BANCA D'ITALIA

Temi di discussione

del Servizio Studi

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Number 474 - June 2003

IDENTIFYING THE SOURCES OF LOCAL PRODUCTIVITY GROWTH

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Abstract

Using firm-level based TFP indicators (as opposed to employment-based proxies) we estimate the effects of alternative sources of dynamic externalities at the local geographic level. Contrary to previous empirical work, we find that industrial specialization and scale indicators positively affect TFP growth at the city-industry level, while we do not find evidence that either the degree of local competition or productive variety impact on subsequent productivity growth. Employment-based regressions yield nearly the opposite results, in line with previous empirical work. We show that such regressions could suffer from serious identification problems when interpreted as evidence of dynamic externalities. This calls into question the conclusions of the existing literature on dynamic agglomeration economies.

JEL classification: R11, O47.

Keywords: local growth, productivity, dynamic externalities.

Contents

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1. Introduction[1]

Since Marshall (1890) emphasized the importance of local scale economies for agglomeration (through technological spillovers, input-output linkages and labor market externalities), alternative theories have been proposed to illustrate how the intensity and composition of productive activity impacts on local economic performance.[2] Early empirical works tried to determine whether differences in aggregate productivity levels among locations can be significantly explained by measures of the intensity of economic activity.[3] Findings in Jaffe, Trajtenberg and Henderson (1993) and Rosenthal and Strange (2000) suggest that information spillovers are an important source of externalities. A related strand of literature tries to asses what composition of the local industrial structure, if any, is more conducive to such externalities, focusing in particular on the role of sectoral specialization (localization economies) and of product variety (urbanization externalities)[4] in determining within and across industry spillovers.

In light of the central role played by technological externalities in modern growth theories, recent works focus on the possibility that externalities arising from local mutual interactions might not just cause differences in productivity levels but also in growth rates across locations. In a seminal paper, Glaeser, Kallal, Scheinkman and Shleifer (1992) estimated the effects of alternative potential sources of technological spillovers on economic growth at the local level. They found strong evidence that indicators of localization economies (also called MAR economies from Marshall-Arrow-Romer) have a negative growth-effect in a cross section of US cities, while urbanization (or Jacobs) economies, spurred by productive variety, are positively related to subsequent growth. Adopting a slightly different approach,

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[1] This paper is dedicated to the memory of Antonio Alonzi, who, together with Antonietta Mundo and Salvatore Giovannuzzi of INPS, supplied us with the firm level data. We thank Antonio Ciccone, Andrea Lamorgese and seminar participants at the Bank of Italy, the Universidad Carlos III and NARSA meeting 2002 for useful discussions. Marco Chiurato and Elena Genito provided excellent research assistance. We also thanks the Italian Social Security Service (INPS) for supplying us with their firm-level data. We are responsible for any mistake. The views expressed here are our own and do not necessarily reflect those of the Bank of Italy. Email: cingano.federico@insedia.interbusiness.it; schivardi.fabiano@insedia.interbusiness.it

[2] See, for example, Henderson (1974) for an early contribution and Eaton and Eckstein (1997) for a recent one.

[3] See, for example, Sveikauskas (1975), Segal (1976), Ciccone and Hall (1996).

[4] The seminal contribution for urbanization economies is in Jacobs (1969); Duranton and Puga (2001) offer an interesting modelization of such effects over the industry life cycle.

Henderson, Kuncoro and Turner (1995) found positive effects of productive specialization in the case of mature capital-goods industries, while productive variety seemed to be more important for newly established high tech industries. Further studies helped to extend the now-called "urban growth" literature to countries other than the US (see, for example, Combes (2000) for France, Cainelli and Leoncini (1999) for Italy and Bradley and Gans (1996) for Australia). Their results tend to confirm the initial finding that productive specialization has a negative impact on growth, while evidence on urbanization economies is less clear-cut. Such findings are quite puzzling, particularly because they not only imply the absence of intra-industry technological spillovers, but also that there are dynamic *disadvantages* to spatial concentration.

We argue that results obtained by the literature might be affected by a simple identification problem that could explain the controversial findings. Theories of dynamic externalities predict a relation between local structure and productivity; owing to the lack of local productivity data, existing works have been based on employment growth regressions, relying on the assumption that productivity increases result in proportional employment gains through shifts in labor demand. This approach implicitly assumes that changes in *labor supply* are independent of local conditions. This is a rather strong assumption: for example, congestion externalities, such as higher rents and pollution, are likely to influence mobility choices, potentially breaking or even reversing the causality chain going from agglomeration economies to productivity and employment growth.[5]

We overcome this problem by using a measure of growth closer to the theoretical notion of dynamic externalities. We exploit balance-sheet data on a large sample of Italian manufacturing firms to construct a measure of sectoral TFP with a high degree of geographical disaggregation, applying a production function estimation procedure that allows us to account carefully for endogeneity and selection problems (Olley and Pakes 1996). We then regress productivity growth at the city-industry level against precise employment-based beginning-of-period indicators of the local industrial structure. Our contribution to the literature is twofold. First, we construct a test of location economies that does not rely on the identification assumptions required for the employment growth regressions. To our knowledge, this is

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[5] In their study of city-wide characteristics (i.e. without sectoral breakdown) and city population growth, Glaeser, Scheinkman and Shleifer (1995) explicitly acknowledge that urban growth regressions can only capture the impact of local conditions on both productivity and quality of life changes.

the first paper that uses TFP data with a high degree of both geographical and sectoral disaggregation to test agglomeration theories.[6] Second, given that we also have detailed information on employment growth, we can run the regressions previously used in the urban-growth literature and compare the results with those of the TFP regressions. This will give an indication of the relevance of the identification issues in interpreting the employment-based regressions as evidence for agglomeration economies.

In terms of the first point, our main results can be summarized as follows. We find that indicators of specialization-MAR economies have sizeable effects on productivity: doubling the share of sectoral employment in a given location brings about an average increase in sectoral TFP of 0.2 per cent per year, a per cent increase in the average growth rate. We also find evidence that the city size matters: doubling initial employment in manufacturing raises TFP by 0.4 per cent per year. These results are consistent with a broad theoretical literature on urban growth, but in contrast with the findings of most of the empirical literature so far. We do not find that other possible sources of externalities, such as urban diversity, local competition or average firm size matter for TFP growth.

To address the relevance of the identification issues in employment growth regressions, we first construct a simple model of local conditions, productivity growth and employment determination, which formally shows that identification requires changes in labor supply to be independent from local conditions affecting productivity growth. We assess the empirical relevance of this assumption by running employment growth regressions, finding results that are opposite to the TFP ones and in line with those of the previous literature. We perform several robustness checks and extensions, all pointing to the relevance of the identification problem. Taken together, this evidence suggests that employment growth might be ill-suited to infer the sources of dynamic productivity growth, casting serious doubts on the interpretation of the results previously found in the literature as evidence for or against dynamic externalities.

The rest of the paper is organized as follows. In section 2 we describe the data sources and TFP estimation at the local geographical level, while section 3 discusses the empirical specification and the main results obtained with TFP. Section 4 formally illustrates

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[6] Henderson (2001) is the only other paper we are aware of that deals with direct estimation of dynamic externalities through plant-level production function estimation. His approach and results will be discussed and compared with ours in section 4.

the identification issues affecting employment growth regressions and discusses results from such estimates, comparing them with those obtained for TFP. Section 5 concludes.

2. Measuring Local TFP

2.1 *Data*

As in most of the existing literature, the unit of observation in our analysis is defined by sectoral activity at the local level. Our geographical units are the local labor systems (LLS), defined as groups of municipalities characterized by a self-contained labor market, as determined by the National Institute for Statistics (NIS) on the basis of the degree of working-day commuting by the resident population. Using 1991 Census data, the NIS procedure identified 784 LLSs covering the whole national territory.[7] Given that externalities are likely to arise mainly from direct interaction, this is the ideal geographical unit to study local spillovers. In terms of the sectoral classification, we restrict our attention to manufacturing, given the well-known problems in estimating productivity in services. Following the territorial analysis of NIS, we use the 10-sector classification system reported in Table 1, which achieves a good compromise between the need for homogeneity within sector and that of a sufficient number of observations by sector for a statistically reliable analysis. Our unit of observation is the LLS-sector (L-S onward).

To obtain information on productivity and on its determinants at the L-S level, we combine data from three different sources. First, we exploit several waves of the National Social Security Institute, NSSI (*Istituto Nazionale Previdenza Sociale*) archives on the universe of Italian firms (1986-1998) to compute precise measures of the local industrial structure. For all firms with at least one employee, the firms' archives provide information on the total number of employees working in each year (with a breakdown between production and non-production workers), their average yearly earnings and some firm characteristics. In particular, for each firm we know the address (municipality and ZIP code) and the sector of activity (specified with a three digit breakdown), which together allow us to classify each firm in the corresponding L-S. We use these data to compute the employment-based measures of the local

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[7] The average land-area is 384 square kilometers, with a population density of 188 inhabitants per sq. km. Population levels range from 3,000 in the smallest LLS to 3.3 million in the largest.

industrial structure (such as indexes of productive specialization, variety, firm size and local competition).[8]

The NSSI dataset has no information on production or capital stock, so that it cannot be used to compute TFP. We therefore resort to a sub-sample of firms drawn from the Company Accounts Data Service, CADS (*Centrale dei Bilanci*), a large dataset collected by a consortium of banks interested in pooling information about their clients and containing detailed balance-sheet information. Data refer to a sample of between 30,000 and 40,000 firms and have been available on an annual basis since 1982. Since the data are used by banks to extend loans, they are carefully quality controlled and contain actually reported (as opposed to imputed) figures.[9] Firms in the sample account for approximately half of the total employment in manufacturing and, according to a report by the CADS (1992), for an even higher share of sales. Table 1 reports industry-level averages for three variables of interest (value added, capital stock -constructed using the permanent inventory method, see Appendix A- and employment) in 1991.

The use of a sub-sample of firms entails two kinds of problem. First, not all the existing L-S will be present in the sample, as we established through a comparison with NSSI data (the universe). If we consider for example 1991, the CADS dataset has at least one firm for 2,453 L-S out of 6,372 ; in terms of LSS, 539 of them are in our sample, against a total of 784. Given that the selection criteria is independent from localization, the probability that a given L-S is represented in our sample increases with the number of firms in it, so that we will tend to exclude L-S with low levels of sectoral employment. In fact, the average sectoral employment in excluded L-Ss is only 75 workers, against almost 1,400 for those included. In terms of coverage, included L-Ss account for a share of total sectoral employment that ranges from 86 per cent for wood to 98 per cent for metal products. Notice that the exclusion of L-S with very low sectoral employment is very much in line with previous literature, which generally only considers metropolitan areas (Glaeser et al. 1992).

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[8] The archives allowed for the computation of indicators that require firm-level information (see next section) that could not have been computed using Industry Census data, available only at the aggregate level.

[9] The CADS dataset has been used, among others, by Guiso and Parigi (1999) to study the effects of uncertainty of firms' investment decisions, by Pagano, Panetta and Zingales (1998) for the choices of going public, by Sapienza (2002) for the effects of banks mergers on interest rates on loans, by Guiso and Schivardi (2000) to explore the impact of information spillovers on firms' behavior.

The second potential problem comes from the fact that firms are not randomly chosen. Though previous comparisons indicate that the CADS information is not too far from being representative of the whole population in terms of the frequency distribution by sector and geographical area (Guiso and Schivardi 2000), the focus on the level of borrowing skews the sample towards larger firms. This can be noticed from the last two columns of Table 1, comparing average employment and number of firms at the sectoral level for the CADS and the NSSI databases in 1991: the left-hand skewness of the size-distribution of Italian firms (in manufacturing, firms with 5 employees or less constitute approximately 60 per cent of the firm population but less than 10 per cent of total employment) accounts for much of the observed differences. Moreover, since banks are most interested in firms that are creditworthy, firms in default are not in the dataset, so that the sample is also tilted towards higher than average quality borrowers. While we have no direct way to account for potential selection problems affecting our productivity growth estimates, we will show that employment growth regressions based on CADS data (the sub-sample) and the NSSI data (the population) yield very similar results (see section 4). Therefore, we are confident that the selection criteria, based on turnover thresholds and on multiple banking relationships, are unlikely to induce any spurious correlation between the estimated local TFP growth rates and our explanatory variables. We will also include detailed sectoral and geographical controls in our growth regressions to account for error in measurement that is correlated across space or lines-of-work.

Considering the precision of our productivity growth estimate, the average number of observations at the city-sector level is 8.5 (Table 4, last row) and, given that both the sectoral and the geographical classification are fairly detailed, in many cases we end up computing TFP with just a few firm-level observations. While this is likely to introduce noise, we think our measure is sufficiently precise for our purposes. First, as we have seen above, CADS firms account for a large share of output. Second, in order to account for the different precision with which TFP is computed, we will estimate our regressions using weighted least squares, with the weights determined by the number of firm-level observations available. We will also perform several additional robustness checks.

The final data source is the Census, from which we obtain additional economic indicators at the local geographical level. In particular, we used the Italian “Population Census”

(Censimento Generale della Popolazione, 1981) to calculate measures of human capital in the LLSs, obtained as average schooling of the working age population, and the 1981 Service and Industry Census, used as an alternative source of employment data in our robustness checks.

2.2 *Estimation Procedures*

We exploit our detailed firm-level dataset to measure TFP at the L-S level. We maintain that production takes place using the usual Cobb-Douglas function $Y = AK^{\alpha_s}L^{\beta_s}$, where K and L denote the stock of capital and labor and A is the TFP, and where we allow for the coefficients α_s and β_s to vary across sectors. The traditional method assumes perfect competition in the input markets and constant returns to scale in production (Solow's assumptions) and calculates $\widehat{\beta}_s$ as the labor share in each sector and $\widehat{\alpha}_s$ as its complement to 1. The availability of firm-level data, however, allows us to estimate the coefficients directly. The advantages of estimating the production function with firm data is that Solow's assumptions are not required. In fact, the Italian labor market is heavily regulated, so that the perfect competition hypothesis is hard to justify. Moreover, by dismissing the assumption of constant returns to scale, we can disentangle TFP growth from scale effects internal to the firm, determined by the production technology and therefore independent from externalities at the local level. Indeed, with Solow's method any effect of the scale of production would be attributed to TFP, potentially introducing relevant measurement error.

The direct estimation of the production function faces well-known econometric problems. Since the level of productivity will affect both the firm's input choices and the participation decision, consistent estimation of the production function parameters makes it necessary to address problems of selection and simultaneity. We use a multi-step estimation algorithm proposed by Olley and Pakes (1996), which accounts both for the endogeneity and the selection problems, allowing for unbiased and unconstrained estimation of α_s and β_s. The procedure is briefly summarized in Appendix A. To obtain our measure of city-sector TFP we first calculate productivity at the firm level as a residual, accounting for the fact that the scale of individual plants matters if we do not impose CRS, and aggregated TFP to the city-sector level as the employment weighted average of firm-level TFP.[10] To control for the reliability of the estimates, we also calculate the coefficients using Solow's assumptions, computing $\widehat{\beta}_s$ as the

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[10] Alternatively, we could have used directly the growth of TFP at the firm level without aggregating at the city-sector level. The problem with this approach is that it would have restricted the sample to the surviving firms only, a highly select group, thus reducing the representativeness of the results.

average labor share in each sector and $\widehat{\alpha}_s$ as its complement to 1.[11] In this case, the city-sector estimates of TFP are obtained as $\ln A_{c,s} = Y_{c,s} - \widehat{\alpha}_s \ln K_{c,s} - \widehat{\beta}_s \ln L_{c,s}$ where $X_{c,s} = \sum_{i \in c,s} x_i$.

Table 2 reports the estimated values of α_s and β_s with the two procedures. Production function estimates of $(\alpha_s + \beta_s)$ lie in the range 0.93-1.05, indicating that the CRS assumption is a good approximation for most sectors but that for a few of them it might not be inconsequential for TFP calculations, particularly in the face of changes in the average scale of production. In terms of single coefficients, the Olley and Pakes procedure tends to yield a higher labor coefficient and a smaller capital one, arguably because of deviations of the factor markets from the competitive paradigm. Apart from these differences, the two methods give broadly consistent results, an indication of the reliability of the estimates. In what follows we use the production function estimates as our preferred ones.

Table 3 reports the decomposition of output per worker in the ten manufacturing sectors considered here. The upper part of the table shows that the level of TFP (calculated in 1991) accounts for more than a half of labor productivity, a result that is roughly comparable to those obtained by Bernard and Jones (1996) in a sample of OECD countries. The bottom part of the table presents a standard growth accounting exercise. As shown in the second column, between 1986 and 1998 TFP grew on average at a rate ranging between 1.2 per cent and 4 per cent and was generally lower in the traditional (textiles, footwear etc.) and food sectors than in the production of basic metals and machinery.[12] The accumulation of capital per worker, on the contrary, accounted for large parts of the growth in productivity per worker in the traditional sectors. Further interesting differences emerge, driven by returns to scale. The last column of the table indicates the amount of the productivity increase/decrease due to the change in the productive structure of the firms in the sample. In line with the previous discussion about the coefficients, contributions are generally small. The most noticeable exception is basic metals and, to a lesser extent, technical equipment, where a substantial contribution to labor productivity growth derived from the *decrease* (recall that both sectors are characterized by

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[11] For this method, less computationally intense, we also allowed the coefficients to differ by year and macro area; we did not find a substantial trend in estimated coefficients along either dimensions. We therefore assume that they are constant over time and across areas within a given sector.

[12] The relatively high level of TFP growth is attributable to the fact that the sample is tilted towards higher than average quality firms, as we discussed above.

DRS) in the average scale of production of firms in the sample. This effect is not captured by the Solow procedure, which therefore overestimates TFP growth.

3. Sources of Local Growth

Inference of the existence and extent of dynamic externalities is generally based on the analysis of the relationship between employment growth at the local level and indexes of the local productive structure. Our data allows us to parallel closely the existing literature and compare the results obtained when testing the impact of alternative sources of dynamic spillovers on TFP, as opposed to employment growth rates.

Though the theory lacks clear indications of which should be the relevant variables, since the first empirical works by Glaeser et al. (1992) and Henderson et al. (1995), the focus has been placed on specific employment-based indicators of dynamic spillovers. First, specialized locations should benefit from within-industry knowledge spillovers, as argued by a strand of literature that goes from Marshall (1890) to Arrow (1962) to Romer (1986). These are called MAR-externalities. Empirically, the degree of sectoral specialization of a given location (city) c in a certain sector s is captured by the share of sectoral city employment:

$$\text{Spec}_{c,s} = L_{c,s}/L_c$$

On the other hand, positive externalities could be induced by the scale or diversity of local economic activities outside sector s as a result of cross-fertilization. The effects of productive variety in the city, commonly called Jacobs (1969) externalities, is captured here by a Hirschman-Herfindahl index (Henderson et al. 1995):

$$\text{Variety}_{c,s} = \sum_{j \neq s} \left(\frac{L_{c,j}}{L_c - L_{c,s}} \right)^2$$

The index is defined as the sum of the (squared) shares of other sectors' employment in overall net manufacturing employment in city c. Clearly it will be close to 1 if sector s is surrounded by few, concentrated industries in the city, while it tends to $1/\left(J_c - 1\right)$ if city-employment (at two-digit level) is evenly distributed across different industries.

The variables mentioned have traditionally been the most important, according to the existing empirical literature, for discriminating between specialization versus urbanization economies. Other characteristics of the production structure have been considered, though, as potentially relevant determinants of local productivity. First, some theories predict that fierce product-market competition at the local level could be a source of positive externalities in that, for instance, it fosters the adoption of innovations by firms (these are known as “Porter externalities” after Porter (1990)). Following Combes (2000) we measure local competition as a local Herfindahl index of concentration computed at the firm level

$$\text{Comp}_{c,s} = \sum_{i \in c,s} (L_{c,s,i}/L_{c,s})^2$$

where with $L_{c,s,i}$ is the employment level of firm i belonging to city-industry c, s. The index measures the distribution of the employment shares calculated at plant level within each city-industry: low competition should result in a less uniform distribution of employment across the existing firms.

Finally, we include the average size of plants in the city-industry, a variable for potential effects of firms size structure on growth.[13] To facilitate comparison with the existing literature we will actually use the inverse of average firm size

$$\text{Size}_{c,s} = \frac{1}{\overline{L}_{c,s}}$$

that is the number of firms over employment in the city industry, the same index used by Glaeser et al.(1992).

Indexes have been calculated using the 1986 NSSI archive on the universe of firms. Summary statistics of the main variables used in the empirical analysis are found in Table 4.

3.1 *Productivity Growth and the Local Industrial Structure*

This section illustrates the regression-specification and results obtained regressing the average TFP growth rate calculated over the 1986-1998 period on the above mentioned employment indicators. The “Centrale dei Bilanci” sample is an open one, with entry and exit of firms over time. Hence, in principle, we can compute city-sector TFP growth rates applying several sample selection rules. The results shown in this section are obtained using the most

[13] Pagano and Schivardi (2001), using cross-country data at the sectoral level, find that productivity growth is positively correlated with average firm size and offer evidence that the direction of causality goes from size to growth.

restrictive selection rule, i.e. considering only those city-industries that are represented by at least one firm over the entire time-span. As we discuss later, our results are robust to alternative selection rules.

The adopted specification follows closely that proposed by Combes (2000):

$$(1) \qquad \widehat{A}_{c,s} = \beta_1 \text{SPEC}_{c,s} + \beta_2 \text{VAR}_{c,s} + \beta_3 \text{COMP}_{c,s} + \beta_4 \text{SIZE} + \beta_5 X_{c,s} + u_{c,s}$$

where capital letters indicate log-transformation of the corresponding regressors, and the vector $X_{c,s}$ contains additional controls included on the right-hand side. In particular we controlled for the logarithm of city employment in 1986 l_c, so that the coefficient $\beta_1$can be correctly interpreted as the effect of local relative concentration (sectoral employment share), holding total employment in the city constant (see Combes 1999). We also accounted for the variability in human capital endowment across cities, measured by the average number of years of schooling of the city working-age population in 1981, for the initial level of city-sector TFP and for two sets of dummy variables accounting for the sector of activity and geographical location of the city (macro-area).

The TFP estimates in the L-S are obtained by averaging over the firm level TFP so that the precision of the estimates increases with the number of firms. To reduce the noise coming from potentially imprecise estimates of the L-S for which only a few firms are included in our dataset, we use WLS, where each data point has been weighted by the number of firm-level observations by L-S. This implies that L-S with a higher number of firms will have proportionally more weight in determining the estimated coefficients.[14]

Table 5 summarizes the results obtained estimating different versions of equation (1) by WLS. Column [1] reports the basic specification. First, we find that the elasticity of TFP growth to sectoral specialization, holding total city-size constant, is positive and significant at the 5 per cent level. Our point estimate ($\beta_1 = 0.23$) implies that an increase in sectoral employment that shifted the median city-industry concentration index to the third quartile (raising the share of sectoral employment 3 times) would be associated with an average yearly increase in TFP of nearly 0.5 per cent over the subsequent period. This result is in contrast with existing evidence for other industrialized countries, where industries are found to grow more

[14] The weighting scheme is the same as would be obtained if we used firm-level TFP growth directly as the dependent variable rather than its average in the C-S.

slowly in relatively more concentrated locations (Glaeser et al. 1992, Combes 2000). Second, we find that TFP growth is positively affected by city size. Since we are holding the sectoral composition of production in the city constant, this result can be interpreted as the effect of the size of the local market, consistently with a broad literature on urban growth. The elasticity of productivity to total manufacturing employment in the city is 0.4 per cent , implying that moving from the median to the third quartile in terms of city size increases yearly productivity growth by 0.8 per cent on average. This indicates that scale effects are important determinants of productivity growth at the local level.

We do not find that other possible sources of externalities at the local geographical level matter for our measure of TFP growth. Both the initial range of productive variety and the degree of competition at the beginning of period, capturing Porter and Jacobs externalities respectively, seem to affect the TFP growth positively, but their elasticities are non significantly different from zero (at 10 per cent level), according to our estimates. The same is true for our measure of average human capital in the LLS. We also find weak indications that productivity in city-industries characterized by smaller average firm size tends to grow faster. On the other hand, the coefficient of the initial TFP level in the city-industry is negative and highly significant, capturing convergence in the growth rates across city-industries.

One problem with the results shown in Table 5, col.1, is that the original specification might be missing important determinants of productivity growth at the local level. We tried to control for this possibility by checking the robustness of our estimates to spatially correlated omitted variables. In practice, this amounts to increasing the number of spatial controls included in our baseline regression: as long as (at least part) of the variation in omitted determinants of TFP growth across city industries is picked up by these spatial control variables, and if omitted variables do indeed affect the estimation of the parameters of interest, then adding such variables would change the effect of the included regressors. The results are shown in column [2], where 20 spatial control variables (corresponding to administrative regions) are included, and in column [3], where we control for the 95 Italian provinces in 1986. Our estimates are only slightly affected by adding these controls: in column [2] the specialization coefficient falls slightly and in column [3] the corresponding standard error increases marginally, but the estimate remains significant at the 10 per cent confidence level. The remaining results are unaffected.

The last three columns perform additional robustness checks. Our weighting scheme gives more weights to L-S with a high population of firms. To make sure that this does not influence the results, we run the basic specification as in column [1] without weighting. The specialization coefficient increases to .346 and is estimated more precisely, while that of city size increases marginally. All other results are also unaffected. We also control for different selection criteria. As explained, the baseline specification uses only L-S that were continuously present in the sample. In column [5] we use those that are in the sample in the first and the last year and in column [6] we use all possible information, calculating average TFP growth using all available years, i.e. also L-S that have been in the sample for some years. The number of observations increases from 1,602 to 1,810 and 2,876 respectively. Again, the basic results are unchanged, the major difference being that in the case with more observations (column [6]) the effects of sectoral specialization and average firm size are stronger.

Having established the existence of non-negligible MAR externalities at the city-industry level we also examined how localized these forces are by adding two variables measuring scale and own-industry specialization in the neighboring area, obtained by aggregating our city-sector data to the province level[15]. While the estimated localization effects are not affected in this specification, we do not find that own-industry specialization in neighboring areas matters for TFP growth, as shown in Table 6, cols. 2 and 3 (the first column replicates column [1] in Table 5). This result is in line with previous work based on patents (Jaffe et al. 1993) and employment levels in new establishments computed at the zip code level (Rosenthal and Strange 2000), which found that localization economies attenuate rapidly with distance.

Finally, we checked the robustness of our results using alternative measures of localization-MAR economies. Henderson (2001) argued that the count of own-industry plants would be a better measure of local own-industry activity than the size of own-industry employment. Ciccone and Hall (1996) measured the size of local production scale with the density of economic activity (i.e. the number of workers per unit of non-agriculture land-area) rather than its level. Our results proved to be robust to both changes.

All in all, at this stage we conclude that there is evidence that MAR externalities and scale effects in terms of city size are at work at the local geographical level in Italy, while

[15] Each of the 95 Italian provinces in 1986 contained on average more than 7 Local Labor Systems.

other sources of potential dynamic externalities do not seem to matter for productivity growth in our sample.

4. Local conditions, productivity growth and employment growth

Our findings regarding the determinants of local productivity growth are at odd with those of most of the urban-growth literature, which has obtained robust evidence of negative MAR-specialization externalities and of positive Jacobs urbanization economies. In this section we argue that these differences are likely to be due to a problematic aspect of the specification adopted in previous exercises rather than to the peculiarity of the Italian productive system.[16]

Given the lack of data on productivity at the local sectoral level, previous literature has mostly used employment growth, based on the idea that changes in productivity result in proportional employment changes. To see what assumptions underlie this approach, we construct a very simple model of employment determination at the local level. Consider an economy organized in many different cities C_i, each representing a local labor market.[17] We take a partial equilibrium approach, based on the fact that in our empirical specification each C-S is small with respect to the economy as a whole, so that the assumption that the overall wage rate is given and not influenced by that prevailing in each individual location can be maintained.

Within C_i there is a representative firm producing output with labor as the only input using the production function $F(A_i, l_i)$, where l is labor and A is the level of TFP. Following Glaeser et al. (1992) it is maintained that the growth of TFP depends on the local industrial

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[16] The Italian productive system, characterized by areas with a large presence of small and medium size enterprises (the so called "industrial districts"), could in principle be particularly conducive to interaction-induced externalities. Guiso and Schivardi (2000) study information spillovers among Italian district firms, finding that they significantly influence firms' behavior and performance. Interestingly enough, the motivating example of Porter's (1990) competition effect was the tile industry in Sassuolo, an area around Bologna where there is a heavy concentration of successful tile firms.

[17] For simplicity, we exclude the sectoral dimension but the analysis can easily be extended to include sectoral differences. In practice, due to human capital specificity, segmentation across labor markets can have not only a geographical dimension but also a sectoral one, so that the city in the model can be thought of as a city-sector. The hypothesis of sectoral segmentation and of costs of moving from one sector to another finds empirical support (see for example Shin 1997).

structure, here captured by the vector of (log) variables X_i:

(2) $$\Delta \log A_i = \theta \log X_i$$

where the parameter vector θ captures the dynamic external effects of different local characteristics. The technology is Cobb-Douglas with decreasing returns to scale[18] owing to some scarce factor such as land: $F(A, l) = Al^{\alpha}, \alpha < 1$. The representative firm takes wages as given, so that profit maximization yields a standard labor demand schedule:

(3) $$l^D(w_i, A_i) = (\frac{\alpha A_i}{w_i})^{\frac{1}{1-\alpha}}$$

Equation (3) is the basis for the use of employment changes as proxy for productivity changes in previous empirical work. In fact, given w_i, productivity changes result in proportional employment changes, with $\frac{1}{1-\alpha}$ as the factor of proportionality. One can then substitute $\Delta \log l_i$ for $\Delta \log A_i$ in equation (2) and perform the analysis with employment growth.

The problem with this approach is that it neglects the role of labor supply, an assumption that can have important consequences for the identification of θ. If fact, workers' mobility choices are influenced not only by wage differentials, but also by other aspects of the location and the job, such as amenities, house prices, pollution, congestion, individual preferences regarding jobs, and so on. To see how this might effect identification, we model labor supply by assuming that each worker's utility function is defined over income and city-specific characteristics, with the constant-elasticity form:

(4) $$U\left(w, Z\right) = w^{\delta} Z^{\eta}$$

where income is equal to the wage rate and Z is a vector of relevant city-specific characteristics. Outside C$_i$ there is continuum of workers of mass 1 with reservation utility normalized to zero. A worker can decide to take the reservation utility or pay a moving cost m measured in utility units, and move to take up employment in C$_i$. The problem of the worker

[18] This assumption regarding the aggregate production function does not put any restriction on the degree of returns to scale of the accumulable factors at the individual firm level, and is not in contrast with the estimation procedure, which does not require any assumption as to the degree of returns to scale for capital and labor at the firm level.

is then:

$$\max\{0, w_i^{\delta} Z_i^{\eta} - m\} \tag{5}$$

The worker will move if and only if $w_i^{\delta} Z_i^{\eta} \geq m$.

Workers are distributed around C$_i$ at increasing cost according to the distribution function $g(m)$ which, to get an analytical solution, we assume to be uniform on the interval $[0, M]$. The parameter M measures the average distance of workers from C$_i$: $E(m) = M/2$. At any given level of wage w_i and local characteristics Z_i, all workers with $m \leq w_i^{\delta} Z_i^{\eta}$ will move to take up employment in C$_i$ so that the local labor supply is:

$$l^S(w_i, Z_i) = \int_0^{U(w,Z)} g(m)dm = \frac{1}{M} w_i^{\delta} Z_i^{\eta} \tag{6}$$

Given the vector Z_i, labor supply depends positively on the wage but is decreasing in M: the higher the average mobility cost, the lower the labor force moving to C$_i$.

By equating labor demand (3) and supply (6), taking log, first differences[19] and substituting (2), the relationship between equilibrium labor growth and X_i can be written as:

$$\Delta \log l_i = \frac{\delta\theta}{\gamma} \log X_i + \frac{\eta}{\gamma} \Delta \log Z_i \tag{7}$$

where $\gamma \equiv 1+(1-\alpha)\delta$. Equation (7) makes two points. First, $\frac{\delta\theta}{\gamma}$ constitutes a transformation of the original parameter of interest θ, so that the employment coefficient cannot be interpreted quantitatively in terms of productivity growth. Second, and more importantly, its unbiased estimation requires that changes in all omitted variables that affect labor supply through Z_i should be independent of the set of variables that generate technological spillovers X_i. Stated differently, the identification of dynamic externalities from employment growth requires that the sources of such externalities should not influence labor supply: failing this, local conditions will shift both labor demand and labor supply, giving rise to a classical identification problem.

To check if employment based regressions are affected by such identification problems, we run the regression specification (1) using measures of labor growth recovered from the

[19] We are implicitly assuming that the previous period employment level plays no direct role in determining current period labor supply, so that all persistence in employment comes from persistence in city characteristics Z. This assumption could be removed by directly modeling the mobility choices of workers in the city in the previous period, by assuming symmetrically that they can leave the city to get the reservation utility by paying a moving cost. This modification would slightly complicate the analysis without adding any important insight.

NSSI dataset[20] as the dependent variable:

$$\widehat{l}_{c,s} = \gamma_1 \mathrm{SPEC}_{c,s} + \gamma_2 \mathrm{VAR}_{c,s} + \gamma_3 \mathrm{COMP}_{c,s} + \gamma_4 \mathrm{SIZE} + \gamma_5 X_{c,s} + \epsilon_{c,s} \tag{8}$$

To maximize comparability with the TFP regressions, we estimated this equation using the same WLS scheme and the same sub-sample of city-industry observations we used in the TFP regression. Results, which are reported in Table 7, indicate that productive concentration is associated with lower employment growth at the city-sector level, the opposite of what found for TFP. In particular we find that doubling the share of sectoral employment in a given location will reduce average employment growth in the same sector by 0.75 per cent per year. The partial elasticity of employment growth to city-size is also estimated to be negative and substantial, whereas it had positive impact on TFP growth. Holding sectoral composition and other determinants constant, doubling employment in a given city would reduce the growth rate by more than 1 per cent per year over the subsequent period. We also find that the variety, size and competition indicators, which apparently have no direct effect on TFP growth, significantly affect local employment. In particular, and similarly to what has been found by Combes (2000), we estimate that the average impact of productive diversity in the city on subsequent employment growth of the manufacturing sectors is negative. Similarly to what has been found for France and across US cities, we also estimated a positive partial elasticity of employment to average firm size.

We ran several robustness checks, as we did for TFP specification. We controlled for the existence of spatially correlated omitted variables (cols. 2 and 3) finding that, while most of the previous results are unaffected, the variety coefficient becomes insignificant. We ran the unweighted regressions (col. 4) and found no significant differences with respect to the initial regression. Finally, we also considered a version of our regression where the dependent variable had been obtained from the CADS sample, as opposed to the population (NSSI data). This is a particularly interesting check of the representativeness of the CADS data and therefore of the generality of the results of the TFP regressions. Results are reported in the last column of Table 7. Indeed, we find that the three coefficients that are significant (specialization, city size and competition) are very similar to those in column [1], a result

[20] The NSSI data cover the universe of workers and so are preferable to CADS data. We defer the discussion of the results using CADS data to the robustness analysis.

that we interpret as evidence in favor of the representativeness of the CADS data. Instead, unlike the population based (NSSI data) regressions, the coefficients of firm size and of variety are not significantly different from zero. This, together with the fact that the R^2 is substantially lower in the CADS regression (.16 against .43), suggests that resorting to a sub-sample introduces noise in the estimates and reduces their precision; however, there is no evidence of any systematic bias.

4.1 *Discussion*

While in line with most of the urban-growth literature, the results we obtained from the employment growth regressions are not in accordance with those produced by the TFP regressions. Given that these do not require any identifying assumption, our findings cast serious doubts on the use of employment changes as alternative indicators of dynamic externalities and suggest that the identification problem might go beyond the Italian case. In fact, following a different approach and using US data, Henderson (2001) also recognizes that employment growth regressions might be problematic. Restricting his attention to capital goods and high-tech industries, he estimates plant level production functions with fixed effects that include variables capturing both specialization and urbanization economies at the local level. He finds that for the high tech industry the level of current output at the plant level is positively affected by lagged indicators of specialization, contrary to employment growth.[21] Henderson does not explicitly recognize the identification issue but calls into question allocative shocks, although by definition they should not be systematically correlated with local conditions. Similar conclusions are reached by Dekle (2002) for the Japanese prefectures, although he finds no evidence of dynamic externalities in manufacturing.[22] Taken

[21] Unlike us, his approach, based on within estimation, disregards the cross sectional variability in the data and therefore only uses changes in the industrial structure variables, an approach that, while eliminating the possibility that the results are driven by some unobserved fixed factor, is vulnerable to unobserved innovations that drive changes in both the industrial structure and productivity. Our estimating approach also more carefully controls for endogeneity of inputs and for firm selection. Finally, his specification is not directly comparable with those of the urban growth literature, making comparisons with employment growth regressions less straightforward.

[22] This might be due the fact that his analysis, based on national account data, is constrained to fairly aggregated geographical (49 prefectures) and sectoral (manufacturing as a whole) levels. In fact, the rate of spatial decay of localization externalities has been shown to be very fast (Jaffe et al. 1993, Audretsch and Feldman 1994, Rosenthal and Strange 2000); moreover the relative importance of intra-industry as opposed to cross-industry externalities might be difficult to disentangle using a nine one-digit decomposition of the entire economy.

together, this evidence calls into question the previous interpretations of employment growth regressions in terms of dynamic externalities.

Indeed, there are obvious reasons to believe that the assumption that labor supply changes are independent of local conditions is generally not verified. In terms of the city-size effects, it seems reasonable that indicators of the quality of life, such as pollution, congestion, green lands and so on, should deteriorate more rapidly in highly urbanized areas. Moreover, these are superior goods, so that their demand increases more than proportionally with per capita income, again reducing labor supply in densely populated areas.[23] While it is not so obvious to explain why sectoral indicators could impact labor supply, in a recent paper Glaeser and Kahn (2001) showed that, across US cities, workers' preferences are important determinants of industry-level equilibrium employment.[24] The link between sectoral indicators and labor supply could be explained by a "fishing off the pond" problem, which would dynamically reduce the amount of workers in the local market who are willing or have the appropriate skills to be employed in overrepresented sectors. Also, sectoral concentration might increase the bargaining power of workers, particularly increasing the level of unionization and thus curbing labor supply growth. Finally, the regulation of the labor market, especially in terms of legislation that limits the extent of wage differentials across locations, could impact the way productivity changes at the local level are reflected in employment and wage changes.[25]

This last point opens the way to a final check, based on a wage growth equation. Our model yields the following estimating equation for the rate of change of average wage in the city-industry

$$\Delta \log w_i = \frac{\theta}{\gamma} \log X_i - \frac{\eta(1-\alpha)}{\gamma} \log \Delta Z_i, \tag{9}$$

---

[23] Chatterje and Carlino (2001) construct a model in which agglomeration economies have a linear effect on productivity, while congestion diseconomies increase more than proportionally with city size. They show that their model matches the evolution of US cities in the post-war period, characterized by a decrease in the dispersion of employment density across cities.

[24] In particular Glaeser and Kahn (2001) show that workers' residential preferences are crucial in explaining productive decentralization at the industry level. After calculating the "average" worker-type for each 3-digit SIC industry at the national level, they find that firms belonging to a specific industry are more likely to suburbanize in a given city, the more suburbanized are in that city the type of workers such industry is likely to hire.

[25] From a statistical point of view, the negative specialization coefficient might also signal mean reversion induced by random measurement error in the local employment data.

which is also subject to the identification critique. Based on firm-level average annual compensation of employees available in NSSI archives, we construct a measure of average per capita wage growth rate at the city-industry level and, in line with the previous analysis, run the following regression:

$$\widehat{w}_{c,s} = \delta_1 \text{SPEC}_{c,s} + \delta_2 \text{VAR}_{c,s} + \delta_3 \text{COMP}_{c,s} + \delta_4 \text{SIZE} + \delta_5 X_{c,s} + \varepsilon_{c,s} \tag{10}$$

Results are reported in Table 8, organized like the previous one. The first point that emerges from the table is that the estimates appear less precise than those for TFP and employment: the R^2 is lower (and most of it is due to the effect of the unreported initial wage level, negative and strongly significant) and the coefficients tend to be not very precisely estimated; moreover, when compared with the other tables the point estimates tend to be relatively smaller. With respect to the previous estimates we find that, as in the TFP regressions, city size has a positive and significant effect on wage growth and specialization a positive but generally insignificant one.[26] Instead, almost all coefficients have the opposite signs with respect to the employment growth regressions. When interpreted in a labor demand and supply framework, the opposite response of employment and wages would suggest that equilibrium outcomes are dominated by labor supply movements.

The joint findings of the three sets of regressions are compatible with a story in which wage compression induced by centralized bargaining generates convergence of wages across space and reduces their responsiveness to local conditions. In this case, labor supply becomes an increasingly crucial determinant of equilibrium employment. So, if for example a highly populated area becomes increasingly congested, the failure of wages to compensate for the loss in utility might induce people to move away, with little role for labor demand and therefore for productivity in determining employment levels. Stated more generally, the results point to the fact that labor market outcomes depend on more factors than productivity changes alone.

Taken together, our results indicate that identification problems might be very serious in both employment and wage growth regressions and that, while giving interesting information on the reduced-form relation between local conditions and employment and wage changes, not much can be said about productivity growth. All in all, we think that there are clear indications

[26] The coefficient of firm size indicates that larger firm size is associated with higher wage growth, an effect that is well known in the labor literature on the levels of wages.

that only the direct measurement of TFP can identify dynamic local externalities within this framework.

5. Conclusions

Important empirical works dealing with the estimation of the strength of dynamic externalities at the local geographical level reached controversial results. Existing evidence, based on employment growth regressions, requires that equilibrium employment determination should be demand-driven and changes in *labor supply* independent of local conditions. In this paper we show that, while useful for investigating the determinants of *industry growth* at the local level, employment growth regressions might be misleading if interpreted to discriminate among different sources of *productivity growth* and dynamic externalities, because of serious identification problems. In fact, we find that TFP and employment growth regressions yield almost the opposite results. In particular, TFP growth is enhanced by specialization and city size but not by urban diversity. We conclude that employment-based equations might not be able to disentangle the determinants of local industry-growth from the sources of productivity growth.

In terms of future work, it will be important to extend the TFP analysis to other countries to check whether, as seems likely from our discussion, the insights that we obtain for Italy extend to other economies. At the same time, it will be important to develop models that, by explicitly considering labor supply and mobility choices, allow for differential effects of the local structure on productivity on one side and employment on the other. This will help to give a structural interpretation of results of employment growth regressions previously run in the literature and further guidelines for future empirical work.

Appendix

A.1 **Production function estimation: data and procedure**

This appendix briefly summarizes the data and procedure adopted in the production function estimation. Firm-level variables are drawn from the Company Account Data Service (*Centrale dei Bilanci*) containing balance sheet data on a sample of between 30,000 and 40,000 Italian firms for the period 1982-98. Both value added and investments have been adjusted using the appropriate two-digit deflators, derived from NIS's National Accounts. The capital stock at firm level was obtained from the book value of investment using the permanent inventory method, accounting for sector specific depreciation rates from NIS's National Accounts data. The initial capital stock was estimated using the deflated book value, adjusted for the average age of capital estimated from the depreciation fund. We take care of outliers by excluding firms with values of value added per worker or value added per unit of capital below the first or above the last percentile of the distribution. This procedure does not introduce systematic biases in the results, while improving their stability.

We use the estimation approach proposed by Olley and Pakes (1996). Production takes place through a Cobb-Douglas technology using capital and labor, with parameters α and β, subject to an unobserved (to the econometrician) productivity shock ω. In logs, the production function is

$$y_t = \alpha k_t + \beta l_t + \omega_t + \eta_t \tag{11}$$

where η is a random shock uncorrelated with the other variables. For simplicity, the theoretical model assumes that capital is irreversible (the estimation method works independently from this assumption); moreover, capital is a predetermined variable at t so that it is independent from ω_t, while labor can adjust to the productivity shock. The firm also decides whether to continue production or shut down, in which case it collects a savage value Φ. The dynamic programming problem of the firm is represented by the Bellman equation:

$$V(k_t, \omega_t) = \max\{\Phi, \max_{i_t, l_t}[\pi(k_{t,} l_t, \omega_t) - c(i_i) + E(V(k_{t+1}, \omega_{t+1}))]\} \tag{12}$$

$$\text{s.t. } k_{t+1} = (1-\delta)k_t + i_t,\ F_\omega(\omega_{t+1}|\omega_t) \tag{13}$$

where π is current profit, $c(.)$ is the cost of investment and $F_\omega(\omega_{t+1}|\omega_t)$ is the probability distribution of ω_{t+1} given ω_t, assumed to be stochastically increasing. The dynamic programming problem delivers three policy functions: a continuation function $\chi(k_t, \omega_t) = \{0, 1\}$, an investment function $i(k_t, \omega_t) \geq 0$ and an employment function $l(k_t, \omega_t)$. The continuation decision takes the form of a threshold value $\underline{\omega}(k)$ for the productivity shock below which it is optimal to exit.

The continuation decision and the input choices depend on the capital stock and the unobservable productivity shock. This implies that OLS estimation of (11) has two sources of bias. First, the labor input is correlated with ω; second, it can be shown that $\underline{\omega}(k)$ is decreasing in k, which induces a selection issue: the higher the capital stock the more likely it is that firms remain in the market even with low realizations of ω. This implies that if selection is not accounted for the capital coefficient will be downward biased, because of the negative correlation between ω and k.

Olley and Pakes propose a procedure to correct for both biases. For the simultaneity bias they approximate the unobservable ω with a non-parametric function of investment and current capital stock. In fact, the investment function is invertible so that there exits a function relating the productivity shock to the stock of capital and investment:

$$\omega_t = h(i_t, k_t) \tag{14}$$

Given that the shape of $h(.)$ depends on the functional forms of the primitives and in general has no analytical representation it is approximated by a polynomial series in i and k. The coefficient of the labor input is therefore consistently estimated by OLS on:

$$y_t = \beta l_t + \phi(i_t, k_t) + \eta_t \tag{15}$$

where

$$\phi(i, k) = \alpha k + h(i, k) \tag{16}$$

Define the estimated value $\hat{\phi} = y - \hat{\beta} l - \hat{\eta}$.

To estimate the capital coefficient we need to account for selection. To do so, in a first step we estimate a probability of survival as a function of (i_t, k_t) via a probit estimation of the continuation decision in a power series of i and k. Define the estimated probability as $\hat{P}$. We can now introduce a Heckman-type correction in the estimation of the capital coefficient. In fact,

$$E(y_{t+1} - \beta l_{t+1} | k_{t+1}, \chi_{t+1} = 1) = \beta k_{t+1} + E(\omega_{t+1} | \chi_{t+1} = 1, \omega_t) \tag{17}$$

Using the definition of conditional expectation and (14), it can be shown that the conditional expectation of ω_{t+1} can be expressed as a function of P and h, say $g(P, h)$. Using (16),the estimating equation therefore becomes

$$y_{t+1} - \beta l_{t+1} = \beta k + g(\hat{P}, \hat{\phi} - \alpha k) + \xi_{t+1} + \eta_{t+1} \tag{18}$$

where ξ is the innovation in ω. The last step therefore requires the non-linear estimation of equation (18), where the unknown function g is replaced by a power series in $\hat{P}$ and $\hat{\phi} - \alpha k.$

We implement the procedure using polynomial approximations of the fourth degree in all stages to approximate h, P and g. Results are stable when going from a third to a fourth degree, an indication that the polynomial approximations are sufficiently accurate. In terms of results, we find that the simultaneity bias does not affect the estimation of the labor coefficient to a large degree, while selection is very important for the capital coefficient. This is the same pattern observed by Olley and Pakes with data from the telecommunications equipment industry in the US.

Tables

Table 1

Firms' characteristics (Average values)

		CADS				NSSI	
Sector		Val.add.*	Cap stock*	Empl.	N. obs	Empl.	N. obs
1	F	4617	9596	92	1516	10	25819
2	T&C	2769	4287	82	2335	13	43784
3	L&F	1637	1634	53	820	12	13254
4	W&C	1756	3086	55	1167	7	27830
5	T&Gl	4017	9912	88	1260	15	14001
6	BM	6393	17065	157	711	39	4224
7	Mach	4441	5935	112	5582	14	91606
8	Chem	7460	14843	128	2013	27	13785
9	P&P	4325	7375	90	992	12	15634
10	TEq	9692	36191	555	489	115	2353
	Total	4749	8418	113	16885	14	261549

Note: * thousands of 1991 euros. Sectoral classification: F=Food, beverages and tobacco; T&C=Textiles and clothing; L&F= Leather and footwear; W&C=Wood, products of wood and cork; T&Gl=Timber, construction materials and glass; BM=Basic metals; Mach=Metal products, machinery and equipment; Chem=Rubber, plastic and chemical products; P&P=Paper, printing and publishing; TEq.=Transportation equipment.

Production function coefficients: factor share and direct estimates

Sector		Factor shares		Direct estimates		
		β	α	β	α	$\alpha + \beta$
1	F	0.56	0.44	0.63	0.39	1.02
2	T&C	0.60	0.40	0.58	0.37	0.95
3	L&F	0.61	0.39	0.62	0.43	1.05
4	W&C	0.63	0.37	0.70	0.35	1.05
5	T&Gl	0.58	0.42	0.67	0.37	1.04
6	BM	0.65	0.35	0.60	0.33	0.93
7	Mach	0.67	0.33	0.72	0.28	1.00
8	Chem	0.60	0.40	0.70	0.29	0.99
9	P&P	0.66	0.34	0.72	0.32	1.04
10	TEq	0.74	0.26	0.70	0.26	0.96

Note: α is the capital coefficient and β the labour one. The first estimates use the traditional Solow approach, the second the direct estimation of the production function coefficients using the Olley and Pakes (1996) procedure. See Table 1 for the sectoral labels.

Table 3

Labor productivity decomposition

	y/l	TFP	$\alpha * k/l$	$\gamma * l$
	Levels, 1991 (log)			
F	3.80	1.97	1.71	0.12
T&C	3.41	2.33	1.34	-0.26
L&F	3.33	1.78	1.32	0.23
W&C	3.40	1.86	1.32	0.22
T&Gl	3.72	1.86	1.64	0.22
BM	3.64	2.64	1.49	-0.49
Mach	3.58	2.56	1.02	0.00
Chem	3.90	2.76	1.27	-0.12
P&P	3.81	2.24	1.34	0.23
TEq	3.54	2.85	1.06	-0.37
	Growth rates, 1986-1998 (% per year)			
F	3.24	2.29	0.97	-0.02
T&C	3.32	2.22	1.07	0.03
L&F	3.20	1.64	1.51	0.04
W&C	3.40	3.18	0.13	0.09
T&Gl	3.61	3.34	0.29	-0.02
BM	4.60	4.03	-0.15	0.72
Mach	4.18	4.00	0.18	-0.00
Chem	3.53	3.18	0.29	0.06
P&P	3.15	2.70	0.49	-0.03
TEq	1.94	1.15	0.61	0.18

Note: The first column is overall labour productivity, the second is the TFP contribution, the third capital accumulation and the last returns to scale. See Table 1 for the sectoral labels.

Table 4

Descriptive statistics

City-industry variables	Statistics		
	Mean	Median	Std
TFP average yearly growth	0.027	0.027	0.033
Specialization index	0.172	0.100	0.179
City size	16,533	6,082	49,193
Average firm size	25.20	12.12	89.51
Variety index	0.126	0.089	0.107
Competition index	0.199	0.122	0.216
Average yrs of schooling	7.516	7.495	0.757
Number of firms*	8.456	3.000	24.54

Note: Statistics based on the sample of 1602 city-industry observations used in the regressions shown in the paper; * number of firm-observations available by city-industry to calculate aggregate TFP.

Table 5

City-industry productivity growth

	[1]	[2]	[3]	[4]	[5]	[6]
Special.	.230**	.199*	.206*	.346***	.206*	.394***
	(.111)	(.113)	(.117)	(.125)	(.110)	(.162)
City size	.401***	.390***	.447***	.492***	.395***	.619***
	(.095)	(.093)	(.094)	(.115)	(.094)	(.118)
Firm size	.357*	.296	.321	.563*	.343*	.596**
	(.209)	(.206)	(.211)	(.294)	(.206)	(.264)
Variety	-.012	-.013	.091	.015	-.009	-.142
	(.119)	(.106)	(.159)	(.119)	(.116)	(.161)
Compet.	.085	.074	.097	.214	.088	.022
	(.102)	(.098)	(.094)	(.132)	(.101)	(.124)
Spt ctrls	5	20	95	5	5	5
Weights	YES	YES	YES	NO	YES	YES
No. of obs.	1,602	1,602	1,602	1,602	1,810	2,876
R^2	0.43	0.45	0.49	0.41	0.44	0.19

Note: Dependent variable: annual TFP growth rate at the L-S level. All regressions include sector dummies. Spatial controls are macro areas, regions and provinces. The first four columns are based on the sample of C-S continuously in the database, the fifth in the database in 1986 and 1998, the last in the database in any year. *** indicates significance at 1 per cent , ** at 5 per cent and * at 10 per cent.

Table 6

City-industry productivity growth: neighbourhood externalities

	[1]	[2]	[3]
Specialization	.230**	.262**	.219*
	(.111)	(.124)	(.126)
Neighbourhood's	-	-.066	-.043
specialization	-	(.111)	(.112)
City size	.401***	.383***	.373***
	(.095)	(.094)	(.094)
Firm size	.357*	.352*	.292
	(.209)	(.206)	(.204)
Variety	-.012	-.004	-.008
	(.119)	(.118)	(.106)
Competition	.085	.077	.068
	(.102)	(.101)	(.097)
Spt ctrls	5	5	20
Weights	YES	YES	YES
No. of obs.	1,602	1,602	1,602
R^2	0.43	0.43	0.45

Note: Dependent variable: annual TFP growth rate at the L-S level. All regressions include sector dummies. Spatial controls are macro areas, regions and provinces. *** indicates significance at 1 per cent , ** at 5 per cent and * at 10 per cent .

City-industry employment growth

	[1]	[2]	[3]	[4]	[5]
Special.	-.750***	-.586***	-.698***	-1.38***	-1.08***
	(.210)	(.209)	(.201)	(.267)	(.525)
City size	-1.105***	-1.047***	-1.08***	-1.38***	-1.44***
	(.127)	(.128)	(.140)	(.192)	(.354)
Firm size	.648*	.914**	.803**	.129***	-.134
	(.360)	(.369)	(.384)	(.48)	(-.837)
Variety	.828***	.813***	.319	.472**	.249
	(.164)	(.177)	(.226)	(.217)	(390)
Compet.	-.839***	-.796***	-.895***	-.795***	-1.25**
	(.155)	(.160)	(.159)	(.235)	(.485)
Spt ctrls	5	20	95	5	5
Weights	YES	YES	YES	NO	YES
Data Source	NSSI	NSSI	NSSI	NSSI	CADS
No. of obs.	1,602	1,602	1,602	1,602	1,602
R^2	0.43	0.47	0.53	0.32	0.16

Note: Dependent variable: annual employment growth rate at the L-S level. All regressions include sector dummies. Spatial controls are macro areas, regions and provinces. All regressions based on the sample of C-S continuously in the database. *** indicates significance at 1 per cent , ** at 5 per cent and * at 10 per cent .

City-industry wage growth

	[1]	[2]	[3]	[4]	[5]
Special.	.050	.035	.015	.009	.162**
	(.037)	(.034)	(.033)	(.039)	(.070)
City size	.098***	.106***	.097***	.083***	.288***
	(.028)	(.024)	(.030)	(.031)	(.056)
Firm size	-.230***	-.292***	-.333***	-.151**	-.060
	(.068)	(.062)	(.062)	(.063)	(.108)
Variety	.033	.074**	.024	.015	-.013
	(.037)	(.035)	(.034)	(.033)	(.070)
Compet.	-.060*	-.073**	-.064*	.023	-.025
	(.035)	(.030)	(.030)	(.035)	(.066)
Spt ctrls	5	20	95	5	5
Weights	YES	YES	YES	NO	YES
Data Source	NSSI	NSSI	NSSI	NSSI	CADS
No. of obs.	1,602	1,602	1,602	1,602	1,602
R^2	0.29	0.35	0.41	0.67	0.38

Note: Dependent variable: annual wage growth rate at the L-S level. All regressions include sector dummies. Spatial controls are macro areas, regions and provinces. All regressions based on the sample of C-S continuously in the database. *** indicates significance at 1 per cent , ** at 5 per cent and * at 10 per cent .

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