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

PRELIMINARY DRAFT

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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 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 minor 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 higher average TFP levels within UA do not seem to be mainly driven by a selection effect pushing less efficient firms out of the market. Rather, a firm sorting effect appears to stand out, suggesting that more productive firms gain strong 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 technologies.

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

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1. Introduction

The forces pushing toward spatial concentration 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, extensive local amenities coupled with high congestion costs. Industrial 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 recent survey and empirical analysis on Italian districts, see Iuzzolino and Micucci, 2011).

In the present paper, 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) May local productive advantages associated to UA and ID coexist in the same country? iii) Are they comparable in magnitude? iv) How have these agglomeration economies 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 and third questions are 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 (NIC) on one side and by the advent of information and communication technologies (ICT) on the other.

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.[1] 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

[1] See Melo et al (2009) for a survey of the empirical literature and a meta-analysis based on papers estimating the intensity of agglomeration economies.

small firms incidence indicators would signal that spatial clustering at the single industry level 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.

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 denoting 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 white-blue collars 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 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. Then we conclude, suggesting some directions for future research.

2. Industrial districts and urban areas as drivers of agglomeration economies

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.[2]

ID usually exhibit a strong specialization in manufacturing activities. The thick inter-linkages between the ID firms produce economies that are external to the individual plant but internal to the ID area. Belonging to the local community generates mutual trust and knowledge, thereby facilitating transactions. Because of these positive externalities, producers of intermediate goods can increase their degree of productive specialization being confident that they will be able to sell at least part of their products within the ID area. Likewise, the local labor market can improve worker-firm matching. Cooperation along the productive chain will combine with a very though competition between firms producing the same product (horizontal competition). Finally, ID community may also include local institutions and the financial system. All these features are likely to translate into higher productive efficiency for

[2] 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.

ID firms, i.e. into their ability to produce more output for given inputs as compared to other firms located outside ID areas.

UA represent other locations where productivity advantages are likely to arise due to the large amount of population residing and working within their borders. The large size of the local market could make firms in UA more productive because of (a) selection effects, (b) the production of local amenities attracting highly skilled individuals and (c) the externalities generated by the interactions between firms and workers in the same sector (Marshall externalities) or in different industries (Jacob externalities).

As usual, 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 lower productive efficiency in cities. Moreover, they can augment local land prices thereby inducing firms using intensively this input factor in their production to locate outside UA. 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 when indivisibilities are important or when transactions are more efficiently carried out in a hierarchical organization. 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).

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 favour 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 (Rosenthal and Strange, 2004).[3] 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.

[3] 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.

On the contrary, the empirical literature in Italy focused mainly on the productivity advantages associated to ID.[4] 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 to respectively 2 and 4.1 percent. The average difference in the per capita value added between firms in and out of districts is around 1.3 per cent. The technical (in)efficiency differential, measured using the distance from the efficient frontier, is (negative) positive for 8 out of 13 of the sectors considered and it lies within a range between zero and 5 per cent.

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.

Last, 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.[5] Foresti, Guelpa and Trenti (2009) show, in a descriptive fashion, the fading of a district effect using different balance sheet indicators; e.g., in 2006 the authors calculate that return on investment for non district firms was around 6.5 per cent in 2006 and about 0.25 percentage points lower for district firms.

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 the National Institute of Statistics using a

[4] For a short review of the papers assessing ID advantages see the list reported in Table 1.
[5] On the structural evolution of the ID see also Rabelotti, Carabelli and Hirsch (2009).

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 locations are then aggregated into larger regions called Local Labor Markets Areas (LLMA). Through this procedure, within LLMA labor mobility is maximized while mobility across LLMA's is minimized. The outcome of this procedure mapped the Italian territory into 784 LLMA in 1991 (686 in 2001)[6]. Notice 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, ie $l_a = \frac{(x_{am}/x_a)}{(x_{\bullet m}/x_{\bullet\bullet})} > 1$ 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 & medium 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

6 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 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.

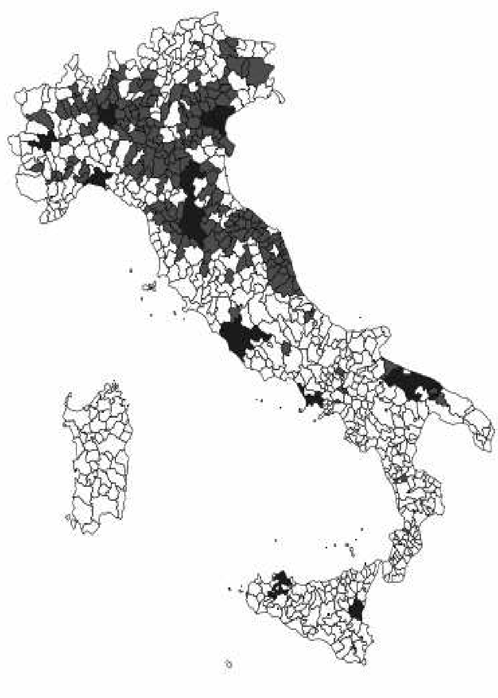
the local specialized industries. For *d*, the following condition must hold: $s_{ad} = \left(x_{ad}^{small} / x_{ad} \right) > .5$.

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.

According to this definition then, ID are LLMA's with a specialization in the manufacturing sector and for which medium and small enterprises represent a significant share of employment both in the manufacturing sector as a whole and in the most prominent among the single specialized manufacturing activities. 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.

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 two non overlapping sets of localities (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.

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



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.

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 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.

Only one third of the firms in database, however, 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.

Capital stock figures were estimated through the perpetual inventory method applied to yearly investment expenditure flows (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; 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 about 28,700 firms for 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. 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 County, IDs fall behind both with respect to UA and to non agglomerated firms (Table 4).

The North-South gap that emerges in all of the three agglomerating categories (ID, UA and none of the above) is more accentuated for ID. The productivity of the latter, measured by per capita value added, is in the South about 30 per cent less than the national average. For UA and non-ID/UA firms in the South, the figures are 23 and 16 per cent lower with respect to the national average. The sector 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 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[7]; 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). We run distinct regressions for each industry at two digits of the SEC classification.

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

[7] 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.

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.

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:

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

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[8](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:

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

[8] 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.

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 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 LLMAs).

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.

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.

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 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).

The three specifications considered in Table 6 were subsequently estimated by splitting the panel into two sub-periods, 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 time periods, while the productivity premium estimated for IDs shows a decline, from about 4 percent to 2 percent, loosing statistical significance when regional fixed effects are introduced (see Tab. 7, Model III).

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 static and dynamic productivity advantages the productive units located in ID. As a first step towards the identification of the factors that may explain this occurrence, in this section we first provide some new evidence on the role of the skill composition of the labor force and subsequently on selection, agglomeration and firm sorting.

7.1 - The role of human capital

A first 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 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 covers a slightly lower number of firms, due to imperfect matching of firm codes in the two data sets, and to a slightly shorter time 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). 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 functions estimates (not reported for the sake of brevity) 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 ID. These results make sense in light of theoretical a priori.

However, the evidence that in ID blue collars are relatively more productive than white collars 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 (see the report on recent tendencies of Italian manufacturing by Brandolini and Bugamelli, 2009).

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 (Tab. 10). On the contrary, 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.

7.2 - Other potential sources of local productivity advantages: selection agglomeration and firm sorting

As clearly indicated by Combes et al (2010), looking at the entire TFP distribution helps disentangling between rival theories that would be otherwise observationally equivalent when looking at the conditional mean only.

Hence, when agglomeration is the main driver of productivity advantages denser or more spatially concentrated areas should exhibit a rightward shift in the entire TFP distribution and this positive impact should have the same magnitude across the different quantiles. Alternatively, a Darwinian selection process across heterogeneous producers would induce a left truncation in the TFP distribution, thus denser or larger local markets should exhibit a productivity advantage concentrated in the lower tail of the distribution. Finally, according to a different group of models, more productive firms could obtain larger benefits by locating in larger or denser markets, thereby making the upper tail of the TFP distribution thicker.[9]

As a further attempt at identifying the sources of local productivity advantages, we extend our econometric analysis to a quantile regression.[10] By doing so, we can explore the impact of

[9] See Nocke (2006) and Baldwin and Okubo (2006).
[10] For an analysis similar to ours see Arimoto et al (2009).

our covariates on all the moments of the TFP distribution and not only on the conditional mean and again compare them across UA and ID. Results are reported in Table 11.

Several interesting patterns can be detected from these additional estimates. 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 form 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.

Thus in the light of the remarks above, our findings indicate that agglomeration economies play an important role in determining the productivity differences across regions. However, they are not the sole driver for them as it is shown by the fact that the impact of the spatial concentration is differentiated across the quantiles of the TFP distribution. More specifically, we find evidence of a modest selection effect associated to the ID while we detect a stronger firm sorting effect in the UA (see the large estimated parameters for the UA dummy in the higher percentiles regressions in Table 11), i.e. more efficient firms benefit more by locating in UA.

The absence of a selection effect in cities could seem puzzling at a first sight. However this could be explained by the spatial scale that we used in our analysis. Actually, Italy represents a sort of integrated market, as far as the trading of manufacturing goods is concerned. Hence, the geographical partition based on LLMA's adopted in this paper might not always correctly define the 'relevant market' in the case of many manufacturing activities.[11]

Despite these limitations, we can still recover the idea that a larger community of final consumers may stimulate productive efficiency for the firms located in UA. Notably, even within very narrowly defined activities it is possible to distinguish mass production from those specialty goods that are custom-made and whose delivery is often facilitated by face-to-face interaction between buyers and sellers. Introducing this distinction into heterogeneous firms

[11] Actually 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.

models, it is possible to show that small firms producing quality goods will concentrate in larger cities in order to benefit from proximity to the sources of demand (Holmes and Stevens, 2005 and 2010). If the higher quality of these specialty goods is reflected into higher prices, we will also observe a larger productivity level for these firms as our TFP measure is based on revenues deflated with a common industry-wide price indicator.[12] In this perspective our evidences could indicate that the effects emphasized by Holmes and Stevens are not empirically relevant in the case of the Italian manufacturing activities.

8. Final remarks

This paper has investigated the issue of local productivity advantages, using data referred to about 29,000 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 agglomeration economies exert 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). As regards the broader geographical pattern, our estimates confirm prior evidence that firm in the North of the Country are more productive than those located in the Centre and, above all, in the South.

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 exclude that cities advantage depends strictly on a selection effect. At the same time, the empirical evidence appears to support the existence of a firm sorting effect, i.e. more efficient firms seem to benefit more by locating in UA.

[12] For an attempt at correcting, the so called 'output price bias' in the estimation of the production function, see Del Gatto, Ottaviano and Pagnini (2008).

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. The beginning of the 2000s, characterized by the introduction of Euro, the rapid diffusion of ICT and the growing globalization emerges as a turning point.

Our results cautiously suggest that firms operating within UA, (far) 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. In order to identify the most effective strategy to face the new millennium challenges, the urgent question to answer is how and why it happened.

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. &	Roi,	+2.0 p.p.
				Roe	+4.1 p.p.
			Stochastic Frontiers – ML estimates	Value added per worker	+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	Share of export on total sales	+ 3.6 p.p.
			Probit estimates	Exporter status (dummy)	+20 %
Bagella et al. (2000)	Export performance				
Becchetti, De Panizza and Oropallo (2003)	Firms performance	Firm level 103,073 obs.	Fixed effect estimates	Export per worker (log)	+1.1
	Export performance			Value added per worker (log)	+5.0
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)	+ 0.023
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
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.

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

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

	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.

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

	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 drawn by INPS dataset (White and Blue collars). Estimation period: 1995-2002.
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. - (2) Standard errors are corrected for clustering at the level of individual LLMAs. - (3) It includes 20 region fixed effects.

Table 9

Estimation results on firm-level data using only one labor input drawn by INPS dataset (White + Blue collars). Estimation period: 1995-2002.
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***	0.000	0.135***
	(0.01)	(.)	(0.01)
Large size	0.322***	0.000	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	188275	188275	188275
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 data. - (2) Standard errors are corrected for clustering at the level of individual LLMAs. - (3) It includes 20 region fixed effects.

Table 10

Estimation results on firm-level data using two labor inputs (White and Blue Collars) and two distinct coefficients for ID and UA. Estimation period: 1995-2002.
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) 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 11

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

	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)	(0.00)	(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***
	(0.03)	(0.01)	(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***
	(0.02)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)
South	-0.640***	-0.404***	-0.317***	-0.249***	-0.219***	-0.202***	-0.196***	-0.190***	-0.156***
	(0.03)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)
N	344,353	344,353	344,353	344,353	344,353	344,353	344,353	344,353	344,353
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),

Appendix 1. - Imputing employee data

Average unit labor cost measured on the sub-sample of firms for which employment counts information is available provide the basis information utilized 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 utilized 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,

$$\phi_{it} = h(l_{it}) \quad (6).$$

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

$$q_{it} = \alpha\, l_{it} + \beta\, k_{it} + \rho_0 + \rho_1 l_{it} + \rho_2 l_{it}^2 + \ldots + \rho_1 l_{it}^p$$
$$= \widetilde{\alpha}\, l_{it} + \beta\, k_{it} + \widetilde{\phi}_{it} \qquad (7)$$

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

Expression (7) 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[13].

As a consequence, omitting to control for firm size in (4) 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) 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:

$$\phi_{srt} = \frac{1}{L_{srt}} \sum_{i \in (r,s,t)} L_{it} \phi_{it} \qquad (8)$$

[13] The correlation between inputs and the residual term stemming from equations (7) when p>1 provides an additional argument in favour of estimation methods that can cope with this issue, like the Olley-Pakes and Levinshon-Petrin procedures.

Using data at this level of aggregation, equation (4) was re-estimated by weighted least squares, using the number of firms in each stratum as weight. Estimation results, displayed in Table 8, while confirming the prior evidence of a productivity surplus in UAs and IDs, show a larger differential, especially in favour 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 8, 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 (8), were first netted of sectoral, size and statistical imputation effects, by running the following regression:

$$\phi_{rst} = \alpha shflagimp_{rst} + \beta avfirmsize_{rst} + \lambda_s + \varepsilon_{rst} \quad (9)$$

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 (9) 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 excess 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 UAs and IDs is confirmed also for the subsample of small firms, as is the ranking of UAs and IDs.

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/Sector level *(standard errors (1) in brackets)*			
	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/Sector level, by period
(standard errors (1) *in brackets)*

	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* (1) *in brackets)*		
	WLS	I.V.
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.

Weighted Least Squares estimation of TFP at LLMA/Sector level; small firm sample (1)
(standard errors (2) *in brackets)*

	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) Firms 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/Sector level; small firm sample (1), by period

(standard errors (2) *in brackets)*

	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 Observation	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) Firms with below sector-year median employment level. - (2) Standard errors are corrected for clustering at the level of individual LLMAs.

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