

[4] The semi-parametrical methodology proposed by Levinshon and Petrin (2003) uses the intermediate production inputs to solve the simultaneity problem between input in the production function and the shock serially auto-correlated of the production technology. The use of intermediate inputs (raw materials) as productivity proxy implies that the definition of the input demand is represented as a function of productivity (un-observed) and capital$m_{it} = m_t(k_{it},\ \omega_{it})$. If the hypothesis that the demand of intermediate goods follows a positive increased production function is verified, it is possible to derive then following expression for the productivity itself$\omega_{it} = s_t(k_{it},\ m_{it}\ )$. In this way, it is expresses as a function with observable variables, such as the capital (k_{it}) and the intermediate inputs (m_{it}). Staring form the added value (v_{it}),, the productivity measure implies the estimation of the following equation: $v_{it} = \beta_0 + \beta_l l_t + \beta_k k_t + \omega_t + \eta_t \quad \Rightarrow \quad v_{it} = \beta_l l_t + s_t(k_{it}, m_{it}\ ) + \eta_t$

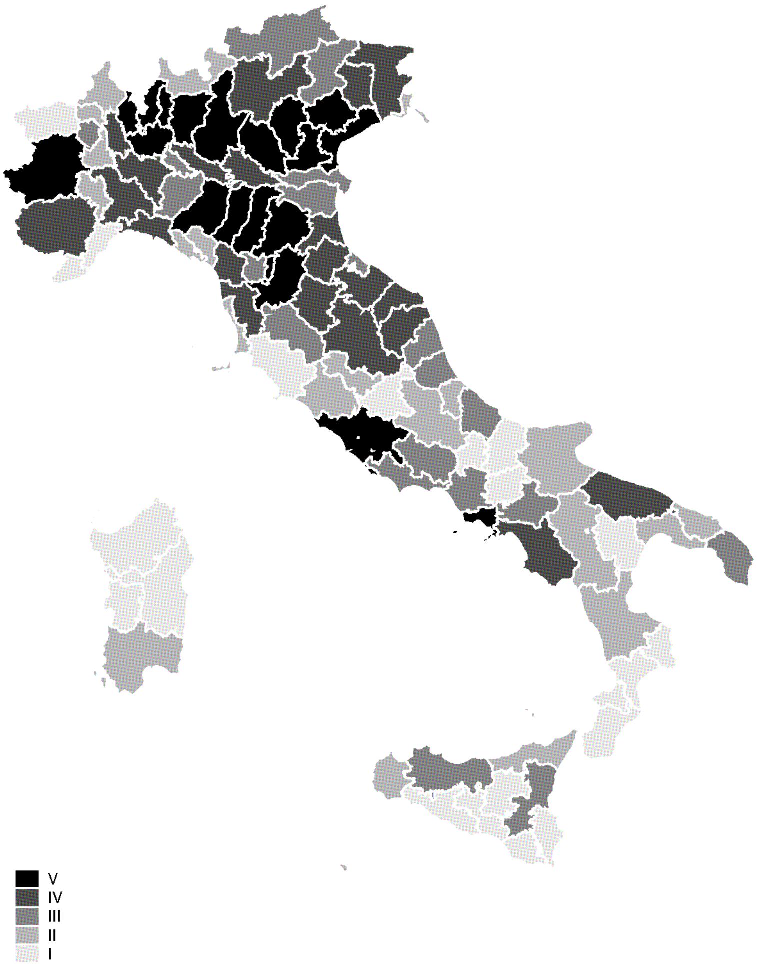
[5] In detail, we use 2 digit production prices to deflate Value Added, total fixed assets prices for Capital, production prices of intermediate inputs for Materials and Consumer price index for Services.

[6] Note that since TFP tend to be relatively noisy we have also set as missing those observation reporting a TFP level above (below) the 99^{th} (1^{st}) percentile of the year distribution.

redistribution of firms towards lower levels of productivity. Looking at the within-industry productivity dispersion, the 90th to 10th percentile ratio highlights a more heterogeneous picture: in 2001 the industry average 90th -10th ratio is 1.28, meaning that higher productive firms were able to reach a level of production 1.28 times higher with respect to low productive ones. In 2010, given the average decline in productivity the ratio rises to 1.34, meaning that dispersion increased along with the average contraction in TFP.

The rationale for our econometric analysis stems from the variability of both TFP (our dependent variable) and local external conditions at the level of the 103 Italian counties. The geographical distribution of manufacturing-firm TFP at the county level averaged over 2001-2010 is rather uneven as shown in Figure 2.

Figure 2: Average Levinshon-Petrin TFP over the period 2001-2010

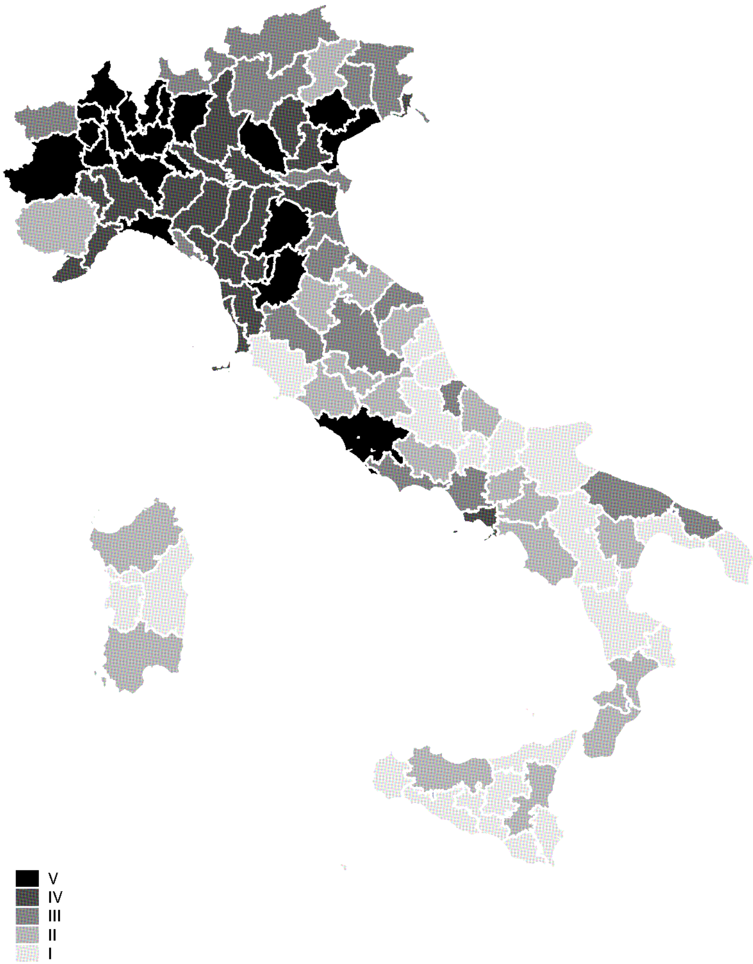


Note: Productivity values are cut into five classes corresponding to distribution quintiles, darker color are associated with higher values, the darkest color representing the top 20 % of Italian county productivity distribution

In our analysis, we use external factors as exogenous variables that can be grouped into different sets representing respectively the endowment of physical and financial infrastructures, human and social capital as well as proxies of county proximity to markets. Since each of these sets encompasses complex phenomena, we extract Principal Components from several variables to provide a synthetic measure of county's endowments as discussed in Section 3. The selection of the empirical variables used to characterize each set is based on the availability of the data for the 103 Italian counties over the period considered. We have tested different proxies provided by the Italian Statistical Institute (ISTAT), the Bank of Italy, ADS Stampa, EU-Espon. The variables used in the regressions and the sources of the data are shown in Table A1 in the Appendix.

Also for the explanatory variables, we find a remarkable variability among Italian counties. For instances, Figures 3 and 4 show respectively the geographical distribution of the values of the Multimodal Accessibility index elaborated by ESPON,[7] and some measures of local financial development. The Multimodal index captures the boundaries of European markets reachable from each EU county (NUTS3) weighted by their dimension (in terms of GDP and income).[8] The index reports market proximity taking into account different transportation infrastructures like roads, railways and airport networks.

Figure 3: Multimodal Accessibility index, 2001 values



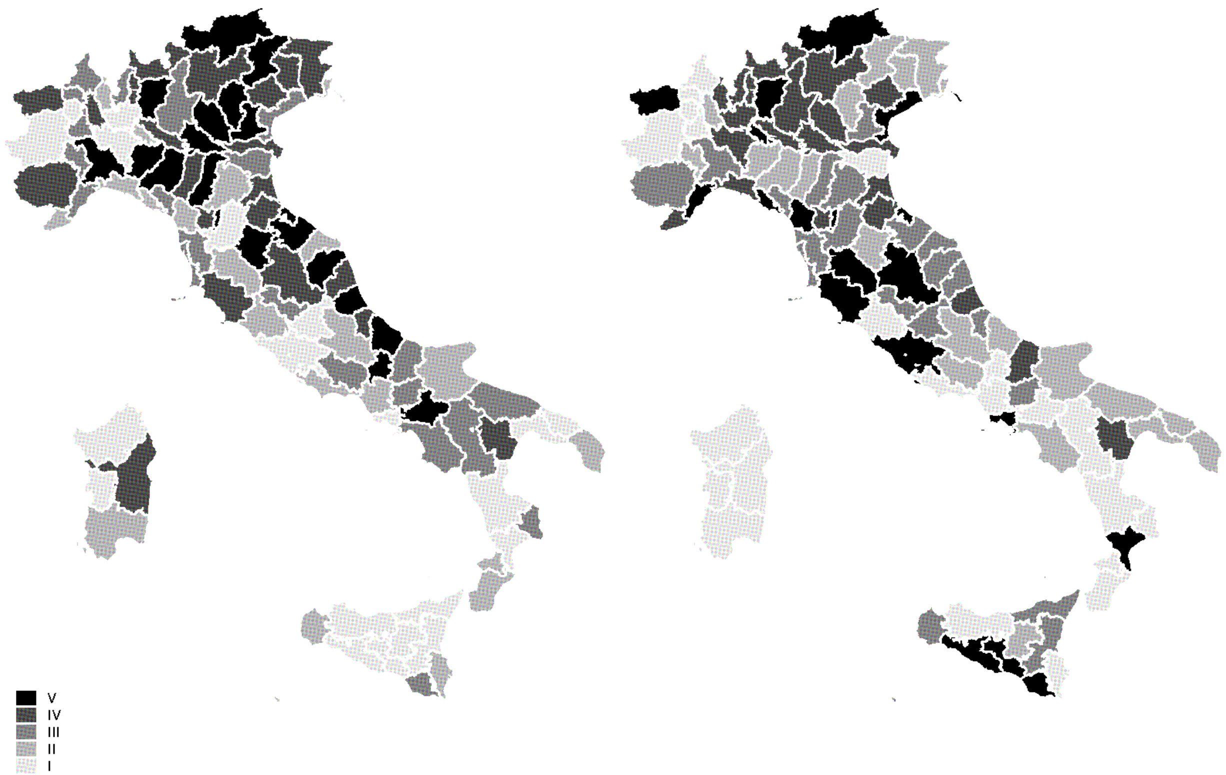
Note: series values are cut into five classes corresponding to distribution quintiles, darker color are associated with higher values; the darkest color represent the top 20 % of county accessibility.

[7] The European Observation Network for Territorial Development and Cohesion adopted by the European Commission on 7 November 2007, www.espon.eu
[8] For a detailed assessment of the index see Spiekermann, K., Wegener, M. (2006).

Figure 4 reports the spatial distribution of two measures of financial infrastructures: financial development (left), measured as the ratio of business to total outstanding credit; and financial innovation (right) computed as the growth rate of the financial development measure.[9] Also in this case, the distribution of the data shows a high degree of heterogeneity across counties.

[9] See Aghion et al (2005) and Michalopoulos et al (2011).

Figure 4: Financial development (left) and financial innovation (right); averge 2001-2010



Note: series values are cut into five classes corresponding to distribution quintiles, darker color are associated with higher values; the darkest color representing the top 20 % of county values.

5 Empirical Results

As discussed in Section 3, we use a two-stage econometric approach where in the first stage firm-level TFP is regressed upon a series of explanatory variables at the firm level and a county fixed effect. Then, in the second stage, we regress the 103 values of the county fixed effect on local structural variables. Table 4 shows the second stage regression results: in column (1) we report coefficients estimated with heteroskedasticity-robust standard errors, while in column (2) standard errors are obtained through a bootstrapping procedure, in order to deal with the fact that some regressors have been themselves estimated with PCA. It is worth noting that also the dependent variable is estimated – using first-stage Eq. 1 – but in this case measurement errors would be captured by the error term v_m.[10]

As shown in Table 4, the estimated coefficients of the explanatory variables show the expected sign, even though not all are statistically significant. The global performance of the regressions is satisfactory, provided that accounts for more the 60 percent of the variability of the county specific fixed effects. The local context seems relevant in affecting manufacturing performances in Italian counties. Among the statistically significant variables, social capital (trust and crime incidence), financial proxies and market potential seem to be the most important determinants of local competitiveness. In column (3) we test the robustness of our estimate with respect to dummy meant to capture the structural difference between Northern and Southern Italian regions, something that is often mentioned as a specific feature of the Italian economy. Our results are robust to the inclusion of this additional control, showing that our findings are not driven by the North-South gap. In column (4) we perform another robustness test concerning the possible role of highly urbanized areas. Urban agglomeration may enhance competition between firms and may lead to higher average productivity levels (see Combes et al. 2012). Our dummy for urban areas takes the value one if a county shows a population density above the 90^{th} percentile of the distribution: the urban dummy itself is not significant while the other results are broadly unaffected.

[10] Results available upon request.

Table 4: Stage-two estimation results

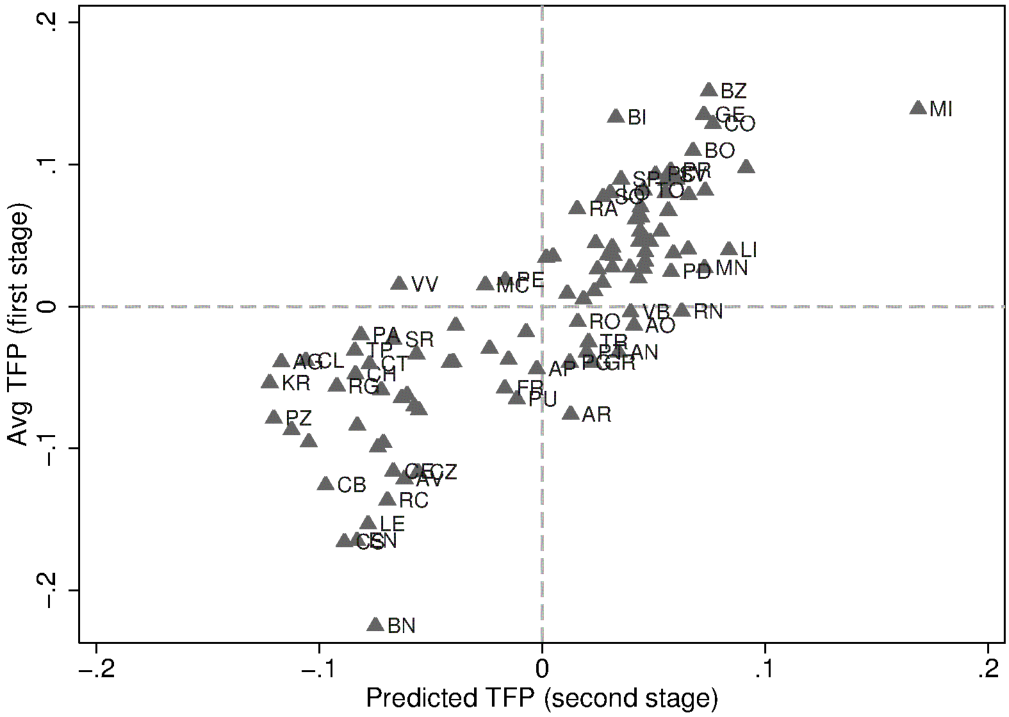
Dep. Variable TFP(1st Stage)	(1)	(2)	(3)	(4)
Human Capital	0.014*	0.014*	0.011	0.011
	(0.008)	(0.008)	(0.007)	(0.007)
Social Capital	0.064***	0.064***	0.046***	0.045***
	(0.014)	(0.015)	(0.013)	(0.013)
Crime Incidence	-0.008**	-0.008*	-0.009**	-0.008**
	(0.004)	(0.004)	(0.004)	(0.004)
Credit Inefficiency	-0.015***	-0.015***	-0.010***	-0.012***
	(0.004)	(0.006)	(0.003)	(0.004)
Financial Development	0.013***	0.013**	0.011***	0.010***
	(0.003)	(0.006)	(0.003)	(0.003)
Market Potential	0.076***	0.076***	0.053**	0.048**
	(0.021)	(0.021)	(0.024)	(0.024)
South			-0.044***	-0.044***
			(0.016)	(0.016)
Urban Areas				0.021
				(0.016)
Constant	3.823***	3.823***	3.897***	3.913***
	(0.109)	(0.112)	(0.117)	(0.119)
Observations	103	103	103	103
R^2	0.633	0.633	0.657	0.662

*Note: Columns (1), (3) and (4) provide estimates with heteroskedasticity robust standard errors. Column (2) uses a bootstrapping procedure to obtain standard errors. *** p<0.01, ** p<0.05, * p<0.1.*

Figure 5 shows the correlation between the normalized actual and predicted TPF for each of 103 Italian counties. On the vertical axis we plot average TPF over 2001-2010 as resulting from first-stage estimation, while on the horizontal axis we plot the predicted TPF values as stemming from the regression of column 4 in Table 4. On each axis we plot distance from the mean values. Counties showing productivity levels in line with the predicted ones cluster around the 45° line; counties above the diagonal are associated with TFP values above the estimated ones, while those below the diagonal show values lower than predicted.

Figure 5: Observed and predicted productivity at the Italian county level

(2001-2010, mean centred).



In the upper right quadrant of Figure 5 one can find counties where manufacturing firms are on average the most efficient both in term of observed and predicted TFP, while the opposite is true for counties located in the lower left quadrant. Firms located in counties above the diagonal on average perform better in terms of productivity than what is implied by their own set of local external variables as predicted by our estimate. The opposite is true of firms located in counties below the diagonal.

Table 6: Top and bottom counties according to predicted and observed TPF

County	TFP 2nd Stage	TFP 1st Stage
Milano	1	2
Prato	2	7
Livorno	3	33
Como	4	5
Bolzano	5	1
...	...	...
Caltanissetta	99	70
Foggia	100	91
Agrigento	101	72
Potenza	102	89
Crotone	103	79

Table 6 reports the ranking of the first/last five counties with respect to the predicted (from stage two estimation) and observed TFP (from stage one), as shown in Figure 5. Among the first counties, Milan, Prato, Livorno, and Como are below their potential while Bolzano is doing better than predicted.[11]

6 Concluding remarks

We analyse productivity growth differentials across 68.000 Italian manufacturing firms over 2001-2010, in order to disentangle internal from external productivity drivers. We perform a two-stage procedure in order to extract fixed-effects for 103 counties where the firms of our sample are located (stage one), and regress them upon a number of external factors that could affect productivity dynamics (stage two). We find that the quality of the local environment plays a very relevant role in explaining productivity differentials. Among the statistically significant variables, social capital (trust and crime incidence), financial proxies and market potential seem to be the most important determinants of local competitiveness. We have tested for the robustness of our estimate with respect to dummy meant to capture the structural

[11] See Table A2 in Appendix for a complete list.

difference between Northern and Southern Italian regions, and find that our findings are not driven by the North-South gap.

Our methodology also allows us to rank Italian counties according to their predicted total factor productivity, and to estimate the gap between actual and predicted productivity for each of 103 Italian counties. In this way we are able to identify "outperformers" (i.e. firms located in counties performing better in terms of average actual productivity than what is implied by their own set of local external variables) and "underperformers" (firms located in counties where average actual productivity is below what is predicted by the local set of external variables).

Further empirical research is required to explain the remaining one third of cross-county productivity dispersion in Italy. Nonetheless, this framework provides an interesting tool in order to investigate how much of this dispersion can be accounted for by external factors such as human and social capital, infrastructures, financial development, and to assess which of these drivers are actually significant. The more these variables can be shown to foster, or hinder, local productivity, the more policymakers can target instruments to promote productivity convergence towards the best practices as suggested, for instance, in the "Europe 2020" policy framework. The local external drivers of manufacturing firm productivity are also relevant in order to define the conditions for decentralized wage negotiation, as more information can be available for firms and trade unions in order to distinguish among performance improvements due to skills and efforts from improvements due to the local environment.

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Appendix I: Variables and County Ranking

Table A1: External Factors endowment, variables used in the estimation of step two

Covariate	Underlying Variables (multiple vars in case of Principal Compent)	Description	Source
Crime	Penal Institutions	Number of beds in penal institutions for 1000 inhabitants over 18 years old	Istat
	Convicts	Number of convicts for 100 beds	Istat
	Crime incidence	Number of reported crimes	Istat
Financial Efficiency	Unpaid loans (Mln Euro)	Not reimbursed credits – million of Euros	Bank of Italy
	Number of unpaid loans	Number of person signaled to the vigilance authority to be at risk of default	Bank of Italy
	Efficiency credit	Ratio of outstanding credit / risky credit	Bank of Italy
Credit Availability	Number of Branches by type of institution	Number of Banks and financial institutions	Bank of Italy
	Private Credit over GDP	Credit issued to private sector over county GDP	Bank of Italy, Istat (GDP)
	Credit	Credit to public and private sector (excluding financial and assurance)	Bank of Italy
Market Potential	Multimodal Accessibility index	Using road, rail and airports networks	Espon
Human Capital	College Degree	Number of college degrees in science (mats, engineering economics)	Istat
Social Capital	Newspapers	Newspapers per inhabitant	ADS Stampa

Note: Market Potential, Human and Social capital are not computed using principal component analysis.

Table A2: Relative Competitiveness of Italian Counties

County	Predicted TFP from Stage Two (Eq. 2)	Observed TFP from Stage One (Eq. 1a)
Milano	1	2
Prato	2	7
Livorno	3	33
Como	4	5
Bolzano	5	1
Varese	6	15
Mantova	7	43
Genova	8	3
Bologna	9	6
Trieste	10	18
Imperia	11	32
Rimini	12	55
Trento	13	12
Venezia	14	35
Padova	15	46
Parma	16	8
Bergamo	17	22
Savona	18	9
Lecco	19	13
Cremona	20	17
Gorizia	21	26
Piacenza	22	10
Novara	23	29
Treviso	24	34
Pavia	25	40
Udine	26	27
Verona	27	44
Torino	28	14
Firenze	29	23
Modena	30	20
Massa.Carrara	31	25
Lucca	32	28
Vicenza	33	47
Reggio nell'Emilia	34	24
Aosta	35	58
Verbano.Cusio.Ossola	36	56
Brescia	37	42
La Spezia	38	11
Ancona	39	67
Biella	40	4
Roma	41	37

County	TFP 2nd Stage (Eq. 2)	TFP 1st Stage (Eq. 1a)
Pisa	42	31
Ferrara	43	41
Lodi	44	16
Belluno	45	36
Sondrio	46	19
Siena	47	49
Alessandria	48	45
Cuneo	49	30
Vercelli	50	52
Grosseto	51	74
Terni	52	63
Pistoia	53	66
Pordenone	54	54
Rovigo	55	57
Ravenna	56	21
Arezzo	57	88
Perugia	58	73
Forlì.Cesena	59	53
Asti	60	38
Rieti	61	39
Ascoli Piceno	62	77
Viterbo	63	60
Pesaro e Urbino	64	85
Latina	65	69
Pescara	66	48
Frosinone	67	81
Nuoro	68	64
Macerata	69	51
Cagliari	70	59
L'Aquila	71	71
Sassari	72	75
Napoli	73	87
Catanzaro	74	96
Teramo	75	68
Matera	76	86
Brindisi	77	83
Avellino	78	97
Isernia	79	84
Vibo Valentia	80	50
Siracusa	81	62
Caserta	82	95
Reggio di Calabria	83	99
Salerno	84	93

County	TFP 2nd Stage (Eq. 2)	TFP 1st Stage (Eq. 1a)
Messina	85	82
Bari	86	94
Benevento	87	103
Catania	88	76
Lecce	89	100
Palermo	90	61
Oristano	91	90
Enna	92	101
Chieti	93	78
Trapani	94	65
Cosenza	95	102
Ragusa	96	80
Campobasso	97	98
Taranto	98	92
Caltanissetta	99	70
Foggia	100	91
Agrigento	101	72
Potenza	102	89
Crotone	103	79