Local Drivers of Manufacturing Productivity: An Empirical Study of the Italian Counties ◊

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Abstract

We analyse productivity growth differentials across 68,000 manufacturing firms located in 103 Italian counties, in order to disentangle internal from external productivity drivers. We find that a limited set of external local drivers related to financial conditions, social capital and market proximity explain approximately two-thirds of the cross-county manufacturing productivity dispersion in Italy. This framework can provide useful information in order to design more targeted regional policies at the national and EU level, including policies aimed at fostering convergence and at decentralising wage negotiations.

[JEL Classification: R11, R15, L60]

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1. Introduction

Low productivity dynamics is a main concern for Southern EU economies, especially since the outburst of the world financial crisis of 2007-8 and the EU sovereign debt crisis of 2011. The weakness of productivity trends makes it difficult to improve living standards, make public finances sustainable, and to cope with the membership arrangements of the European Monetary Union. These considerations apply even more forcefully to productivity trends in the manufacturing sector. Industry is by definition more open to international trade than many service sectors, and is traditionally associated with a more competitive context where productivity has to rise faster than in the tertiary sector. Manufacturing productivity has been sluggish in several EU Southern economies over the last twenty years, and this has contributed to the worsening of aggregate economic outcomes. An interesting issue in this respect is to analyse how much of the productivity performance is related to the behaviour of drivers internal to manufacturing firms, or to external drivers associated with some features of the geographical location of the enterprises. Italy, for instance, is the EU country where inter-regional differences in per capita income are the largest, according to estimates by the EU Commission. Interestingly, this is not only reflected in the well-known North-South divide, but is also true at a more disaggregated level. Very deep differentials also persist in the level and dynamics of productivity across Italian regions or counties.

An intriguing and policy- sensitive question is to investigate how many of these differentials can be accounted for by local external factors such as human and social capital, market proximity, infrastructures, financial development, and to assess which of these drivers are truly significant. The policy implications of measuring the local external drivers of productivity growth are far-reaching. For instance, the more some of the external factors listed above can be shown to account for local productivity dynamics, the more policymakers can focus on the right targets in order to set favourable conditions for inter-regional convergence towards higher productivity standards. The reduction of geographic economic imbalances in Europe is one of the main objectives of EU regional policies, as suggested in the "Europe 2020" policy framework, and one of the main expenditure items in the EU budget is devoted to that objective.

Wage setting rules and practices can be also affected if one recognizes that part of a firm's productivity outcomes are not due to internal efficiency or to the quality of the internal inputs, but rather to external factors beyond the boundaries of the firm. If this is the case, wage setting at local or company level must take into account not only the effort and the quality of the internal inputs, but also the local conditions affecting productivity performance.

In this paper, we focus on productivity growth differentials across 68,000 Italian manufacturing firms over the period 2001-2010, in order to disentangle internal from external productivity drivers. A two-stage procedure is implemented for extracting fixed-effects from productivity dynamics for 103 home counties (stage one), and regressing them upon a number of external factors that could affect local productivity (stage two). We find that 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, financial variables, social capital and market proximity seem to be the most important determinants of local competitiveness. The paper is organized as follows. In section 2, we provide a brief review of the recent empirical literature on internal and external productivity drivers. In section 3 we describe our empirical methodology while in section 4 we outline our variables and their sources. In section 5, we provide econometric results and discuss them. Section 6 offers some concluding remarks.

2. A selected review of the empirical literature

Firm efficiency and competitiveness in principle depend both on internal and external (local) drivers. Internal factors include elements regarding both the structure and the strategy of the firm itself, such as a centralised or decentralised organisation, the quality of human and physical resources, investments in innovation, and others. External drivers encompass various aspects of the environmental context in which a firm operates, such as market access, national or regional credit conditions, physical infrastructures and intangible capital, and others. Most of these external factors may affect the productivity performance of relatively similar firms if these firms are located in different areas of the same country.[1]

Differences in the level and dynamics of productivity of similar firms across space can also stem from differences in the quality and efficiency of various production factors available at local level. Several studies have analysed the evolution of spatial disparities at regional level over time (for a survey, see Brailinch et al., 2014). One of the main findings of this literature is that international

[1] A different strand of the literature focuses on firm heterogeneity without necessarily considering the role of the external "environment". See for instance Melitz and Ottaviano (2008).

output differences are only partially explained by physical and human capital accumulation, while most of the variability is accounted for by total factor productivity (henceforth, TFP) measured by a residual term (see Caselli 2005, Hsieh and Klenow 2010).

This in turn implies that, among other elements, local institutions can also be a determinant of the competitive advantage of regions, in the same way that national institutions appear to shape the competitive advantage of countries. Cultural features can also influence economic development, either directly or indirectly through the functioning of institutions. Using regional data for Europe, Tabellini (2010) analyses the relationship between regional incomes (and their evolution) and proxies of cultural environment such as trust, providing evidence on this relationship.[2]

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

As different empirical studies use different measures of firm performance, the first step in order to investigate the econometric relationship between external factors and firm outcomes is to identify a

[2] **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.

proxy for economic performance at the firm level. In this paper, we use total factor productivity (TFP) which reflects a complex set of phenomena, most of which are not always directly observable, such as innovation, labour organization, managerial ability, increasing labour force experience, 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 performances across firms within most sectors. And second, the fact that the most productive firms (those located in the upper tail of the distribution) are more likely to survive in the market and gain market shares. 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 in principle under the control of the firm, while external factors are generally 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 point out that these factors are not enough to explain persistent TFP variability within industries. Information Technology (IT) has been another fundamental factor for productivity dynamics in recent years, as suggested by Jorgenson et al. (2005, 2008) among others. Oliner et al. (2007) claim that productivity growth in IT industries explains most of the aggregate productivity growth in the U.S. over the last two decades.

R&D expenditure is another likely candidate to contribute to TFP performance. In a recent paper, Medda and Piga (2014) estimate the private returns of R&D from both upstream (supply driven) and downstream (demand driven) using a cross section of Italian manufacturing firms over the period 1998-2000. After controlling for endogeneity, they find significant evidence of a positive relationship between a firm’s innovative activity and productivity.

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 in most empirical studies. For instance, Fox and Smeets (2011) use matched employer-employee data for Danish firms and 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. They suggest that part of such variability could be due to external factors such as agglomeration externalities, specialised input markets, physical infrastructures, market access and business services, regulation, and others.

Adopting a more general framework, Escribano et al. (2008) study the effect of five sets of external variables on TFP in a sample of Turkish firms. These five categories include: physical infrastructures, institutions and crime incidence, financial conditions and economic governance, labour markets, and the innovation environment. They find that productivity is more closely related to the social and institutional environment than to other sets of variables.

3. The econometric set-up

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

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

Where y_{imt} represents the TFP of firm *i* located in county *m*, at time *t*.[3] The vector $\mathrm{Z}_{\mathrm{it}}^{'}$ contains firm-level controls, including the log of firm age its squared value. For a robustness check we have also re-estimated the first stage including a set of production quintiles dummies in order to provide a control for firm size (see Table 5 in Section 5).[4] Finally, the vector $\mathrm{Z}_{\mathrm{it}}^{'}$ also contains industry and year fixed effects.

The vector $X_{mt}^{'}$ contains variables meant to approximate external TFP drivers in county *m* over the relevant time interval. As external drivers, we consider several indicators of tangible and intangible factors: human capital, crime incidence, credit availability and financial development and a county's proximity to EU markets.

Since most of these variables encompass complex phenomena, we often use different proxies for each variable, extracting a Principal Component to synthesize the local endowment for each specific

[3] TFP is computed using the Levinshon-Petrin (2003) methodology (see Section 4).
[4] Quintile dummies guarantee a larger deal of flexibility, but we also use the log of sales as a control for production size. Results are robust and available upon request from the authors.

driver. The use of Principal Component Analysis (PCA) in this context allows us to extract the valuable information from a set of variables in a more parsimonious way.[5]

In detail, we directly include in X'_{mt} human capital (proxied by the log of science graduates), and a measure of EU market proximity (the log of the multimodal accessibility index).[6] As for other external drivers, we include the largest Principal Component extracted from the underlying variables. In the PCA we include among indicators for the incidence of crime: the number of beds in penal institutions, the number of convicts per 100 beds and the number of reported crimes. The Principal Component for financial development and efficiency is extracted from: the value of non-reimbursed credits, the number of persons signalled to the bank vigilance authority for default and the ratio between risky and total bank credit. The PCA for credit restrictiveness has been run using: the number of domestic, foreign and cooperative banks branches; the stock of credit issued to the business sector and the growth rate of the ratio of business to overall credit. On average, the variance explained by the largest principal component is around 70%, indicating an overall good fit for the PCA. Finally, α_m represents the county fixed effect.[7]

Including environmental variables (X'_{mt}) directly in Equation (1) could raise a serious clustering problem. Since TFP is firm-specific, while external variables varies only at county level, this will generate a potential bias in the estimated standard errors proportional to the correlation within each cluster (see Moulton 1986). Possible solutions 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. Moreover, the two-stage procedure helps to provide a control for within-cluster heterogeneity (see Brunello and Cappellari, 2008).

From the first stage we derive a county-specific productivity effect conditional on individual firm characteristics (age, age squared, production size quintiles, and industry by year). In the second step the estimated county-level effects are then regressed on a set of local external factors that may affect firm performance. In greater detail, in the first stage we regress firm-level total factor productivity (over the period 2001-2010) on a set of relevant firm level covariates as in Equation (2):

[5] The PCA is used to extract the information for physical infrastructures, financial development and the incidence of crime. See Table A1 in the Appendix for a list of the variables used to identify the principal component in each class.
[6] See Section 4 for a description of the index.
[7] See Woolridge (2006).

$$y_{imt} = \alpha_m + Z_{\mathrm{it}}^{'} \beta_{\mathrm{k}} + \varepsilon_{imt} \quad (2)$$

From first-stage Equation (2) we recover the county fixed effect α_m that can be interpreted as a county average measure of productivity, conditional on firm characteristics and sectorial composition.

In the second stage, the county-specific fixed effects are regressed over a set of local variables $X_m^{'}$ that has been constructed as described before. In order to cope with possible endogeneity of the variables included in vector $X_m^{'}$ the empirical proxies for county external effects are measured as averages over the three or five years before 2001 (the starting year of our TFP exercise).

The second-stage estimated equation is thus given by Equation (3):

$$\gamma_m = \theta + X_m^{'} \beta_k + v_m \quad (3)$$

where γ_m is the average county productivity conditional of individual firm characteristics i.e. the estimate of α_m in the first-stage Equation (2). Starting from the estimated Equation 3 it is possible to derive predicted average productivity for each county as $\widetilde{\gamma}_m$. The difference among observed and predicted values of γ_m provides a useful metric to evaluate relative manufacturing competitiveness in 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 Equation (2) - the difference between the observed and predicted values could then be interpreted as an indicator of actual firms' performance relative to the expected one. If $\gamma_m > \widehat{\gamma}_{\mathrm{m}}$ for county *m*, this means that in such a county observed average productivity is higher than the predicted one – given the relative endowment of external factors (vector $X_m^{'}$). On the other hand, if $\gamma_m < \widehat{\gamma}_{\mathrm{m}}$ county *m* shows average firm productivity below what could have been expected given its endowments, signalling a lower ability of firms to benefit from the local business environment.

4. Data description and the measuring of TFP

We use individual firm-level data from Bureau Van Dijk (AIDA dataset), which contains balance sheet data for approximately 68 thousand Italian manufacturing firms over the period 2001-2010, 15 thousand (22.6%) of which are included for the whole period. Table 1 shows the number of observations throughout the 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% are located in Southern regions and the Islands. This feature of the dataset correctly characterises the spatial distribution of economic activity in Italy. The sectorial composition of the sample also appears to be fairly stable over time.

Table 1: Number of firms observed per 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.	Per cent.
Centre	9,010	17.52
Islands	1,012	1.97
North-East	16,480	32.04
North-West	20,412	39.68
South	4,523	8.79
Total	51,437	100

Our measure of TFP is computed using the semi-parametric approach proposed by Levinshon and Petrin (2003), using material inputs and services as proxy for capital.[8] Value added, capital stock, material inputs and services have been deflated using two-digit indexes from Eurostat.[9] To control for outliers and measurement errors, we have excluded all negative observations as well as all observations with a growth rate above (below) the 99th (1st) percentile of the distribution.[10]

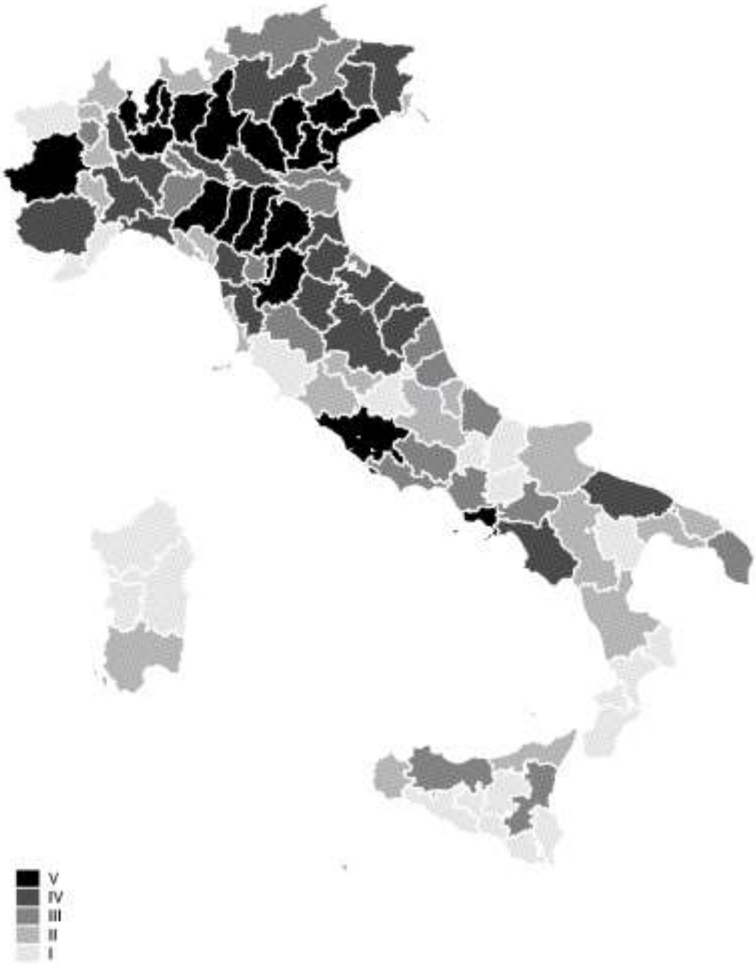
The rationale for our econometric analysis stems from the variability of both TFP (our dependent variable) and local external conditions at the level of the 103 Italian counties. The geographical distribution of manufacturing-firm TFP at the county-level averaged over 2001-2010 is rather uneven, as shown in Figure 1.

[8] 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 serially auto-correlated shock 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 for intermediate goods follows a positive increased production function is verified, it is thus possible to derive the following expression for the productivity itself$\omega_{it} = s_t(k_{it},\ m_{it}\ )$. In this way, it is expressed as a function with observable variables, such as capital (k_{it}) and the intermediate inputs (m_{it}). Starting from the added value (v_{it}),, the productivity measure implies the estimation of the following equation: $v_{it} = \beta_0 + \beta_l l_t + \beta_k k_t + \omega_t + \ \eta_t \ \Rightarrow\ v_{it} = \beta_l l_t + s_t(k_{it}, m_{it}\ ) + \ \eta_t$

[9] More specifically, we use two-digit production prices to deflate value added, total fixed assets prices to deflate capital, production prices of intermediate inputs for materials and the consumer price index for services.

[10] Note that since TFP tends to be relatively noisy we have also set as missing those observations reporting a TFP level above (below) the 99th (1st) percentile of the year distribution. Results are robust to different thresholds.

Figure 1: Average Levinshon-Petrin TFP dynamics in Italian counties over 2001-2010



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

We proxy external drivers with 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 a county's proximity to EU markets. As described in Section 3, we extract Principal Components from several variables to provide a synthetic measure of a county's endowments. The selection of the empirical variables used to characterise 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, and the EU-Espon database. The variables used in the regressions and the sources of the data are shown in Table A1 in the Appendix. For the explanatory variables as well, we find a remarkable degree of variability among Italian counties. For instance, Figure 2 shows the geographical distribution of the values of the multimodal accessibility index elaborated by ESPON.[11] 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).[12] Hence, this index describes EU market proximity from each county, taking into account the (weighted) travel distance across European counties' using different transportation infrastructures (roads, railways and airport networks). The high geographical dispersion of external factors across counties, evident from Figure 2, also apply to other variables, such as financial indicators, crime incidence, and others.[13]

Figure 2: EU market multimodal accessibility index (2001 values)

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

[11] The European Observation Network for Territorial Development and Cohesion created by the European Commission on 7 November 2007, www.espon.eu

[12] For a detailed assessment of the index see Spiekermann, K., Wegener, M. (2006).

[13] Statistical evidence is available upon request.

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 3 shows the second-stage regression results obtained from the estimation of Equation (3). It should be recalled that, in order to cope with possible endogeneity of the variables included in vector $X_m^{'}$, the empirical proxies for county external effects are measured as averages over the three or five years before 2001 (the starting year of our TFP exercise).

Column (1) reports 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 variables have themselves been estimated with PCA. It is worth noting that the dependent variable is also estimated – using first-stage Equation (2) – but in this case measurement errors are captured by the error term v_m.

Table 3: Stage-two estimation results

Dep. Variable TFP(1^{st} Stage)	(1)	(2)	(3)	(4)
EU proximity	0.138***	0.138***	0.075***	0.078***
	(0.017)	(0.019)	(0.023)	(0.027)
Financial Develop.	0.020***	0.020**	0.013***	0.013***
	(0.005)	(0.008)	(0.004)	(0.004)
Credit Restrictiv.	-0.024***	-0.024***	-0.012**	-0.012**
	(0.006)	(0.007)	(0.005)	(0.005)
Human Capital	0.013	0.013*	0.010	0.010
	(0.008)	(0.008)	(0.008)	(0.008)
Crime Incidence	-0.009**	-0.009**	-0.010**	-0.010**
	(0.004)	(0.004)	(0.004)	(0.004)
South			-0.070***	-0.069***
			(0.018)	(0.019)
Urban Areas				-0.004
				(0.013)
Constant	3.400***	3.400***	3.703***	3.691***
	(0.078)	(0.085)	(0.108)	(0.121)
Observations	103	103	103	103
R-squared	0.536	0.536	0.616	0.616

*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.*

As shown in Table 3, 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 they account for more than 60 per cent 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, financial proxies and EU market proximity seem to represent the most important determinants of local competitiveness. In column (3) we test the robustness of our estimate with respect to a dummy whose purpose is to capture the structural gap between Northern (advanced) and Southern (backward) Italian regions, something that is often mentioned as a specific feature of the Italian economy.[14] 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 urbanised 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 75th percentile of the distribution: the urban dummy itself is not significant while the other results are broadly unaffected.[15]

As a further robustness test, we have excluded from the first stage estimation the dummy variables for the size quintile dummies. The corresponding second stage results for this alternative specification are reported in Table 4 and largely confirm previous findings. Table 5 reports instead the coefficients obtained from another empirical specification, where we have directly estimated the model in Equation (1) on firm level data, including both firm controls and county specific covariates. This is the one-stage econometric strategy alternative to our preferred one. However, results are consistent with those of Tables 3 and 4, showing that our findings are not driven by the two-stage estimation strategy.[16]

[14] See for instance Aiello and Scoppa (2000).
[15] Setting the threshold for urban areas at the 90th or 95th percentile of the density distribution does not alter the main results.
[16] See for instance Van Biesebroeck (2007, 2008).

Table 4: Stage-two estimation results without firm size controls in the first stage

Dep. Variable TFP(1st Stage)	(1)	(2)	(3)	(4)
EU proximity	0.185***	0.185***	0.112***	0.114***
	(0.024)	(0.024)	(0.027)	(0.032)
Financial Develop.	0.033***	0.033***	0.025***	0.025***
	(0.008)	(0.012)	(0.006)	(0.007)
Credit Restrictiv.	-0.043***	-0.043***	-0.030***	-0.030***
	(0.008)	(0.010)	(0.007)	(0.007)
Human Capital	0.013	0.013	0.009	0.009
	(0.010)	(0.010)	(0.010)	(0.010)
Crime Incidence	-0.000	-0.000	-0.001	-0.001
	(0.006)	(0.006)	(0.006)	(0.006)
South			-0.081***	-0.081***
			(0.023)	(0.023)
Urban Areas				-0.003
				(0.017)
Constant	3.432***	3.432***	3.783***	3.774***
	(0.108)	(0.109)	(0.124)	(0.143)
Observations	103	103	103	103
R-squared	0.600	0.600	0.651	0.651

*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.*

Table 5: One-stage joint estimation of TFP and county fixed effects

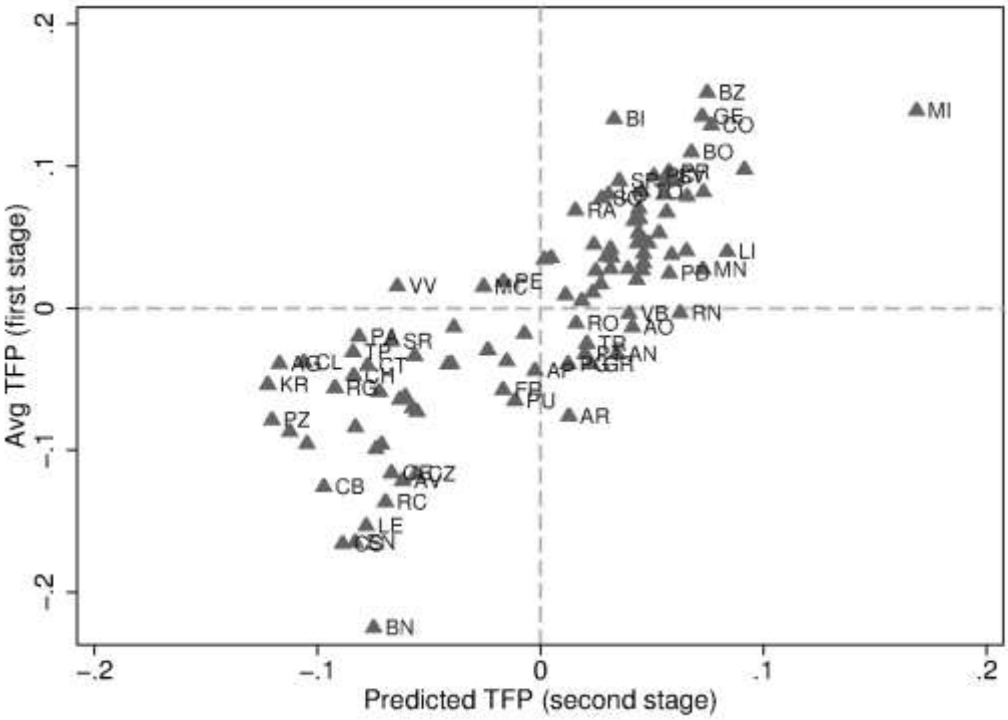
Dep. Variable TFP	(1)	(2)	(3)	(4)	(5)
EU Proximity	0.076**	0.162***	0.162***	0.119***	0.114***
	(0.031)	(0.018)	(0.017)	(0.020)	(0.022)
Fin Develop.	0.012***	0.011***	0.011***	0.008***	0.008***
	(0.003)	(0.003)	(0.003)	(0.001)	(0.001)
Credit Restrictiv.	-0.011*	-0.017**	-0.017**	-0.010***	-0.011***
	(0.006)	(0.007)	(0.006)	(0.002)	(0.002)
Human Capital	0.004	0.012*	0.012*	0.009	0.008
	(0.012)	(0.007)	(0.007)	(0.008)	(0.008)
Crime Incidence	-0.010	-0.014***	-0.014***	-0.014***	-0.013***
	(0.009)	(0.003)	(0.003)	(0.003)	(0.003)
South				-0.071***	-0.072***
				(0.013)	(0.014)
Urban Areas					0.009
					(0.013)
Firm Level Var:					
Age	0.017**	0.032***	0.033***	0.034***	0.034***
	(0.006)	(0.004)	(0.004)	(0.005)	(0.005)
Age^2	0.004*	-0.003***	-0.003***	-0.004***	-0.004***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Size: Quintile 2	0.191***	0.194***	0.194***	0.194***	0.194***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Size: Quintile 3	0.381***	0.386***	0.386***	0.386***	0.386***
	(0.004)	(0.003)	(0.004)	(0.004)	(0.004)
Size: Quintile 4	0.591***	0.598***	0.599***	0.598***	0.598***
	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)
Size: Quintile 5	1.041***	1.053***	1.053***	1.052***	1.052***
	(0.016)	(0.013)	(0.013)	(0.013)	(0.013)
FE	Year	Sector, Year	Sector*Year	Sector*Year	Sector*Year
Observations	460,979	460,979	460,979	460,979	460,979
R-squared	0.497	0.497	0.596	0.598	0.598

*Note: standard errors in parenthesis clustered at the county level *** p<0.01, ** p<0.05, * p<0.1. All regressions include a constant, not reported.*

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 a result of our 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.

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

(2001-2010, mean centred).



On each axis we plot the 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.

In the upper right quadrant of Figure 5 one can find counties where manufacturing firms are on average the most efficient, both in terms 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.

6 Concluding remarks

We analysed productivity growth differentials across 68,000 Italian manufacturing firms over 2001-2010, in order to disentangle internal from external productivity drivers. We performed a two-stage procedure in order to extract fixed-effects for 103 home counties of the firms (stage one), and regressed them upon a number of external factors that could affect productivity dynamics (stage two). A rather limited set of external drivers accounts for approximately two thirds of the variability of the county-specific fixed effects. Among the statistically significant variables, social capital (trust and the incidence of crime), financial proxies and market proximity seem to be the most important determinants of local competitiveness. We have tested the robustness of our estimate with respect to a dummy whose purpose was to capture the structural difference between Northern and Southern Italian regions, and discovered that our findings are not driven by the North-South gap. We also performed another robustness test concerning the possible role of highly urbanized areas, and found that the urban dummy itself is not significant while the other results are broadly unaffected.

The empirical results in this paper offer interesting policy hints. For instance, if we combine the information provided in Table 3 on the weight of the external factors in determining the local productivity conditions across 103 Italian counties, with the evidence on the geographic gaps in the endowment of these factors, we get useful policy suggestions on the external drivers that should be targeted by local or national policymakers in order to set the right conditions for productivity convergence towards the most favoured Italian counties. In the context of the EU regional policy frameworks, the more one gets a clear picture of the external factors affecting local productivity dynamics, the more policymakers can focus on the right targets in order to set conditions potentially conducive to regional convergence towards higher productivity standards. Recall that the reduction of geographic economic imbalances in Europe is a policy target for which a large amount of resources from the budget of the EU Commission are devoted.

Our methodology also allowed 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. Firms located in counties performing better in terms of average actual productivity relative to what is implied by their own set of local external variables, can be viewed as outperformers, while firms located in counties where average actual productivity is below what is predicted by the local set of external variables can be viewed as underperformers. Decentralized wage setting practices can take advantage of this evidence, if ones recognises that part of a firm's productivity outcomes are not due to internal efficiency nor to the quality of the internal inputs, but to external factors beyond the boundaries of the firm. If this is the case, wage setting at the local or company level can take into account not only the effort and the quality of the internal inputs, but also the local conditions affecting productivity performance.

Further empirical research is required to explain the remaining one third of cross-county productivity dispersion in Italy, as well as to refine our set of local external independent variables. Nonetheless, this framework provides an interesting tool in order to investigate how much of this dispersion can be accounted for by a limited set of external factors, with clear implications for policy design and assessment.

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Appendix I: External variables used in the estimation of the county fixed effects

Table A1

External variable	Underlying Variables (multiple vars in case of Principal Compent)	Description	Source
Crime Incidence	Penal Institutions	Number of beds in penal institutions for 1000 inhabitants over 18 years old	Istat
	Convicts	Number of convicts per 100 beds	Istat
	Crime incidence	Number of reported crimes	Istat
Financial Development	Unpaid loans (Mln Euro)	Not reimbursed credits – million of Euros	Bank of Italy
	Number of unpaid loans	Number of persons signalled to the vigilance authority to be at risk of default	Bank of Italy
	Efficiency credit	Ratio of risky over total credit	Bank of Italy
Credit Restrictiveness	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
EU Market Proximity	Multimodal Accessibility index	Using road, rail and airports networks	Espon-EU
Human Capital	College Degree	Number of college degrees in science (mats, engineering economics)	Istat

Note: Market Potential and Human Capital are not computed using principal component analysis.