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Mapping local productivity advantages in Italy: industrial districts, cities or both?

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MAPPING LOCAL PRODUCTIVITY ADVANTAGES IN ITALY: INDUSTRIAL DISTRICTS, CITIES OR BOTH?*

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Abstract

In this paper we compare the magnitude of local productivity advantages associated to two different spatial concentration patterns in Italy, i.e. urban areas (UA) and industrial districts (ID). UA typically display a huge concentration of population and host a wide range of economic activities, while ID are located outside UA and exhibit a strong concentration of small firms producing relatively homogenous goods.

We use a very large sample of about 29,000 Italian manufacturing firms observed over the 1995-2006 period and resort to a wide set of econometric techniques in order to test the robustness of main empirical findings. We detect local productivity advantages for both UA and ID. However, firms located in UA attain a larger Total Factor Productivity (TFP) premium than those operating within ID. Besides, it turns out that the advantages of ID have declined over time, while those of UA remained stable.

Differences in the white-blue collars composition of the local labor force appear to explain only a small fraction of the estimated spatial TFP differentials. Production workers (blue collars) turn out to be more productive in ID, while non-production workers (white collars) are more efficiently employed in UA. By analyzing the quantiles of the sample TFP distribution, we document how more productive firms gain stronger benefits from locating in UA.

On the whole, our analysis raises the question whether Italian ID are less fit than UA to prosper in a changing world, characterized by increased globalization and by the growing use of information and communication technologies.

Key words: Urban areas; Industrial districts; Agglomeration economies; Productivity; Blue and White collars; Italian economy.

JEL classification: c52, r12, d24

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1. Introduction

The forces pushing toward spatial agglomeration manifest themselves in different ways even when they are analysed within the same country and sector of economic activity. Urban areas (UA) typically display a huge concentration of population, a wide range of economic activities, including a highly diversified service sector, and extensive local amenities coupled with high congestion costs. Industrial clusters or districts (ID) instead are usually located outside UA, exhibit a strong concentration of small firms producing relatively homogenous goods and, although in a different way, may also be affected by some congestion problems due to the crowding of firms and workers (for a survey of the empirical literature related to agglomeration economies, see Rosenthal and Strange, 2004, and Melo, Graham, and Noland, 2009).

In the present paper, with regard to Italian economy, we address several questions concerning these two spatial concentration patterns: i) Are plants located in UA and ID more productive than establishments located elsewhere? ii) Are the local productive advantages in the two spatially concentrated areas comparable in magnitude? iii) How have they been evolving in recent years?

Answering the first question may help shedding light on the mechanisms that are responsible for generating agglomerations economies, a long debated issue in the literature. The second question is relatively new and especially relevant in the context of the Italian economy. Finally, the last question aims at documenting how the comparative advantages of UA and ID evolved in the new scenario brought about by increasing competition from newly industrialized countries on one side and by the advent of information and communication technologies (ICT) on the other (Glaeser and Ponzetto, 2010).

The empirical literature on agglomeration economies has usually addressed similar questions by regressing average productivity across areas on a series of explanatory variables including local market size, usually proxied through population or population density, the sectoral diversification of the local economy, its relative specialization in a specific sector and the share of small firms. In this context, positive partial correlation between productivity and market size or diversity is usually interpreted as providing evidence that urbanization is responsible for agglomeration economies, while a positive coefficient for the specialization or small firms incidence indicators would signal that spatial clustering in the ID's is the main driver of the local productive advantages.

In the present paper we take a slightly different route by mapping the Italian territory into three non overlapping areas: a) UA, defined as those locations whose population is above a certain threshold; b) ID, identified through a complex algorithm that will be defined later in the paper; c) the rest of the locations that are not included in the definition of UA and ID. We then measure average local productivity differentials by regressing firm-level indicators of productive efficiency on UA and ID dummies plus a set of controls[1].

Apart from allowing for a straightforward comparison of the magnitudes of productivity gains associated to ID and UA, the advantages of this empirical strategy are manifold. Good proxies of the positive externalities associated to UA are usually difficult to devise and are in any case related to the fact that population living in that area has to be above a certain threshold for these agglomeration forces to produce their effects (this consideration equally applies to negative externalities, namely congestion effects). The identification of ID is also a quite complex task. In Italy, an official definition of ID is produced by the National statistical institute (Istat) as the outcome of a multi-step algorithm. Considering that mimicking the latter in a regression analysis using a set of continuous variables would be both demanding and inefficient, we chose to summarize the complex structural characteristics featuring Italian ID by means of a dummy variable that singles out the local labor markets that are classified as ID in the Istat's taxonomy.

To deal with the aforementioned research questions, we resort to a panel of about 29,000 Italian manufacturing firms observed over the period 1995-2006. The major findings of the paper are the following. The two different spatial concentration patterns associated to UA and ID are both able to generate local productivity advantages. However these advantages are stronger in UA as compared to those observed in the ID. Moreover, we find that comparative advantages in cities remained stable over the period 1995-2006, while those in the industrial districts declined. We also show that productive advantages in UA persist even controlling for differences in workforce composition across areas. Production workers (blue collars) appear to be more productive in ID, while for UA we estimate a higher productivity of non-production workers (white collars), a professional category that is becoming increasingly important to upgrade production. Finally, through a quantile regression, it is shown that ID exhibit a

[1] For a survey of recent empirical work on productivity differentials across firms, see Syverson (2010).

stronger positive impact on the lower tail of the TFP distribution, while UA benefit more firms belonging to the upper tail. Several shocks like the introduction of Euro, the rapid diffusion of ICT and the growing globalization affected the Italian economy at the beginning of 2000s. Our results suggest that urban areas reacted to those events more effectively than ID did.

The rest of the paper is organized as follows. Section 2 presents a brief review of literature investigating the importance of agglomeration effects for firms' productivity. Sections 3 and 4 discuss, respectively, the territorial level of analysis and the data. Section 5 reports the TFP estimation. Section 6 analyses the impact of spatial concentration on firms' TFP. Section 7 discusses the results, also disentangling the role of human capital on firms' productivity; final remarks are illustrated in Section 8.

2. Industrial districts and urban areas as sources of local productivity advantages

Spatial concentration may generate local productivity advantages through different mechanisms. First agglomeration economies in the form of technical or knowledge spillovers, labor market pooling and proximity to local buyers or sellers, may increase the productivity of firms located in densely populated areas. A recent literature points to a different mechanism based on selection, i.e. large markets will attract more entrants thereby fostering competition and inducing less efficient firms to exit from the local market.[2] Finally, other contributions stress the sorting of firms or workers.[3] Ex ante heterogeneous firms may have different capabilities to exploit local productivity advantages. For instance, less efficient firms could soften competition by locating in less dense areas or large and more productive firms could be better able to exploit the benefits generated from different kinds of agglomeration economies.

As explained in the introduction, urban areas and industrial districts represent examples of geographic concentration displaying different and sometimes orthogonal characteristics. The

[2] For this class of models see Melitz (2003) and Melitz and Ottaviano (2008). Syverson (2004a) analyses the effects of the local market size on productivity and firm selection in the special case of the concrete industry where transport costs are relevant. Syverson (2004b) and Del Gatto, Ottaviano and Pagnini (2008) investigate how selection effects vary across different industries in response to a set of their characteristics (elasticity of demand, openness to trade). Their implicit assumption is that markets in many manufacturing activities are integrated through trade within the same country.

[3] The literature on sorting is rapidly increasing and mainly centred on workers: see Combes, Duranton and Gobillon (2008) for France and Matano and Naticchioni (2011) for Italy. About the theoretical literature on firm sorting, see also Baldwin and Okubo (2006) and Okubo, Picard and Thisse (2010). Nocke (2006) pursues a similar line of research however moving from the tenets of oligopoly theory.

question that we want to address is weather and to what extent these differences will reflect into the strength of local productivity advantages generated by the two environments.

According to several scholars the Italian industrial takeoff following the II World War period was triggered by the growth and diffusion of ID areas. These correspond to regions with a high concentration of small firms, cooperating along the productive chain of a unique final good.[4] ID usually exhibit a strong specialization in manufacturing activities. Moreover, ID community may also include local institutions like political parties, associations and also a network of local banks.

UA represent locations where a large amount of population reside and work. This concentration of people will attract the settlement of a diversified set of activities including services like transportation and recreation. This will induce also the production of local amenities (cultural activities) and disamenities due to congestion (pollution and so on).

Given these characteristics, it is likely that both UA and ID will be able to generate some kinds of agglomeration economies. An important question is whether these economies will be produced by the interactions between firms and workers within the same industry (Marshall externalities) or alternatively belonging to different sectors of economic activity (Jacob externalities). It is evident that Marshall externalities can be more easily associated to ID while Jacob externalities are likely to arise in UA.

To avoid the paradoxical outcome of an economy concentrated in just one type of region, these local productivity advantages have to be traded off against other forces varying with the nature of the productive process and that may induce firms to locate outside ID and UA areas. Congestion costs for instance may generate several examples of mismanagement of resources within a firm thereby lowering productive efficiency in cities.[5] Although ID can partially save on congestion costs due to their specialization in a specific industry, they might also be exposed to the problems caused by the crowding of firms and workers within a relatively narrow area. With a specific reference to ID, their productivity advantages can be reduced

[4] Becattini (1990) provides a conceptualisation of the industrial district, defining it as a socio-territorial entity which is characterised by the active presence of both a community of people and a population of firms in one naturally and historically bounded area. Thus, an economic definition of the industrial district which aims at being comprehensive will have to include both the network of links between firms and the above mentioned social conditions. For a recent survey and empirical analysis on Italian districts, see Iuzzolino and Micucci (2011).

[5] Moreover, they can augment local land prices thereby inducing firms using intensively this input factor in their production to locate outside UA.

when indivisibilities are important. In those circumstances, the network externalities generated within ID are weak and production tasks can be more efficiently performed within large and hierarchical organizations. Finally these sources of local comparative advantages may change across time because of the evolution of technology or of the changes in the competitive setting taking place domestically or in international markets (liberalizations and so on).

As for the selection effects and sorting, it is difficult to say a priori weather they will be stronger in ID and UA and hence we will postpone their discussion to Section 7.

The empirical literature on the sources of local productivity advantages analyzes the effects of UA mainly through the size of the local market. A positive correlation between market size and productivity is usually interpreted as evidence that cities favor productive efficiency. Doubling city size would increase productivity by an amount ranging from 3 to 8 per cent according to the paper and the country considered.[6] As far as we know, no paper estimated that elasticity for Italy. The contribution that it is closer to that goal is the one by Cingano and Schivardi (2005). In particular, they showed that moving from the first to the third quartile of city-size distribution would rise Total Factor Productivity (TFP) yearly growth rate by 0.6 per cent for a sample of Italian manufacturing firms.

Unlike the contributions referred to other countries emphasizing urban effects, the empirical literature in Italy focused mainly on the productivity advantages associated to ID.[7] In particular, Signorini (1994; see Table 1), using data referred to the provinces of Prato and Biella, find that firms in districts have higher per capita value added. Fabiani et al. (2000) generalize the analysis to the whole Italian territory showing that between 1982 and 1995 firms in ID outperformed the companies located outside their borders. In 1995, ID firms' advantage in term of ROI (return on investment) and ROE (return on equity) amounted respectively to 2 and 4.1 percent. The average difference in value added per worker between firms in and out of districts is around 1.3 per cent. Moreover, ID firms result less inefficient than isolated ones in 8 out of 13 of the sectors considered[8].

[6] Rosenthal and Strange (2004). See also Melo, Graham and Noland (2009) for a survey of this literature and for a meta-analysis of the relation between productivity and city size.
[7] For a short review of the papers assessing ID advantages see the list reported in Table 1.
[8] The authors use a stochastic frontier approach to measure inefficiency. They define technical inefficiency as "the failure to produce the maximum possible output for any chosen combinations of inputs", including "…the inefficiency arising from the managerial and organisational structure and the socio-economic environment in which firms operate". Fabiani et al., (2000), p. 58.

Cainelli and De Liso (2005) estimate the effects of clustering of the firms into ID areas on productivity, disentangling process and product innovation and detecting the latter as mainly responsible of productivity advantages in favor of ID firms. They find that the district effect, measured as the difference in terms of value added growth rates, ranges between 2.0 and 2.6 per cent.

Cingano and Schivardi (2005) offer indirect evidence of a positive district effect by showing that augmenting local sectoral specialization (a characteristic associated to ID) would increase local TFP growth by 0.2 and 0.4 per cent, depending on the adopted specification. Despite this quite unanimous consensus, the most recent studies have shown that the localization advantages of the ID are at least partially vanishing (maybe due to districts-externalities reducing effect of globalization). If we observe the inner features of the industrial districts, relevant structural changes have recently occurred and this can affect their evolution in the future.[9] Foresti, Guelpa and Trenti (2009) use balance sheets indicators for a wide sample of manufacturing firms (unbalanced panel) over the period 1991-2006. Controlling for different characteristics (e.g. sectoral specialization, size) they find signs of a fading of the district effect during the late nineties and the early 2000's.

3. ID and UA definition in Italy and some structural differences

To assess the existence of local productivity advantages one needs first to map ID and UA areas. In Italy, IDs are officially defined by Istat using a multistep algorithm. Although not free of flaws, this methodology rapidly became a sort of benchmark for assessing the so called ID premium, i.e. the productivity gain associated to the location in an ID area. Here we will then describe the methodology used to define these areas.

The departure point are the data on daily commuting flows from place of residence to place of work available for the 8,100 municipalities in Italy. Contiguous municipalities are then aggregated into larger areas called Local Labor Markets Areas (LLMA) using a procedure which maximizes labor mobility within LLMA and minimizes that across LLMA. The outcome of this procedure mapped the Italian territory into 784 LLMA in 1991 (686 in 2001)[10]. Notice

[9] On the structural evolution of the ID see also Carabelli, Rabellotti and Hirsch (2009).

[10] In the following, the empirical analysis is carried out on the basis of the 1991 map of IDs. The choice is motivated by the opportunity of using a classification that is predetermined with respect to the sample period considered in the analysis. In this way, simultaneity problems, due to possible feedback effects from local

that LLMA's represent an ideal partition to analyze many agglomeration effects since most of them are conveyed though the interactions taking place within the local labor market. However, this zoning system can be sometimes problematic as far as the definition of the relevant market for manufacturing products is concerned (more on this below).

IDs are defined as those LLMAs satisfying the following conditions:

a) specialization in the manufacturing sector, i.e. $l_a = \frac{(x_{am}/x_a)}{(x_{\bullet m}/x_{\bullet\bullet})} > 1$ where x_{am} denotes the number of employees in area *a* and in all the local manufacturing industries, x_a denotes the total employment (including service and the building sector) in the area, and $x_{\bullet m}, x_{\bullet\bullet}$ are the corresponding figures at national level.

b) $s_a = \frac{(x_{am}^{small}/x_{am})}{(x_{\bullet m}^{small}/x_{\bullet m})} > 1$ where the upper index 'small' indicates the number of employees working in small and medium sized enterprises.

c) Let $l_{as} = \frac{(x_{as}/x_{am})}{(x_{\bullet s}/x_{\bullet m})}$ denote the location quotient for each specific manufacturing industry *s* and define the 'dominant manufacturing industry' *d* as the one for which $l_{ad} > 1$ and the level of employment is at maximum among the local specialized industries. For *d*, the following condition must hold: $s_{ad} = (x_{ad}^{small}/x_{ad}) > .5$.

d) Finally, in the case there is only one medium-sized enterprise, the share of small enterprises employment must exceed half of employment in the medium one.

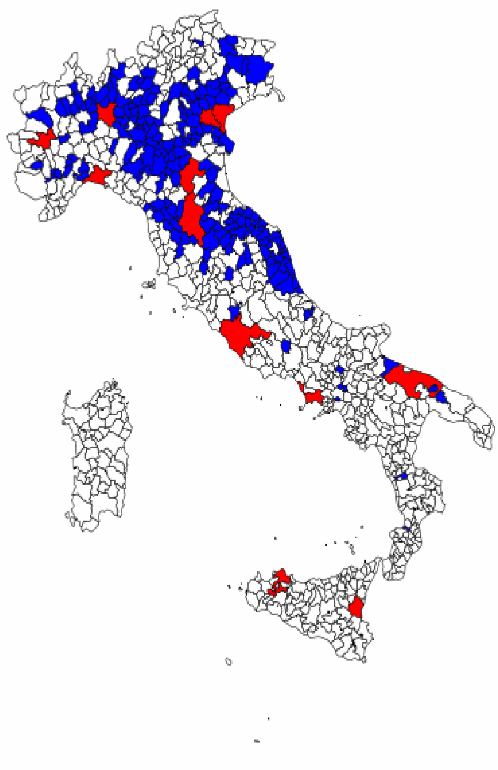
Put simply, according to this definition, ID are LLMA where medium and small enterprises represent a significant share of employment both in the manufacturing sector as a whole and in the specialization sector. Notice that condition under a) nearly automatically rules out the possibility that an UA can be defined as an ID since the former are usually characterized by the presence of a large service sector.

productivity dynamics to the likelihood that a LLMA is classified as an ID, are reduced. However, our main results remain substantially unaffected when using the 2001 map.

As for the mapping of the urbanization phenomenon in Italy, we use a very simple definition: UA are those LLMA's for which the resident population is above 500,000 inhabitants. Although Italy was historically known as the 'country of one hundred cities', it did not see the development of the urban giants featuring the economies both of several developed and underdeveloped countries. Hence, setting a relatively low threshold level to define UA seems to be consistent with the low degree of urbanization in the Italian economy. By using these categories we obtain three non-overlapping sets of localities (the third one is defined as a complement with respect to the groups of LLMA included in ID and in UA; see figure 1). Only Padua had characteristics matching both the definition of ID and UA; we opted for including that LLMA into the ID group of locations.

In 1991 the algorithm singled out 199 IDs (out of 784 LLMAs), while in 2001 the number of IDs dropped at 156 (out of 686). As the map clearly shows, a prominent spatial feature of the agglomeration phenomena in Italy is their localization almost exclusively in the North and in the Centre of the country. As for the spatial distribution of UA, it turns out that they are spread more uniformly across the different macro regions of the country.

Fig. 1 - Map of ID (in blue) and UA (in red) in 1991



4. Data

The empirical analysis presented in this paper was carried out on a large panel of approximately 29,000 Italian manufacturing firms (not plants), observed over the period 1995-2006, and built as follows.

Yearly balance sheet figures on value added, consumption of intermediate goods, fixed investment and capital stock were drawn from the Chamber of commerce-Company Accounts Data Service database (Centrale dei Bilanci / Cerved). Additional firm level data, including the sector of economic activity (up to the 4 digits SIC sector classification), firm location (municipality where the firm is established) and number of employees were also included as auxiliary information in the database.

The information about the municipalities where firms are located allows us mapping them into the 784 LLMAs and hence into the three area types described above. Only one third of the firms in the database report employment data. To overcome this shortcoming, missing employment figures were imputed by means of a statistical procedure, using total labor cost as the main auxiliary information in order to recover missing data on the number of employees (see the Appendix 1 for the details of this methodology). In fact, unlike the information on the number of employees, data on total labor costs are available for all the firms in the sample.

The capital stock at firm level has been estimated from the book value of investment using the permanent inventory method and accounting for the sector-specific depreciation rates from the Italian National Accounts data. The capital stock in the initial year has been estimated using the deflated book value, adjusted for the average age of capital calculated from the depreciation fund (see Bond et al., 1997). Nominal value added and consumption of intermediate goods figures were deflated by using industry specific price indexes.

Firms with less than 5 employees were removed from the sample since data were very noisy for that size class. Our final dataset includes 392,874 observations, nearly equally distributed over the two sub-periods (1995-2000 and 2001-2006; see Table 2). Due to the exclusion of some outliers (see more on this below), we actually use 344,353 observations in our econometric analysis: this means we have on average about 28,700 firms per year, a very large sample compared to those used by all the previous contributions on the same topic.

Slightly more than a half of the observations refer to firms in ID and nearly one fourth to UA. Coherently with the characteristics of the entire population (see Istat, 2006) the share of firms located in the south of Italy is quite small both in UA and in ID sample.

On average, UA firms hire 77.5 workers as compared to 43.9 and to 54.4 employees hired by IDs and non-ID/UA firms. Clearly, our sample is partially biased toward large firms especially if we consider the prevalence of small enterprises within the Italian manufacturing industries. This characteristic mainly reflects our choice to drop firms with less than 5 employees from the sample and in a lesser degree is also related to the fact that the Centrale dei Bilanci / Cerved database does not include specific firm categories like sole proprietors. Although we are aware that this fact may generate some caution in the interpretation of our results, we strongly prefer dropping firms below the aforementioned threshold in order to avoid a worsening of the data quality. Average firms size for the entire sample dropped from 88 to 67 employees between the two sub-periods while remained constant in the ID areas (Table 3).

As far as the ranking of areas in terms of labor productivity is concerned, the descriptive statistics show that in the North of Italy firms in ID have a higher per capita value added than non agglomerated areas, but lower with respect to UA. In the Centre-South of the Country, ID fall behind both with respect to UA and to non agglomerated firms (Table 4).

The North-South gap in labor productivity (that amounts to 25-30 percent, a result in line with other studies[11]) emerges in all the types of areas (ID, UA and the other locations not included in the previous two groups) and is larger for ID. The sectoral distribution reveals that about 45 per cent of the observations are related to the metal and metal products, mechanical and machinery, textiles and apparel industries.

5. TFP estimation

Our estimation strategy proceeds in several steps. First, production function estimates at firm-level are obtained using different methodologies and total factor productivity (TFP) for each firm is computed as the residual of the estimated production function. Second, firm-level

[11] The North-South economic divide is an issue of paramount importance for the Italian economy (see for example: Cannari, Magnani and Pellegrini, 2009). Investigating it in relation to the geographical distribution of agglomeration economies could be rewarding. However this falls outside the research scope of the present paper.

TFP estimates are regressed on a set of independent variables with the purpose of uncovering productivity differentials across the three groups of areas defined in the previous section.

In order to derive individual TFP measures, the following standard Cobb-Douglas production function was considered:

$$Q_{i\in(r,s)t} = \Phi_{it} L_{it}^{\alpha_s} K_{it}^{\beta_s} \quad (1)$$

where *L* and *K* denote labor and capital inputs used to produce the amount of output *Q* in the year *t* by firm *i* belonging to sector *s* and located in LLMA *r* [12]; α_s and β_s are the production function coefficients, that are allowed to vary across sectors.

After log transformation the following estimating equation ensues (lowercase letters denote logs):

$$q_{it} = \alpha_s l_{it} + \beta_s k_{it} + \phi_{it} \quad (2)$$

from which the firm-level log-TFP can subsequently be computed as the residual:

$$\hat{\phi}_{it} = q_{it} - \hat{\alpha}_s l_{it} - \hat{\beta}_s k_{it} \quad (3)$$

provided that consistent estimates of parameters α_s and β_s are available.

Equation (2) was estimated by ordinary least squares (LS), individual firm fixed effects (FE) and Levinsohn and Petrin (LP) methods to control for input-output simultaneity, (see Levinsohn and Petrin, 2003). As for the latter methodology, it is based on the idea that the error term in (2) can be decomposed into two components: $\phi_{it}=\omega_{it}+\varepsilon_{it}$ where the first is observed by the firm but not by the econometrician while the second one is assumed to be an i.i.d. noise uncorrelated with the inputs. To eliminate the correlation between ω_{it} and input choice LP propose to use the following control function: $m_{it}=f_t(\omega_{it}, k_{it})$ where the demand of the intermediated inputs such as electricity, fuel and materials is considered a function of the productivity shock observed by the firm and the (predetermined) capital stock at time t. Under the assumption that the latter function is monotonic in m_{it} it is possible to invert $\omega_{it} = f_t^{-1}(m_{it}, k_{it})$

[12] To avoid cluttering notation, in the following we drop the reference to the LLMA and the sector when indexing variables referring to the individual firm.

and substitute this expression into (2). By doing so, the unobserved component in the firm productivity causing the simultaneity bias is eliminated and equation (2) can be estimated through non parametric methods after some additional moment restrictions. This methodology does not assume that the unobserved productivity component be time invariant as in the FE, moreover it does propose a control function solidly based on profit maximization; finally it is also relatively easy to implement and less demanding in terms of data requirements as compared for instance to the Olley and Pakes (1996) procedure.[13]

Considering that the elasticity of output to capital and labor inputs may vary considerably across industries, due to intrinsic differences in productive technologies, we run distinct regressions for each industry according to the two-digit SIC classification. In this way we were also able to control for sector-specific time trends, by introducing temporal fixed effects in the panel estimation procedure. To allow for some degree of firm heterogeneity within each two-digit SIC industries, fixed effects at the level of three-digit SIC codes were also included.

Firms with less than 5 employees were dropped from the sample prior to estimation for data reliability issues. Following the same line of reasoning, firms attaining extreme values of the K/L ratio were also excluded. As a result, the final sample dropped to about 28,700 firms per year. Despite the trimming and quality controls, the size of our sample is at least double than those used in similar papers on Italian manufacturing firms.

Estimated labor and capital elasticities are displayed in Table 5. Overall, results obtained according to the three estimation methods do not show large differences, although the LS estimates exhibit slightly larger values as compared to those resulting from FE and LP methodology, thus confirming the likely presence of the expected positive simultaneity bias. LP estimates show generally larger elasticities for the capital input and correspondingly lower estimates for the labor input as compared to FE, the sum of the two coefficients attaining very close values in the two cases. Decreasing returns to scale (RTS) seem to be the prevalent regime in our estimates, although a formal test of constant RTS did not reject the null for the majority of sectors considered in the analysis. Estimated TFP levels are highly correlated across the three estimation methods, the Pearson correlation coefficient attaining values equal or higher than 0.95.

[13] Olley and Pakes (1996) propose the control function based on investment rather than on intermediate goods. The trouble is that this function cannot be inverted when investment is zero, a frequent occurrence in the data including our sample of manufacturing firms. For this reason we resort to the LP methodology.

6. Estimation results on TFP differentials

Based on firm-level TFP estimates obtained according to the procedure detailed in the previous section, we run the following regression:

$$\hat{\phi}_{it} = \delta UA + \eta ID + \rho \; flagimp_{it} + \Sigma_h \mu_h \; firmsize^h_{it} + \gamma_g + \lambda_s + \varpi_t + \varepsilon_{it} \quad (4)$$

where

- UA and ID are binary dummies indicating firms located in UA or ID and δ and η are unknown coefficients measuring average TFP differentials between these two types of LLMAs and the remaining ones, which act as the reference group;
- *flagimp* is a control dummy signaling if L_{it} has been either imputed or alternatively reported by the firm;
- *firmsize*^{h} is dummy variable taking value 1 if the size of the firm, measured by the number of employees, belongs to the *h*-th of *H* classes resulting from a discretization of the range of possible employment levels (size categories are : small firms <= 49 employees; medium firms: 50-249; large firms: > = 250);
- γ_g , λ_s and ω_t are area[14](macro areas are: North West, North East, Centre; South), industry and year fixed effects;
- ε_{it} is an error term defined as the sum of two independent random components, an LLMA component and a purely idiosyncratic residual:

$$\varepsilon_{it} = \iota_r + \eta_{it} \quad (5).$$

Through the inclusion of a firm size indicator in the specification we get rid of the differences in productivity levels that may depend on the fact that IDs can be more favorable areas for small business location (see Appendix 2 for a discussion on the relation between TFP and firm size). The geographical fixed effects γ_g allow for unobserved, time invariant factors affecting firm productivity across different areas. Industry fixed effects control for the

[14] Two broad partitions of the Italian territory are considered on this respect, corresponding, with some minor exceptions, to the NUTS1 and NUTS2 levels of the European regional classification.

influence that different sectoral composition between UA and ID might have on the estimation results as well as for the well known problem of comparing productivity levels across different sectors.

Finally, the rationale for introducing a control for the data imputation process lies in the opportunity of avoiding that any systematic bias possibly affecting our TFP estimates for firms with imputed employment levels is transmitted to the estimates of spatial productivity differentials (which, in any event, would only occur if the share of imputed observations is not the same across UA, ID and other LLMA).

Given the assumptions about the error term in (5), we estimate eq. (4) by clustering error terms at the individual LLMA level. Estimation results for this specification and for LP estimation method are displayed in Table 6.[15]

The estimated TFP differential is positive and highly statistically significant for both UA and ID. With respect to the reference group, a larger advantage is estimated for firms located in UA (10 percent) as compared to those operating within IDs (3 percent). In unreported evidence we show that these results do not change when using TFP obtained through OLS or FE estimation methods. Moreover, we tested that the coefficients for UA and ID are systematically different. For instance for Model I in Table 6, we run a Wald test and obtain an $F(1,688)$ with value 66.31 showing that we can strongly reject the null hypothesis that the two coefficients are not significantly different. This test is carried out throughout all the other specifications and the results based on it always reject this hypothesis. To save on space we do not report the results of these tests.

In line with previous evidence, firms located in the Centre and, above all, in the South achieve much lower productivity levels compared to those located in the North; the estimated gap is about 24 percent for Southern firms and 3 percent for those located in the Centre.

Estimated coefficients display a significant non linear relationship between firm size and log-TFP, suggesting that medium-sized firms have productivity levels only slightly superior to small firms, while a higher advantage is attained by large firms. However, the nexus between firm size and productivity may depend on the characteristics of the local environment. More precisely, we expect that small-sized firms exhibit comparative advantages by locating in ID

[15] For the sake of brevity, estimation results for the *flagimp* variable are not reported. In all cases, the estimated coefficients turned to be negative and significant. This finding suggests that firms that do not report employment data are less productive than the average firm. In any event, including or excluding this control variable did not alter significantly our main estimation results.

areas. To explore this issue, we introduce into the regression the interaction between firm size and LLMA type (ID and UA). This exercise indeed shows that the productivity disadvantage of smaller firms is less marked inside ID. Overall, estimates of the productivity surplus in UA and ID obtained with the baseline specification are confirmed.

A slight reduction of TFP advantages in favor of UA and ID is observed when the three area dummies are replaced by a full set of fixed effects for the 20 Italian administrative regions (Table 6, Model III).

Our production function estimates do not take into account the so called output price dispersion problem.[16] Specifically, valued added has been deflated by a common industry wide price index. If firms in UA set higher prices these would end up in the residual (see equation 3) and hence would bias upward the estimated urban productivity premium. Prices in UA could be higher provided firms located there have a stronger market power, produce higher quality goods or because congestion or life costs are larger in cities compared to other areas. This potential criticism can be easily dismissed on the grounds that local conditions can hardly have a significant effect on the prices of the manufacturing goods as the relevant market for them is the entire country if not the world as a whole. Moreover, if any it is likely that local conditions would have the effect of inducing firms in cities to quote lower and not higher prices. This could occur for instance either because competition is tougher in cities or because the wholesale and retail trade sector is larger and more efficient there compared to other areas. Hence, the magnitude of our estimated urban productivity premium could be excessively conservative as it might be even larger once output price dispersion were taken into consideration.

To check our results, we modify the UA definition by using two different population thresholds set to 200,000 and 900,000 inhabitants and rerun equation 4 accordingly. Notice that using the lower threshold would make the interpretation of results more complex as now some ID's can also be included in the group of UA. In unreported evidence, we show that local productivity advantages in UA defined according to the two thresholds are a bit lower that those estimated in the baseline specification. As for ID's, we obtain similar results in the case of the 200,000 population threshold while the ID productivity premium vanishes when using the larger one (900,000 inhabitants). The latter result is due to the fact that the non ID and non UA areas now encompass highly productive locations that are not at a disadvantage as

[16] See Del Gatto, Ottaviano and Pagnini (2008) for a discussion and a possible empirical solution to this problem.

compared to ID's. Although we modify our UA definition as a robustness check, we want to emphasize that our previous choice of 500,000 inhabitants have the twofold advantage of generating a non overlapping classification of the area types and at the same time of defining a threshold above which it is likely that urbanization phenomena fully display their effects.

We also run distinct regressions for each industry and unreported results indicate that comparative advantages associated to ID and UA do not differ much across sectors. In Appendix 3 we report additional robustness checks, based on running similar regressions to equation (4) at aggregate rather than at individual firm level, using instrumental variables and for the subsample of small sized firms. These additional checks confirm our results.

7. Discussion of the main results

One of the main results of our analysis is that firms located in UA outperformed in terms of productivity advantages those located in ID. As a first step towards the identification of the factors that may explain this occurrence, in this section we provide additional evidence on the evolution of the local productvitiy advantages, the role of the skill composition of the labor force and finally on a quantile regression analysis of the data.

7.1 - The evolution of local productivity advantages in the UA and ID

During the twelve years covered by our analysis, the Italian economy was affected by important transformations. The rapid and increasing diffusion of Information and communication technologies (ICT), the upsurge of China, India and Brazil in the international trade and finally the introduction of euro, all together induced a deep restructuring of Italian manufacturing firms. Moreover, all these factors probably gained momentum in the second part of the period. Actually, the euro was introduced in 2001, new technologies fully displayed their effects on workplace organization in the same period and finally China's share rise on world trade accelerated after the 2000. The question we want to investigate is whether these transformations favored more either the firms located in UA or those established in ID.

To this aim, the three specifications considered in Table 6 were subsequently estimated by splitting the panel into two sub-periods of the length, respectively ranging from 1995 to 2000 and from 2001 to 2006. The main findings point to a relative stability of the TFP advantage in UA over the two sub-periods, while the productivity premium estimated for ID shows a decline, from about 4 percent to 2 percent, loosing statistical significance when regional fixed effects are introduced (see Table 7, Model III). These results suggest that firms located in UA have faced the shocks that hit the world economy better than district firms did.

There might be several explanations for this finding, here we hint at some. On one hand, it is possible that the larger endowments of skilled workers in UA allowed a more efficient use of the new technologies and a better ability to rise the product quality and introduce product innovation in response to increased competition (see the next sub section on this topic). On the other, firms might have benefitted from the diversity of the UA environment. In a period where the ability to update products and to innovate were crucial for firms success, the interactions with enterprises belonging to other industries including the service sector magnified the possibility for firms under restructuring to undertake new modes of production and to experiment new strategies.[17] The same advantages could not be reproduced by the interactions within ID as they involve small manufacturing firms belonging more or less to relatively similar industries.

7.2 - The role of human capital

A source of comparative advantage for cities may be traced back to higher human capital endowments. In fact, UA may be especially successful in attracting more educated people because they allow skilled workers higher chances to find a good match with a firm on the thick and diversified local job market. At the same time, cities may attract highly educated people through the local supply of urban specific amenities. The empirical evidence detailing higher labor force educational attainments in larger cities is outstanding. For the Italian case, recently Di Addario and Patacchini (2008) confirmed that high skilled workers concentrate in the most populated cities and benefit from a urban wage premium.

If, ceteris paribus, firms located in UA hire more skilled workers than firms operating in other local labor systems do, omitting to control for the skill differential in the labor force will result in larger residuals in the estimated production function, which can be wrongly attributed to higher TFP levels.

In order to provide some new evidence on the role of human capital on productivity in local labor markets, we relied on a measure of labor-force composition at firm level obtained

[17] The mechanism we are describing is similar to the 'nursery effect' of Duranton and Puga (2001) with the difference that we do not believe that it can be restricted to young and small sized firms.

from the Italian social security administration (Istituto Nazionale Previdenza Sociale, INPS) archives. The INPS database covers the entire universe of Italian firms with at least one employee and provides information on the total number of employees broken down into production and non-production workers, respectively defined as white and blue collars in what follows.

Using Italian data, Castellani and Giovannetti (2010) show that the share of blue collars is strongly associated with firm's TFP, thus highlighting a possible misspecification in the production function. On this respect, the authors suggest that the labor input should be split into different components capturing the different skill intensities, allowing for a more flexible specification of the production function.

Building on this argument, we resort to a new set of production function estimates that include explicit controls for the labor force composition at the firm level. To do so, we pooled data on the number of blue and white collars from the above-mentioned INPS archives with our original Centrale dei Bilanci/Cerved (CEBI) database. The resulting panel includes a lower number of firms, due to imperfect matching of firm codes in the two data sets, and to a shorter time period covered by the INPS archive (the time interval is limited to the period 1995-2002).

Using this database, we replicated our multi-step estimation strategy. In the first step the Levinsohn and Petrin method was employed to estimate the following augmented production function:

$$q_{it} = \alpha_s^b l_{it}^b + \alpha_s^w l_{it}^w + \beta_s k_{it} + \tilde{\phi}_{it} \quad (2b)$$

where l^b and l^w and respectively denote (the log of) the number of blue and white collar employees. Subsequently, the revised TFP estimates obtained from the residuals of eq. (2*b*) were used to run a TFP regression analysis akin to the one detailed in equations (4) and (5). Regression results based on TFP estimates derived from model (2*b*) are reported in Table 8. Considering that the augmented production function was estimated on a different sample, in order to provide a proper benchmark, we also re-estimated TFP levels fitting the baseline Cobb-Douglas production function specification (Eq. 3) to the pooled INPS/CEBI data set. All in all, relying on a different panel of firms, featuring partially dissimilar employment data, does not appear to affect estimation results in a substantial way, as can be directly checked by comparing results in Table 9 and Table 6.

Upon controlling for labor force composition, the estimated TFP advantage of firms located in UAs remains large, only slightly declining compared to the baseline results (from about 9 p.p to about 8; see Tables 8 and 9). In other words, the productivity differential in favor of UA-located firms does not appear to depend (or depends only to a small fraction) on the fact that the labor force composition in UA is characterized by a larger share of skilled workers.

As a further refinement, we have obtained new estimates of the augmented production function specification, allowing the elasticity of output for the two labor inputs to take different values for firms located in ID and UA. This less restrictive specification is introduced in order to take into consideration the fact that white collars could be more productive in UAs, while blue collars may be more efficiently employed within ID.

On the one hand, the growing literature on urban agglomeration has underlined the role of cities in the generation and transmission of new ideas that can spur innovation and productivity. On this respect, highly educated workers may be better equipped than less skilled ones to benefit from the flow of information that is diffused within urban areas by recurrent face-to-face interactions (Glaeser, Rosenthal and Strange, 2009; Glaeser and Ponzetto, 2010). On the other hand, the literature on industrial districts has emphasized the impact of agglomeration on the skill accumulation on part of production workers, whose ability to "make things well" benefits from the local "industrial atmosphere" (according to a well-known Marshall's definition) facilitating learning by doing.

Extended production function estimates (reported in Table 10) provide support to the hypothesis that white collars are more productive in UA (the estimated elasticity is higher for firms located in UA compared to non agglomerated areas), while blue collars appear to be more productive in non urban areas. These results make sense in light of theoretical a priori. However, the evidence that in ID blue collars are relatively more productive then those in UA could not be good news for ID economic perspectives. In fact, in the current competitive framework, connoted by a rapidly increasing competition from newly-developed countries, the role of white collars may turn out to be crucial in order to foster innovation and quality upgrading of the firms' products.[18]

[18] See the report on the recent evolution of Italian manufacturing sector by Brandolini and Bugamelli (2009) and also the discussion in Glaeser and Ponzetto (2010).

When different output elasticities to labor inputs are allowed for, estimated TFP differentials mark a slight erosion of the productive advantage of UA. Nonetheless, the latter remains significant and substantial, ranging between 4.4 and 6.9 p.p according to the different specifications (Table 11). The coefficient of the ID dummy now becomes not statistically significant, suggesting that the TFP differential in favor of ID uncovered by our baseline estimates may essentially be attributed to the larger productivity of blue collars in this environment, rather than to a global shift in the efficiency of the production process. The large advantage of UA is instead only for a small part due to the professional qualification of urban workers: in this sense, it remains unexplained.

7.3 - Quantile analysis

The three sources of local productivity advantages discussed so far, i.e. agglomeration economies, selection and sorting, may have different effects when the TFP distributions of regions with a strong or low concentration of economic activity are compared.[19] Agglomeration economies are assumed to rise the productivity of all the firms in a spatially concentrated region, thus we should expect a rightward shift in the entire TFP distribution. Selection models show that the positive effect of geographic concentration is mainly directed at the lower tail of the TFP distribution as in dense areas less efficient firms are forced to exit from the local market. Finally, if highly skilled workers or more efficient firms benefit more from agglomeration economies or the latter are better able to resist to competitive selection in denser areas, we could have a positive effect on the upper tail of TFP distribution (dilation effects).

To understand how these three forces shape TFP distribution in UA and ID we extend our econometric analysis to a quantile regression.[20] Through that it is possible to enrich the picture of the relationship between the response variable and the regressors at different points in the conditional distribution of the dependent variable. From this point of view, the linear in mean regression analysis adopted so far simply assumes that the effect of the regressors on the conditional mean is representative of the shift in the entire distribution. Apart from this advantage, the quantile regression is also less exposed than the mean regression to the

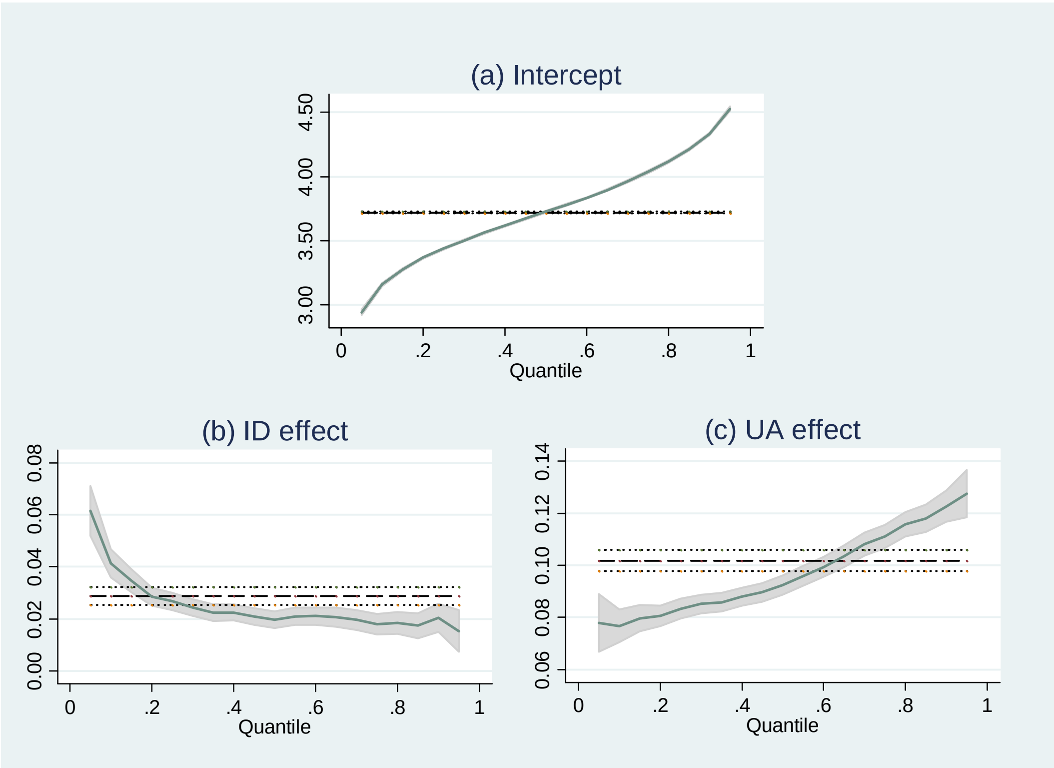
[19] See Combes et al (2009) for a deep discussion on this topic.

[20] For an analysis similar to ours see Arimoto, Nakajima and Okazaki (2009) and Briant (2010). Quantile regression was introduced by Koenker and Bassett (1978).

problems of outliers. Finally, being semiparametric in the sense that avoids assumptions about the distributions of the error terms, this tool is particularly suitable for heteroskedastic data.

Results based on the quantile regression are reported in Table 12. To further improve on efficiency of the estimation, we bootstrapped the standard errors. In figure 2 we also report a graphical analysis including OLS and the quantile regression coefficients for UA and ID

Fig. 2 – Quantile regression: ID and UA effects (1)



(1) The horizontal line corresponds to OLS coefficients, grey areas and horizontal dotted lines denote 95% confidence intervals for the estimated parameters. Quantiles vary from .05 to .95 and are incremented by .05.

Several interesting patterns can be detected from this additional evidence. First, the productivity advantages associated to UA and ID are confirmed across the different percentiles of the TFP distribution thereby showing that previous findings were not restricted to the impact of the covariates on the conditional mean. Moreover, apart from the first percentile of the TFP distribution, UA productivity premium is always above that observed in ID areas, consistently with our previous results. Finally, the productivity advantages associated to ID very neatly shrink as we move from the lower to the upper tail of the distribution while the opposite holds true for the UA.

The fact that ID and especially UA coefficients are positive and significant at all quantiles suggests that agglomeration economies actually shift the entire TFP distribution rightward or that at lest part of them positively affect TFP of all the firms located in dense regions. At the same time, the magnitude of these coefficients vary across quantiles and according to different patterns in ID and UA pointing to the fact that also selection and sorting may contribute to shape the TFP distribution.

As for selection we detected some evidence consistent with it in ID as their productivity advantages are stronger in the lower tail of the TFP distribution while we do not find a similar effect in UA (see Figure 2 panels b and c). The alternative interpretation based on sorting would argue that more efficient firms gain more from the kind of agglomeration economies created in UA while, the other way round, less efficient enterprises are better equipped to gain from the externalities generated in ID.

Although disentangling between these alternative explanations is beyond the scope of the paper, we don't think that selection models can actually contribute to give account of the different patterns in the relationship between geographic concentration and TFP found in ID and UA. The reason is that the zoning system based on LLMA is not appropriate to represent the relevant market in the case of manufacturing products. Actually, Accetturo et al (2011) show that a selection effect may emerge when considering a broader spatial scale.

Hence, we conjecture that the differences between the two curves in Figure 2b and 2c, can be driven by some kind of sorting process. ID are able to generate local productivity advantages that can be more effectively appropriated by less efficient firms while the externalities produced within the urban environment can be better exploited by the most productive enterprises. The thick network of productive relationships generated by the ID seems to favor most those firms that would be very inefficient should they carry out their activity in isolation and outside that network. As for cities, more productive firms that were able to survive to tougher competition in that environment are also likely to be the ones able benefitting more from the interaction with firms in other sectors (diversity) or from the improved matching with a well qualified local labor force.[21] This result is partially at odds with that in Duranton and Puga (2001) showing that cities benefit younger and relatively less efficient firms. It does not fully square up also with the evidence presented by Holmes and

[21] For a model where agglomeration benefits are higher for more productive firms, see Combes et al (2009). For a model combining the toughness of competition associated to cities and a better matching in the local labor market, see Venables (2011).

Stevens (2010) showing that the US cities attract small and less efficient firms producing high quality goods while non urban specialized regions host large and more efficient firms producing standardized goods.

Evidently, all these topics must be investigated more deeply in order to check their robustness and to put forward proposals for possible policy prescriptions.

8. Final remarks

This paper has investigated the issue of local productivity advantages, using data referred to about 29,000 Italian manufacturing firms observed along 12 years (1995-2006). We mapped firms into three non-overlapping categories according to their respective location (urban areas, UA; industrial districts, ID; non-UA/ID) and performed firm-level TFP estimates using a broad set of techniques.

On the whole, our analysis suggests that spatial concentration exerts favorable effects on local productivity. The estimated coefficients for the UA and ID dummies are both positive and significant. However the localization in an UA appears to be largely more favorable than that in an ID (with an estimated coefficient 3 to 5 times larger according the specification utilized).

While manufacturing firms located in UA on average employ a better qualified labor force, TFP estimates that explicitly control for such skill differential show how the productive advantage of large cities appears to be driven only to a minor extent by differences in the human capital endowment of employees. Using quantile regression techniques, we are also able to show that ID generate local productivity advantages that can be more effectively appropriated by less efficient firms while the externalities borne out within cities can be better exploited by the most productive enterprises.

With the purpose of evaluating the dynamic pattern of productivity over the period (1995-2006), we run a new regression analysis splitting the sample in two sub-periods. It turns out that comparative advantages of UA remain stable while those of ID show a tendency to decline over time. Within cities industrial agglomerations have remained vital, even in a period characterized by the growing globalization and by the fall of transportation and communication costs. Thus, our results suggest that firms operating within UA, better than those located in ID, have shown a high degree of resilience to the shocks that hit the world economy over the last decade.

Finally, one should ask what the policy implications of our findings are. Actually the purpose of our work is not to suggest a path for the Italian productive system to follow, nor do we want to propose active policy actions to support ID or UA, since defining optimal policies for clusters is a very difficult task. In fact, the question is: what should these policies do? If the answer is 'to solve major inefficiencies', then policy makers should know exactly where do these inefficiencies come from (see Duranton, 2009, for a more detailed analysis). Appropriate policies are thus not easy to formulate and can even result in a waste of resources if not supported by the deep knowledge of the inefficiencies to deal with (linked for example to congestion or to the disappearing of once existing positive externalities). Only with this knowledge in the hand one could formulate and suggest possible policy actions. The present paper can be considered as a first step in this line of research.

TABLES

Table 1

The importance of being agglomerated: the district effect in Italy

Authors	Strategy		Model	Dependent variable	Agglomeration advantage (1)
Signorini (1994)	Firms performance	Case study on Prato industrial district		Per capita value added	
Fabiani et al. (2000) (2)	Firms performance	Cross section in 1995 (firm level analysis)	Descriptive stats. & Stochastic Frontiers – ML estimates	Roi, Roe Value added per worker	+2.0 p.p. +4.1 p.p. +1.3 %
Gola and Mori (2000)	Export structure	Panel data (firm level) 1,092 obs period 1983-1995	Fixed effect estimates	Normalized trade balance	+ 3.4 %
Bronzini (2000)	Export performance	Data at provincial level; pooled data (1995-1997)	OLS, SURE estimates	Export propensity (log of export per worker as a share of national average)	+7.0 %
Becchetti and Rossi (2000)	Export intensity	Mediocredito survey Firm level data; 1989-1991 (avg) 3,695 obs.	Tobit estimates Probit estimates	Share of export on total sales Exporter status (dummy)	+ 3.6 p.p. +20 %
Cainelli and De Liso (2005)	Firms performance	Period 1992-1995 (2,821 obs)	OLS, IV estimates	Rate of change of real value added	2.0 – 2.6 %
Becchetti and Castelli (2005)	Firms performance	Mediocredito Survey (two waves: 1995-1997 and 1998-2000)		Value added per capita	+1.8 %
Bugamelli and Infante (2005)	Export status	Firm level (31,000 firms, 270,000 obs. 1982-1999).	Probit estimates	Exporter status (dummy)	+ 0.02 p.p.
Cingano and Schivardi (2005) (3)	Firms performance	Firm level (1,602 obs.)	OLS estimates	The elasticity of productivity (TFP) change to the SLL degree of specialization	+ 0.2 / 0.4 p.p.
Foresti, Guelpa and Trenti (2009)	Firms performance	Different indicators, 2006		Roi (descriptive statistics)	- 0.25 p.p.

(1) Difference between firms in districts with respect to firms not in districts. - (2) The authors also perform a sectoral analysis of firms' efficiency using the stochastic frontier approach, finding evidence of less inefficiency for firms localized in districts for 8 out of 13 sectors. - (3) They produce indirect (although robust) evidence in favor of a district effect, testing for LLMA whether the increase of the industry degree of specialization (an index of externality typical of districts) determines a change in TFP growth.

Table 2

The sample: number of observations

Sectors	Industrial Districts	Urban Areas	Other	Total
Food products, beverages and tobacco	9,985	4,837	10,549	25,371
Textiles and textile products	28,656	6,418	7,528	42,602
Leather and leather products	11,847	3,456	2,078	17,381
Wood and products of wood and cork (except furniture)	5,588	1,575	3,898	11,061
Pulp, paper and paper products; recorded media; printing services	9,046	10,048	4,934	24,028
Coke, refined petroleum products and nuclear fuel	290	496	562	1,348
Chemicals, chemical products and man-made fibres	4,938	5,810	2,796	13,544
Rubber and plastic products	11,512	5,152	5,275	21,939
Other on metallic mineral products	10,266	3,205	8,435	21,906
Basic metals and fabricated metal products	40,834	18,479	20,952	80,265
Machinery and equipment n.e.c.	29,635	14,547	12,286	56,468
Electrical and optical equipment	14,387	12,741	7,540	34,668
Transport equipment	3,658	3,725	3,759	11,142
Other manufactured goods n.e.c.	18,371	5,690	7,090	31,151
North-West	80,260	52,260	27,198	159,718
North-East	74,113	18,268	28,630	121,011
Centre	40,088	14,566	16,580	71,234
South and islands	4,552	11,085	25,274	40,911
1995-2000	93,251	46,803	43,783	183,837
2001-2006	105,762	49,376	53,899	209,037
Total	**199,013**	**96,179**	**97,682**	**392,874**

Source: Elaborations on Centrale dei Bilanci, Cerved.

Table 3

Descriptive statistics: Firms' Size (number of employees)

Sectors	Size (average)			Size (median)		
	Industrial Districts	Urban Areas	Other	Industrial Districts	Urban Areas	Other
Food products, beverages and tobacco	53.1	95.4	46.0	19.1	21.5	17.2
Textiles and textile products	44.9	43.8	68.2	20.0	15.9	20.0
Leather and leather products	35.1	32.7	48.2	18.0	17.8	18.6
Wood and products of wood and cork (except furniture)	27.8	25.7	28.9	17.6	13.5	14.3
Pulp, paper and paper products; recorded media; printing services	37.4	57.0	44.0	16.0	14.5	16.1
Coke, refined petroleum products and nuclear fuel	93.7	276.6	39.4	19.0	34.0	14.0
Chemicals, chemical products and man-made fibres	62.8	154.9	87.2	21.0	40.0	19.0
Rubber and plastic products	42.2	77.9	51.0	21.3	21.0	21.1
Other on metallic mineral products	59.3	52.3	36.3	20.0	19.0	16.0
Basic metals and fabricated metal products	36.2	45.5	36.3	16.8	14.8	16.7
Machinery and equipment n.e.c.	47.8	67.2	80.6	19.8	18.5	19.5
Electrical and optical equipment	47.7	92.0	65.1	17.5	17.0	16.3
Transport equipment	104.4	329.6	149.2	23.2	26.0	23.1
Other manufactured goods n.e.c.	34.1	29.1	33.6	17.0	14.4	16.9
North-West	49.0	93.0	60.7	19.1	18.7	18.6
North-East	45.3	51.0	61.9	19.0	18.2	19.2
Centre	32.0	75.7	52.5	16.3	14.7	16.3
South and islands	38.9	50.8	40.2	19.8	15.4	15.7
1995-2000	46.0	88.0	60.6	20.0	18.8	19.6
2001-2006	42.2	67.6	49.3	17.1	16.2	16.0
Total	**43.9**	**77.5**	**54.4**	**18.4**	**17.3**	**17.5**

Source: Elaborations on Centrale dei Bilanci, Cerved.

Table 4

Descriptive statistics: Added value per worker (thousands of euros)						
Sectors	Added value per worker (average)			Added value per worker (median)		
	Industrial Districts	Urban Areas	Other	Industrial Districts	Urban Areas	Other
Food products, beverages and tobacco	64.5	66.7	57.0	159.2	157.2	172.4
Textiles and textile products	43.1	43.5	35.5	73.1	61.1	62.4
Leather and leather products	41.9	41.4	36.6	46.7	33.9	39.5
Wood and products of wood and cork (except furniture)	41.9	44.7	38.9	74.3	69.4	74.8
Pulp, paper and paper products; recorded media; printing services	52.0	55.1	48.9	99.3	81.9	101.9
Coke, refined petroleum products and nuclear fuel	118.5	111.9	92.7	253.4	425.5	224.4
Chemicals, chemical products and man-made fibres	69.6	74.8	66.1	137.2	134.0	141.4
Rubber and plastic products	48.4	49.8	44.6	95.6	96.6	104.2
Other on metallic mineral products	55.2	54.4	50.8	118.1	127.5	139.2
Basic metals and fabricated metal products	51.2	51.7	45.5	80.3	74.6	68.9
Machinery and equipment n.e.c.	53.1	54.8	50.1	60.6	57.1	60.5
Electrical and optical equipment	50.4	54.8	47.0	52.9	51.4	51.9
Transport equipment	46.0	48.3	42.8	70.2	72.0	68.3
Other manufactured goods n.e.c.	39.6	45.0	39.8	57.3	61.5	62.9
North-West	52.2	56.6	51.3	88.2	78.9	88.7
North-East	50.2	52.6	49.7	77.8	72.2	80.9
Centre	44.6	52.9	46.0	63.9	77.1	80.6
South and islands	38.3	43.8	40.5	78.3	91.5	103.9
1995-2000	44.9	48.4	42.2	77.1	76.8	88.0
2001-2006	53.7	58.9	51.1	81.1	80.8	89.7
Total	**49.6**	**53.8**	**47.1**	**79.2**	**78.8**	**89.0**

Source: Elaborations on Centrale dei Bilanci, Cerved.

Table 5

Returns to scale by industry *(standard errors in brackets)*									
	Levinsohn-Petrin			**Fixed Effects**			**Ordinary Least Squares**		
Sectors	Labor coef.	Capital coef.	RTS	Labor coef.	Capital coef.	RTS	Labor coef.	Capital coef.	RTS
Food products, beverages and tobacco	0.572	0.218	0.790	0.673	0.200	0.873	0.837	0.195	1.032
	(0.013)	(0.030)		(0.010)	(0.009)		(0.005)	(0.004)	
Textiles and textile products	0.708	0.272	0.980	0.866	0.131	0.997	0.871	0.123	0.993
	(0.008)	(0.015)		(0.008)	(0.007)		(0.004)	(0.003)	
Leather and leather products	0.716	0.261	0.977	0.842	0.136	0.978	0.884	0.137	1.021
	(0.009)	(0.020)		(0.011)	(0.009)		(0.005)	(0.004)	
Wood and products of wood and cork (except furniture)	0.724	0.235	0.959	0.830	0.110	0.940	0.898	0.125	1.023
	(0.018)	(0.027)		(0.012)	(0.009)		(0.006)	(0.004)	
Pulp, paper and paper products; recorded media; printing services	0.710	0.195	0.905	0.744	0.148	0.893	0.907	0.133	1.040
	(0.016)	(0.015)		(0.010)	(0.008)		(0.005)	(0.003)	
Coke, refined petroleum products and nuclear fuel	0.519	0.557	1.076	0.569	0.242	0.811	0.851	0.219	1.069
	(0.087)	(0.102)		(0.041)	(0.042)		(0.023)	(0.016)	
Chemicals, chemical products and man-made fibres	0.660	0.292	0.952	0.750	0.171	0.921	0.925	0.114	1.039
	(0.018)	(0.029)		(0.013)	(0.012)		(0.007)	(0.005)	
Rubber and plastic products	0.696	0.284	0.981	0.791	0.166	0.957	0.855	0.171	1.026
	(0.012)	(0.019)		(0.008)	(0.008)		(0.005)	(0.003)	
Other non metallic mineral products	0.665	0.312	0.977	0.816	0.131	0.946	0.880	0.171	1.051
	(0.012)	(0.031)		(0.009)	(0.009)		(0.005)	(0.003)	
Basic metals and fabricated metal products	0.727	0.207	0.934	0.821	0.127	0.948	0.871	0.139	1.011
	(0.004)	(0.007)		(0.004)	(0.003)		(0.002)	(0.001)	
Machinery and equipment n.e.c.	0.737	0.212	0.949	0.831	0.135	0.966	0.912	0.102	1.015
	(0.007)	(0.011)		(0.005)	(0.004)		(0.003)	(0.002)	
Electrical and optical equipment	0.730	0.193	0.923	0.825	0.119	0.945	0.904	0.110	1.014
	(0.008)	(0.012)		(0.007)	(0.006)		(0.004)	(0.003)	
Transport equipment	0.758	0.196	0.954	0.873	0.110	0.983	0.911	0.096	1.007
	(0.015)	(0.019)		(0.013)	(0.010)		(0.006)	(0.004)	
Other manufactured goods n.e.c.	0.746	0.210	0.956	0.856	0.139	0.995	0.935	0.107	1.043
	(0.009)	(0.015)		(0.008)	(0.007)		(0.004)	(0.003)	

Source: Elaborations on Centrale dei Bilanci, Cerved

Table 6

Estimation results on firm-level data.
Dependent variable: log of TFP measured through LP method (1)
(standard errors in brackets) (2)

	Model I	Model II	Model III (3)
UA	0.102***	0.108***	0.092***
	(0.01)	(0.01)	(0.01)
ID	0.029***	0.036***	0.016*
	(0.01)	(0.01)	(0.01)
Medium size	0.033***		0.037***
	(0.01)		(0.01)
Large size	0.160***		0.164***
	(0.01)		(0.01)
North-East	-0.001	-0.001	
	(0.01)	(0.01)	
Centre	-0.035**	-0.036**	
	(0.01)	(0.01)	
South	-0.242***	-0.242***	
	(0.01)	(0.01)	
UA*medium		-0.039*	
		(0.02)	
UA*large		0.030	
		(0.03)	
ID*medium		-0.037**	
		(0.01)	
ID*large		-0.001	
		(0.03)	
Number of observations	344,353	344,353	344,353
Adjusted R^2	0.677	0.678	0.679

Source: Elaborations on Centrale dei Bilanci, Cerved
(1) All specifications include year and industry fixed effects plus a control for imputed employees data. - (2) Standard errors are corrected for clustering at the level of individual LLMAs. - (3) It includes 20 region fixed effects.

Table 7

Estimation results on firm-level data, by period.
Dependent variable: log of TFP measured through LP method (1)
(standard errors in brackets) (2)

	Model I		Model II		Model III	
	1995-2000	2001-2006	1995-2000	2001-2006	1995-2000	2001-2006
UA	0.103***	0.102***	0.112***	0.105***	0.094***	0.090***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
ID	0.038***	0.021*	0.048***	0.025**	0.023**	0.010
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Medium size	0.011	0.053***			0.016*	0.056***
	(0.01)	(0.01)			(0.01)	(0.01)
Large size	0.133***	0.187***			0.140***	0.190***
	(0.01)	(0.02)			(0.01)	(0.02)
North-East	-0.002	0.000	-0.002	-0.000		
	(0.01)	(0.01)	(0.01)	(0.01)		
Centre	-0.032	-0.039***	-0.032	-0.039***		
	(0.02)	(0.01)	(0.02)	(0.01)		
South	-0.267***	-0.220***	-0.267***	-0.220***		
	(0.01)	(0.01)	(0.01)	(0.01)		
UA*medium			-0.051**	-0.029		
			(0.02)	(0.02)		
UA*large			0.010	0.052		
			(0.03)	(0.04)		
ID*medium			-0.047***	-0.031*		
			(0.01)	(0.01)		
ID*large			-0.022	0.017		
			(0.03)	(0.04)		
Number of obs.	166,168	178,185	166,168	178,185	166,168	178,185
Adjusted R^2	0.690	0.666	0.690	0.667	0.692	0.668

Source: Elaborations on Centrale dei Bilanci, Cerved
(1) All specifications include year and industry fixed effects plus a control for imputed employees data. - (2) Standard errors are corrected for clustering at the level of individual LLMAs. - (3) It includes 20 region fixed effects.

Table 8

Estimation results on firm-level data,
using two labor inputs (White and Blue collars).
Dependent variable: log of TFP measured through LP method (1)
(standard errors in brackets) (2)

	Model I	Model II	Model III (3)
UA	0.078***	0.078***	0.069***
	(0.01)	(0.01)	(0.01)
ID	0.026**	0.040***	0.014
	(0.01)	(0.01)	(0.01)
Medium size	0.133***		0.137***
	(0.01)		(0.01)
Large size	0.336***		0.344***
	(0.02)		(0.02)
North-East	0.018	0.019	
	(0.01)	(0.01)	
Centre	-0.012	-0.013	
	(0.02)	(0.02)	
South	-0.237***	-0.236***	
	(0.02)	(0.02)	
UA*medium		-0.013	
		(0.02)	
UA*large		0.062	
		(0.04)	
ID*medium		-0.057***	
		(0.01)	
ID*large		-0.060	
		(0.04)	
Number of observations	188,275	188,275	188,275
Adjusted R^2	0.796	0.796	0.797

Source: Elaborations on Centrale dei Bilanci, Cerved, and INPS dataset.
(1) All specifications include year and industry fixed effects plus a control for imputed employees. Data on labor inputs are drawn by INPS dataset. Estimation period: 1995-2002. - (2) Standard errors are corrected for clustering at the level of individual LLMAs. - (3) It includes 20 regional fixed effects.

Table 9

Estimation results on firm-level data,
using only one labor input (White + Blue collars).
Dependent variable: log of TFP measured through LP method (1)
(standard errors in brackets) (2)

	Model I	Model II	Model III (3)
UA	0.089***	0.089***	0.079***
	(0.01)	(0.01)	(0.01)
ID	0.033**	0.046***	0.020
	(0.01)	(0.01)	(0.01)
Medium size	0.130***		0.135***
	(0.01)		(0.01)
Large size	0.322***		0.330***
	(0.02)		(0.02)
North-East	0.015	0.015	
	(0.01)	(0.01)	
Centre	-0.026	-0.027	
	(0.02)	(0.02)	
South	-0.260***	-0.259***	
	(0.01)	(0.01)	
UA*medium		-0.014	
		(0.02)	
UA*large		0.051	
		(0.03)	
ID*medium		-0.053***	
		(0.01)	
ID*large		-0.047	
		(0.04)	
Number of observations	188,275	188,275	188,275
Adjusted R^2	0.801	0.801	0.803

Source: Elaborations on Centrale dei Bilanci, Cerved, and INPS dataset.
(1) All specifications include year and industry fixed effects plus a control for imputed employees. We use only one labor input drawn by INPS dataset (White + Blue collars). Estimation period: 1995-2002. - (2) Standard errors are corrected for clustering at the level of individual LLMAs. - (3) It includes 20 regional fixed effects.

Table 10

Production function coefficients by area type, industry and labor force characteristics
(standard errors in brackets)

	Labor						**Capital**
	White Collars			Blue Collars			
Area Type	*Non-ID/UA*	*Urban Areas (1)*	*Industrial Districts (1)*	*Non-ID/UA*	*Urban Areas (1)*	*Industrial Districts (1)*	
Sectors							
Food products, beverages and tobacco	0,200***	0,043	-0,030	0,256***	-0,023	0,045***	0,264***
	(0,020)	*(0,029)*	*(0,024)*	*(0,018)*	*(0,021)*	*(0,016)*	*(0,064)*
Textiles and textile products	0,182***	0,094***	-0,005	0,355***	-0,057***	0,012	0,407***
	(0,019)	*(0,024)*	*(0,016)*	*(0,013)*	*(0,017)*	*(0,010)*	*(0,027)*
Leather and leather products	0,139***	0,038	0,013	0,398***	0,014	0,008	0,376***
	(0,034)	*(0,038)*	*(0,033)*	*(0,021)*	*(0,017)*	*(0,016)*	*(0,030)*
Wood and products of wood and cork (except furniture)	0,208***	0,020	-0,026	0,408***	0,010	0,017	0,349***
	(0,024)	*(0,039)*	*(0,027)*	*(0,020)*	*(0,018)*	*(0,014)*	*(0,029)*
Pulp. paper and paper products; recorded media; print. services	0,193***	0,055**	-0,052**	0,263***	-0,017	0,049***	0,269***
	(0,021)	*(0,026)*	*(0,024)*	*(0,021)*	*(0,016)*	*(0,014)*	*(0,024)*
Coke. refined petroleum products and nuclear fuel	0,025	-0,009	0,143	0,124***	0,025	-0,084	0,886***
	(0,087)	*(0,143)*	*(0,152)*	*(0,077)*	*(0,107)*	*(0,139)*	*(0,195)*
Chemicals. chemical products and man-made fibers	0,278***	0,105***	0,014	0,167***	-0,091***	-0,006	0,495***
	(0,030)	*(0,028)*	*(0,033)*	*(0,024)*	*(0,028)*	*(0,029)*	*(0,039)*
Rubber and plastic products	0,169***	0,067***	0,021	0,362***	-0,024	0,008	0,439***
	(0,020)	*(0,027)*	*(0,023)*	*(0,021)*	*(0,017)*	*(0,014)*	*(0,028)*
Other non metallic mineral products	0,125	0,063	-0,004	0,312***	-0,020	0,019	0,505***
	(0,018)	*(0,034)*	*(0,021)*	*(0,022)*	*(0,021)*	*(0,013)*	*(0,026)*
Basic metals and fabricated metal products	0,167***	0,042***	0,018	0,413***	-0,017	-0,002	0,301***
	(0,008)	*(0,016)*	*(0,010)*	*(0,008)*	*(0,009)*	*(0,006)*	*(0,015)*
Machinery and equipment n.e.c.	0,251***	0,086***	0,008	0,324***	-0,059***	0,000	0,319***
	(0,013)	*(0,016)*	*(0,013)*	*(0,011)*	*(0,012)*	*(0,010)*	*(0,014)*
Electrical and optical equipment	0,275***	0,082***	0,007	0,266***	-0,062***	0,001	0,358***
	(0,017)	*(0,017)*	*(0,019)*	*(0,015)*	*(0,013)*	*(0,014)*	*(0,027)*
Transport equipment	0,221***	0,050	-0,066	0,313***	-0,042	0,037	0,335***
	(0,031)	*(0,062)*	*(0,035)*	*(0,033)*	*(0,042)*	*(0,023)*	*(0,061)*
Other manufactured goods n.e.c.	0,160***	0,061	0,025	0,404***	-0,026	-0,023	0,291***
	(0,025)	*(0,035)*		*(0.020)*	*(0,023)*	*(0,020)*	*(0,028)*

Source: Elaborations on Centrale dei Bilanci. Cerved and INPS dataset.
(1) Deviations from Non-ID/UA coefficients.

Table 11

Estimation results on firm-level data,
using two labor inputs (White and Blue Collars) and two distinct coefficients for UA and ID.
Dependent variable: log of TFP measured through LP method (1)
(standard errors in brackets) (2)

	Model I	Model II	Model III (3)
UA	0.053***	0.068***	0.044***
	(0.01)	(0.01)	(0.01)
ID	0.002	0.020	-0.010
	(0.01)	(0.01)	(0.01)
Medium size	0.126***		0.131***
	(0.01)		(0.01)
Large size	0.317***		0.324***
	(0.01)		(0.01)
North-East	0.019	0.019	
	(0.01)	(0.01)	
Centre	-0.012	-0.013	
	(0.02)	(0.02)	
South	-0.233***	-0.232***	
	(0.01)	(0.01)	
UA*medium		-0.065***	
		(0.02)	
UA*large		-0.039	
		(0.04)	
ID*medium		-0.073***	
		(0.01)	
ID*large		-0.083*	
		(0.04)	
Number of observations	188,275	188,275	188,275
Adjusted R^2	0.800	0.800	0.801

Source: Elaborations on Centrale dei Bilanci, Cerved, and INPS dataset.
(1) We use two labor inputs drawn by INPS dataset (White and Blue collars) and two distinct coefficients for ID and UA. All specifications include year and industry fixed effects plus a control for imputed employees. Estimation period: 1995-2002. - (2) Standard errors are corrected for clustering at the level of individual LLMAs. - (3) It includes 20 regional fixed effects.

Table 12

Quantile Regression. Estimation results on firm-level data.
Dependent variable: log of TFP measured through LP method (1) (2)
*(standard errors in brackets)***(3)**

	Q01	*Q05*	*Q10*	*Q25*	*Q50*	*Q75*	*Q90*	*Q95*	*Q99*
UA	0.069**	0.078***	0.077***	0.083***	0.092***	0.111***	0.123***	0.128***	0.160***
	(0.02)	*(0.01)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.01)*
ID	0.114***	0.061***	0.041***	0.027***	0.020***	0.018***	0.020***	0.015***	0.023**
	(0.02)	*(0.01)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.01)*
Medium size	0.117***	0.068***	0.064***	0.052***	0.037***	0.019***	0.001	-0.011**	-0.043***
	(0.02)	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.01)*
Large size	0.185***	0.135***	0.141***	0.153***	0.155***	0.162***	0.184***	0.186***	0.192***
	(0.05)	*(0.01)*	*(0.01)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.01)*	*(0.01)*	*(0.02)*
North-East	0.062***	0.010*	0.002	-0.001	-0.003*	-0.007***	-0.014***	-0.012***	-0.028***
	(0.02)	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.01)*
Centre	-0.140***	-0.070***	-0.056***	-0.046***	-0.039***	-0.034***	-0.024***	-0.021***	-0.035***
	(0.03)	*(0.01)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.01)*	*(0.01)*
South	-0.640***	-0.404***	-0.317***	-0.249***	-0.219***	-0.202***	-0.196***	-0.190***	-0.156***
	(0.04)	*(0.01)*	*(0.01)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.01)*	*(0.01)*
N	344353	344353	344353	344353	344353	344353	344353	344353	344353
Pseudo R^2	0.2728	0.4712	0.5137	0.5107	0.4722	0.4212	0.3989	0.3933	0.3856

(1) All specifications include year and industry fixed effects plus a control for imputed employees data. - (2) Q01, ..,Q99 indicate estimation carried at the different percentiles of the TFP distribution (Q01 denote the first percentile and so on). - (3) Bootstrapped standard errors, 20 replications.

Appendix 1. - Imputing employee data

Average unit labor cost measured on the sub-sample of firms for which employment counts information is available provides the information needed to recover missing labor input data. To allow for possible heterogeneity in mean wages, the sample was stratified according to a number of relevant firm characteristics.

In particular, mean wages are allowed to vary across sector, geographical area and type of local labor market. Additional firm-level wage heterogeneity is also controlled for by stratifying the sample according to firm size, measured by value added, and profitability. Larger firms may feature a different skill composition of the labor force, and consequently different mean wages. At the same time, more profitable firms are more likely to pay wage premiums, thus sustaining higher total labor cost for given number of employees.

In each stratum the median of observed firm-level average labor cost was computed, and these estimates were subsequently used to impute missing employment data by taking the ratio of total firm labor cost to the median wage of the stratum in which the firm is classified.

Appendix 2. - The relation between TFP and firm size

Estimates of agglomeration effects on TFP levels discussed so far were based on regression analyses at the firm-level. As such, they tend to be prone to measurement problems and the presence of outliers, possibly affecting estimation results in unexpected ways.

Considering that no constraints on returns to scale where introduced when estimating the production function at the firm level, the introduction of a relationship between estimated TFP levels and firm size can be motivated by the existence of a possibly non (log)linear function linking TFP to firm size. To illustrate the argument, let us assume that the log TFP level can be expressed as a generic function of firm size, measured by the employment level,

$$\phi_{it} = h(l_{it}) \quad (1a).$$

Under the hypothesis that the function *h*(.) can be well approximated by means of a polynomial of order *p*, equation (2) in the main text can be restated as:

$$
\begin{aligned}
q_{it} &= \alpha\, l_{it} + \beta\, k_{it} + \rho_0 + \rho_1 l_{it} + \rho_2 l_{it}^2 + \ldots + \rho_1 l_{it}^p \\
&= \tilde{\alpha}\, l_{it} + \beta\, k_{it} + \tilde{\phi}_{it} \qquad (2a)
\end{aligned}
$$

where $\tilde{\alpha} = \alpha + \rho_1$ and $\tilde{\phi}_{it} = \rho_0 + \rho_2 l_{it}^2 + \ldots + \rho_1 l_{it}^p$.

Expression (2*a*) above shows how, estimating a Cobb-Douglas production function with unrestricted elasticities purges the residual TFP estimates of scale effects only under the restrictive assumption of an exact log-linear relation between individual TFP and firm size. In presence of a more general non linear relation, production function residuals will be correlated with higher powers of the labor input[22].

As a consequence, omitting to control for firm size in equation (4) in the main text may yield biased estimates of agglomeration productivity advantages if size is uneven across different LLMAs classes, (i.e., if the UA and ID regressors are correlated with firm size).

Appendix 3 - Additional robustness checks

In this section we discuss robustness checks based on running similar regressions to equation (4) in the main text at aggregate rather than at individual firm level, using instrumental variables and for the subsample of small sized firms.

Considering that the research focuses on productivity differential at the level of local labor markets, a more robust estimation approach can be implemented if individual TFP levels are aggregated prior to running the regression analysis. To this purpose, data were first aggregated at the level of the industry/LLMA/year by taking employment weighted averages of individual TFP levels, the choice of the weighting variable being motivated by the expectation that data quality deteriorates as firm size decreases:

$$
\phi_{srt} = \frac{1}{L_{srt}} \sum_{i \in (r,s,t)} L_{it} \phi_{it} \qquad (3a)
$$

[22] The correlation between inputs and the residual term stemming from equation (2*a*) when p>1 provides an additional argument in favour of estimation methods that can cope with this issue, like the Olley-Pakes (1996) and Levinshon-Petrin (2003) procedures.

Using data at this level of aggregation, equation (4) in the main text was re-estimated by weighted least squares, using the number of firms in each stratum as weight. Estimation results, displayed in Table a1, while confirming the previous evidence of a productivity surplus in UA and ID, also show a larger differential, especially in favor of urban areas, where it rises to about 17 per cent. Introducing unobserved regional effects lowers the estimated comparative advantages for UA and ID as occurred in the previous section (See Table a1, column 2).

At this stage, a first attempt was made at dealing with the endogeneity issue that is likely to affect the variables identifying urban areas and industrial districts with respect to local productivity levels. In fact, since firm location is not set exogenously but results from individual optimizing choices, plant location can be correlated with unobserved firm characteristics and, in particular, with firm productivity, thus undermining the causal interpretation of the above estimated productivity differential.

Following a standard approach, instrumental variable estimators were used in order to cope with this endogeneity issue. In line with the previous literature (Ciccone and Hall, 1996; Combes et al., 2008), the basic intuition lies in the consideration that history and geology may provide a source of exogenous spatial variation that affects the likelihood of having a city or an ID in a specific location. At the same time we expect that these factors will be uncorrelated with current firm productivity in the manufacturing sector. Taking into account the discrete nature of the endogenous regressors, instruments for the UA and ID dummies were obtained taking the predicted value from a multinomial logit regression of LLMA type on a set of strictly exogenous or predetermined variables. Angrist and Pischke (2008, Sect. 4.6.1) show how such procedure can improve the fit of the instruments in the first stage, thus enhancing the precision of IV estimators.

The set of instrumental variables used in the first stage multinomial logit step includes the log of population density in 1921 and the share of population with an university or secondary school degree in 1971 (history), plus the share of LLMA's land near the coastline and the log of the LLMA average altitude (geography).

IV estimates, displayed in the third column of Table a1, not only confirm previous results but point to larger agglomeration effects on manufacturing productivity levels for both IDs and UAs.

With the purpose of evaluating the dynamic pattern of productivity over the analyzed time interval (1995-2006), the sample was split into two sub-periods. In line with evidences from the baseline model specification, it turns out that comparative advantages for UA remain stable while those of ID show a tendency to decline over time (see Table a2 for detailed estimation results).

To single out aggregate TFP variation across differing LLMA types, in a final stage the other panel data dimensions were collapsed, yielding a single spatial cross-section featuring average TFP figures at the LLMA level. To this purpose, the aggregate TFP levels as defined in (3*a*), were first netted out of sectoral, size and statistical imputation effects, by running the following regression:

$$\phi_{rst} = \alpha shflagimp_{rst} + \beta avfirmsize_{rst} + \lambda_s + \varepsilon_{rst} \quad (4a)$$

where *shflagimpg* and *avfirmsize* denote respectively the share of firms with imputed employment data and the average firm size in each stratum. Weighted least squares estimators were used to take account of the differences in the size of the strata.

Estimated residuals $\hat{\varepsilon}_{rst}$, obtained by fitting equation (4*a*) to the sample data, were subsequently averaged over industries using relative frequencies as weights, and these figures were finally averaged across years, yielding the desired aggregate TFP indicator at LLMA level, $\bar{\varepsilon}_r$. The latter was subsequently regressed on the ID and UA dummies plus geographical controls.

OLS and IV estimation results are displayed in Table a3. The TFP advantage of UAs and IDs appear to stand out even more neatly, especially in the case of IV estimates, that show the highest values across the different model specification here considered (a TFP gain of about 10 and 30 percent respectively for IDs and UAs).

The above outlined specifications were estimated also considering the sub sample of small firms (namely those with below sector-year median employment level.). A twofold purpose motivates the exercise. First, we are interested in evaluating the case of small firms, as the theoretical literature has emphasized that in agglomerated areas they may benefit from external scale economies while remaining small. Second, our results on cities could be distorted by the presence of multiplant firms. Usually these firms locate their corporate headquarters in big cities while their production plants operate outside urban areas. In our data set the local productivity advantages of the latter plants accrue to the urban area where the corporate headquarters reside, thereby distorting the assessment of a productivity premium in UA. To address this problem, we replicate the analysis by restricting the sample to firms with below sector-year median employment level, on the ground that small firms usually are more likely to own a single plant.

Estimation results are reported in Tables a4 and a5 for the various specifications considered. Overall, the productivity advantage of UA and ID is confirmed also for the subsample of small firms, as is the ranking of UA and ID.

On the whole, the robustness analysis carried out in this section confirms the ranking of the productivity advantages across areas as well as its evolution over time.

Table a1

Weighted Least Squares estimation of TFP at LLMA and Sector level *(standard errors in brackets) (1)*	WLS with area dummies	WLS with regional dummies	Instrumental Variables
ID	0.044 ***	0.023 ***	0.063 ***
	(0.004)	(0.004)	(0.007)
UA	0.180 ***	0.163 ***	0.250 ***
	(0.008)	(0.007)	(0.014)
Lsize	0.019 ***	0.027 ***	0.048 ***
	(0.004)	(0.004)	(0.003)
North-East	-0.004		-0.004
	(0.005)		(0.004)
Centre	-0.044 ***		-0.060 ***
	(0.007)		(0.005)
South	-0.274 ***		-0.275 ***
	(0.007)		(0.006)
Number of Observations	46,094	46,094	46,094
Adjusted R^2	0.884	0.886	0.792

Source: Elaborations on Centrale dei Bilanci, Cerved.
(1) Standard errors are corrected for clustering at the level of individual LLMAs.

Table a2

Weighted Least Squares estimation of TFP at LLMA and Sector level, by period
(standard errors in brackets) (1)

	1995-2000 (with area dummies)	2001-2006 (with area dummies)	1995-2000 (with regional dummies)	2001-2006 (with regional dummies)
ID	0.047***	0.040***	0.024***	0.023***
	(0.005)	(0.005)	(0.006)	(0.006)
UA	0.175***	0.184***	0.159***	0.168***
	(0.010)	(0.001)	(0.010)	(0.011)
Lsize	0.010	0.027***	0.020***	0.032***
	(0.006)	(0.005)	(0.005)	(0.005)
North-East	-0.005	-0.002		
	(0.006)	(0.007)		
Center	-0.041***	-0.047***		
	(0.010)	(0.010)		
South	-0.293***	-0.259***		
	(0.010)	(0.009)		
Number of Observations	22,275	23,819	22,275	23,819
Adjusted R^2	0.892	0.877	0.895	0.879

Source: Elaborations on Centrale dei Bilanci, Cerved.
(1) Standard errors are corrected for clustering at the level of individual LLMAs.

Table a3

Estimation of TFP at LLMA level
(standard errors in brackets) (1)

	Weighted Least Squares	Instrumental Variables
ID	0.058 **	0.114 **
	(0.021)	(0.042)
UA	0.184 **	0.332 **
	(0.067)	(0.111)
North-East	-0.019	-0.020
	(0.027)	(0.027)
Centre	-0.050	-0.050
	(0.028)	(0.028)
South	-0.281 ***	-0.259 ***
	(0.025)	(0.029)
Number of Observations	689	689
Adjusted R^2	0.278	0.266

Source: Elaborations on Centrale dei Bilanci, Cerved.
(1) Standard errors are corrected for clustering at the level of individual LLMAs.

Table a4

Weighted Least Squares estimation of TFP at LLMA and Sector level; small firm sample (1) *(standard errors in brackets) (2)*			
	With area dummies	With regional dummies	Instrumental Variables
ID	0.028 ***	0.018 ***	0.055 ***
	(0.003)	(0.003)	(0.008)
UA	0.109 ***	0.099 ***	0.173 ***
	(0.004)	(0.004)	(0.014)
Lsize	0.040 ***	0.037 ***	0.048 ***
	(0.006)	(0.006)	(0.006)
North-East	-0.017 ***		
	(0.003)		
Centre	-0.051 ***		
	(0.004)		
South	-0.258 ***		
	(0.005)		
Number of Observations	35,755	35,755	35,755
Adjusted R^2	0.885	0.866	0.773

Source: Elaborations on Centrale dei Bilanci, Cerved
(1) Small firms are those with below sector-year median employment level. - (2) Standard errors are corrected for clustering at the level of individual LLMAs.

Table a5

Weighted Least Squares estimation of TFP at LLMA and Sector level; small firm sample, by period (1)
(standard errors in brackets) (2)

	1995-2000 (with area dummies)	2001-2006 (with area dummies)	1995-2000 (with regional dummies)	2001-2006 (with regional dummies)
ID	0.037***	0.020***	0.024***	0.013***
	(0.004)	(0.004)	(0.005)	(0.005)
UA	0.108***	0.110***	0.099***	0.101***
	(0.005)	(0.005)	(0.005)	(0.005)
Lsize	0.035***	0.043***	0.032***	0.042***
	(0.009)	(0.009)	(0.009)	(0.009)
North-East	-0.013***	-0.020***		
	(0.004)	(0.004)		
Centre	-0.045***	-0.056***		
	(0.006)	(0.005)		
South	-0.283***	-0.236***		
	(0.007)	(0.007)		
Number of Observations	17,295	18,460	17,295	18,460
Adjusted R^2	0.889	0.882	0.891	0.883

Source: Elaborations on Centrale dei Bilanci, Cerved
(1) Small firms are those with below sector-year median employment level. - (2) Standard errors are corrected for clustering at the level of individual LLMAs.

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