Identifying the Sources of Local Productivity Growth*

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August 2003

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 level. Against previous empirical work, we find that industrial specialization and scale indicators affect TFP growth positively, while neither productive variety nor the degree of local competition have any effect. Employment-based regressions yield nearly the opposite results, in line with previous empirical work. We argue that such regressions suffer from serious identification problems when interpreted as evidence of dynamic externalities. Our results question the conclusions of most of the existing literature on dynamic agglomeration economies.

JEL classification numbers: R11, O47

Keywords: Local Growth, Productivity, Dynamic Externalities

*We thank Johannes Van Biesebroeck, Antonio Ciccone, Susana Iranzo, Andrea Lamorgese, Ariel Pakes, David Rigby, the referees and the editor for very useful comments. We also benefited from discussions with seminar participants at the Bank of Italy, Universidad Carlos III, LSE, NARSA Meeting 2002 and at the workshops on "Cities and Geography" hosted by CERAS in Paris and on "Productivity and Reallocation" hosted by CEU in Budapest. Marco Chiurato and Elena Genito provided excellent research assistance. Many thanks the Italian Social Security Service (INPS) for supplying us with their firm-level data. We are responsible for any mistakes. The views expressed here are our own and do not necessarily reflect those of the Bank of Italy. Correspondence: Bank of Italy, Research Department, via Nazionale 91, 00184 Rome, Italy. Tel: ++39 06 4792 2459 Fax: ++39 06 4792 3720, email: federico.cingano@upf.edu; schiva@stanfordalumni.org.

1 Introduction

Since Marshall (1890) emphasized the importance of local scale economies for agglomeration, alternative theories have been proposed to illustrate how the intensity and composition of productive activity impact on local economic performance (Henderson 1974, Eaton and Eckstein 1997). Early empirical works sought to determine whether differences in aggregate productivity levels between locations can be explained by measures of the intensity of local economic activity (Sveikauskas 1975, Segal 1976, Ciccone and Hall 1996). A related strand of literature inquires into what type of composition of the local industrial structure, if any, is most conducive to externalities, focusing in particular on the role of sectoral specialization (localization economies) and of product variety (urbanization externalities) in determining inter- and intra-industry externalities. In a seminal paper, Glaeser, Kallal, Scheinkman and Shleifer (1992) estimated the effects of alternative sources of externalities on economic growth at the local level.[1] They found strong evidence in a cross section of US cities that specialization and the scale of activity have negative effects on growth, while productive variety is positively related to subsequent growth.[2] Further studies extended the now-called "urban growth" literature to countries other than the US (see, for example, Bradley and Gans (1996) for Australia, Cainelli and Leoncini (1999) for Italy, Combes (2000) for France, and Soest, Gerking and van Oort (2002) for the Netherlands). Their results tend to confirm the initial finding that local productive specialization and scale have a negative impact on growth,

[1] Following Marshall, theoretical studies on the micro-foundations of agglomeration economies traditionally distinguished three broad sources of externalities (labor market interactions, availability of intermediate/final good and knowledge spillovers). In a recent survey, Duranton and Puga (2003) propose a taxonomy based on three mechanisms (namely matching, sharing and learning) that can give rise to agglomeration economies. They argue that the different sources could be linked to the same mechanism, and therefore be observationally equivalent (the "Marshallian equivalence"). The empirical framework we follow here does not aim at distinguishing between either the Marshallian sources or the mechanisms leading to agglomeration. It rather evaluates how these forces combine and act through the scale and the composition of the local industrial structure.

[2] Adopting a slightly different approach, 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.

while the evidence on urbanization economies is less clear-cut. Such findings are quite puzzling, because they imply that there are dynamic *disadvantages* to spatial concentration and *negative* scale effects, the opposite of the theoretical predictions.

We argue that these results might suffer from a simple identification problem. Theories of dynamic externalities predict a relation between local structure and productivity. Due to data limitations, existing works have been based on employment growth regressions, relying on the assumption that increases in productivity result in proportional employment gains through shifts in labor demand. This approach neglects the possibility of labor-saving technological innovations. Moreover, it assumes that labor supply is independent of local conditions. This is a rather strong assumption. For example, negative congestion externalities related to the scale of local productive activity are likely to influence mobility choices; sectoral concentration might imply a higher unemployment risk against sectoral shock, again affecting employment choices. These effects could break or even reverse the chain of causality from agglomeration economies to employment growth.

We overcome the identification problem by using a measure of growth that is closer to the theoretical notion of dynamic externalities. We exploit firm-level data to construct a measure of sectoral Total Factor Productivity (TFP) with a high degree of geographical disaggregation and regress TFP growth at the city-sector level against precise 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 the first paper to use TFP data with a high degree of both geographical and sectoral disaggregation to test agglomeration theories.[3] Second, as we also have detailed information on local employment, we can compare the TFP results with those of the standard employment-based approach.

[3] Henderson (2003) 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.

Our results are easily summarized. First, the productivity regressions show substantial positive effects of both specialization and city-size on local TFP growth. These findings are consistent with a broad theoretical literature on urban growth but in contrast with the previous empirical evidence. We do not find that other possible sources of externalities, such as urban diversity, local competition and average firm size matter for productivity at the local level. Second, the standard employment-growth regressions yield results that are opposite to those of TFP and in line with the previous literature. Since both findings are robust to several checks and extensions, we conclude that employment growth is ill-suited to infer the sources of dynamic productivity growth, casting serious doubt on the results of the literature to date as evidence for or against dynamic externalities.

The rest of the paper is organized as follows. Section 2 discusses the potential problems of using employment growth as an indicator of agglomeration economies. In section 3 we describe the data sources and TFP estimation at the local geographical level, while section 4 presents the empirical specification and compares the results obtained using TFP and employment as growth indicators. Section 5 concludes.

2 Agglomeration economies and employment growth

Key debates in the empirical literature on agglomeration economies bear on the role of the scale of local economic activity in economic performance and the so-called "industrial scope" of local externalities (Rosenthal and Strange 2003). In accordance with a strand of literature running from Marshall (1890) to Arrow (1962) to Romer (1986) (MAR), spillovers are said to act mainly *within* industry boundaries; alternatively, they could depend on cross-fertilization *between* industries, as first argued by Jacobs (1969).[4] The empirical literature following Glaeser et al. (1992) evaluates the industrial scope of local externalities through their impact on urban

[4] Duranton and Puga (2001) model such effects over the industry life cycle, showing that diversity is important in the early phase of the life cycle, while specialization in the late one.

growth. In case of intra-industry spillovers, they argue, growth should be enhanced by the degree of local productive specialization, whereas if local externalities act mainly across industries, then it would be linked to the degree of local productive variety. In the literature the two competing effects are referred to as localization (or MAR) and urbanization (or Jacobs) economies and captured empirically by specific indexes of the employment composition of the local industrial structure (see section 4 for details).

Agglomeration theories predict a relation between the industrial structure and local productivity, owing to the externalities stemming from agglomeration economies. Given that any externality implies a change in output not accounted for by a corresponding change in inputs, the appropriate empirical measure of dynamic agglomeration economies is TFP growth. In practice, however, due to the lack of productivity data at the local level, inference on dynamic agglomeration economies has been based on employment growth regressions. This *indirect* approach requires a correspondence between TFP growth and changes in equilibrium employment. For example, Glaeser et al. (1992) use an illustrative model combining perfect competition in the product market, decreasing returns to labor and a flat labor supply schedule at the local level, which implies that in equilibrium productivity changes translate into proportional employment changes through shifts in labor demand.

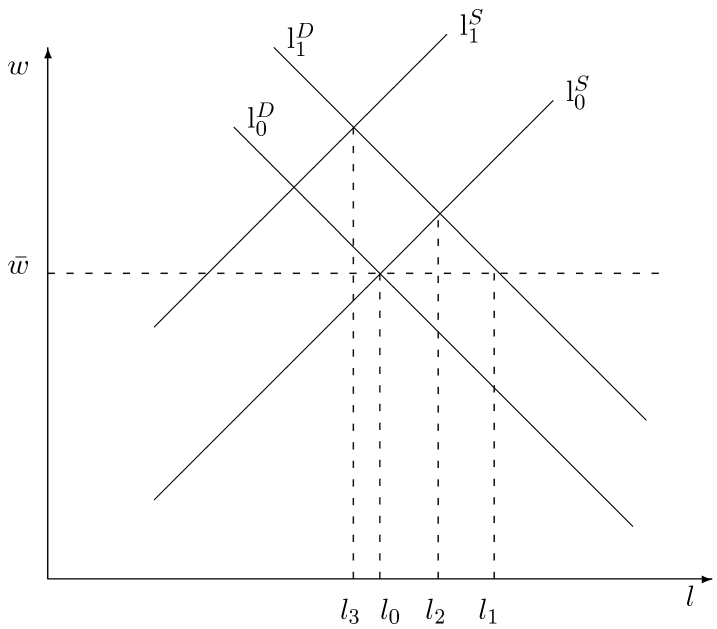
Unfortunately, the assumptions required to correctly identify agglomeration economies by means of employment growth are rather strong. In fact, modern regional and urban economics theories point to several reasons why the chain of implications from productivity changes to equilibrium employment may be broken, so that changes in the latter are an incorrect measure of the former.

First, as also shown by Combes, Magnac and Robin (2003), productivity and employment may diverge if firms in the city-sector (C-S) face a downward-sloping demand curve. In this case, even assuming a flat labor supply schedule, changes in productivity may or may not induce employment growth in the C-S, depending on the elasticity of demand for the good. To see this, suppose that each C-S produces a differentiated good and let the demand function be $x_{cs} = D_{cs}(p_{cs})^{-\sigma}$, where σ is the price elasticity of demand and D_{cs} is a demand shifter. Assume the production function in the C-S is $x_{cs} = A_{cs}l_{cs}$. In equilibrium, the price p_{cs} must equal the marginal cost $mc_{cs} = \frac{w_c}{A_{cs}}$, where w_c is the competitive wage in the city. Hence, in equilibrium $l_{cs} = D(w_c)^{-\sigma}(A_{cs})^{\sigma-1}$. If the demand-effect of the price change is not large enough to compensate for the changes in labor efficiency in production, i.e. if $\sigma < 1$, C-S employment will actually decrease as technology grows, because the gains in productivity will be used more to save on labor than to expand production.

A second problem is that employment-based approaches utterly neglect the role of local labor supply and its interaction with the productive structure. Labor supply can influence the interpretation of the results for two reasons. Due to moving costs, both between locations and between sectors, the local labor supply curve could be upward sloping, and the extent to which changes in productivity translate into changes in employment would depend critically on its slope. In Figure 1, starting from an initial employment level l_0, a given labor demand shift from l_0^D to l_1^D translates into different employment changes according to the steepness of the labor supply curve (l_1 vs. l_2). This problem prevents the quantitative assessment of the strength of agglomeration economies but does not break the monotonicity between labor demand and equilibrium employment changes. Worse, labor supply might also shift in response to local conditions. In this case we would be facing a classical identification problem, and equilibrium employment could not be used to make any inference about labor demand: in Figure 1, even if labor demand increases, a counteracting shift in labor supply could bring about a reduction in equilibrium employment, from l_0 to l_3.

There are several reasons why labor supply might shift in response to local conditions, and in particular to indicators capturing scale and industrial composition externalities. Consider first the case of scale indicators, as the size of local economic activity. Modern theories of urban economics (see for example Fujita (1989)) cite congestion externalities (related to pollution, lack of green areas, cost of housing

Figure 1: Equilibrium employment determination



Note: l_0 is the initial employment level, $l_1 - l_0$ the employment change with a flat labor supply, $l_2 - l_0$ with an upward sloping labor supply and $l_3 - l_0$ with a labor supply that also shifts with local conditions.

etc.) as crucial underlying determinants of households' location choices, with a negative impact on local labor supply. If scale indicators also proxied for negative externalities as well, their net effect on employment growth would be ambiguous, since positive agglomeration-induced changes in labour demand could be offset by shifts in labor supply.[5] Consider now the case of the sectoral composition indicators. In the presence of mobility costs between locations and sectors, diversified cities offer better opportunities to absorb sectoral shocks, while specialized ones imply a high unemployment risk against them. Simon (1988) shows that the frictional component of local unemployment in US cities is higher, the higher the degree of city's sectoral specialization. Hence, workers employed in very concentrated sectors might have an

[5] 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 the size of the local economy. 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.

incentive to move elsewhere in order to reduce the unemployment risk associated with sectoral shocks. In this case the labor supply schedule in the specialized sector will shift inwards, potentially offsetting the positive MAR effects on labor demand.

Finally, and in relation with the negative employment-based evidence on MAR externalities, note that this finding would be compatible with positive effects from specialization if employment in relatively more specialized locations responded less to productivity shocks than in less specialized ones. This might happen if, due to a "fishing off the pond" effect in terms of the skills required for being employed in the sector, the cost of employment reallocation towards the concentrated sector within the city rises with the degree of specialization. In this case the more specialized cities need to attract a relatively larger share of the additional concentrated-sector employment. Due to negative congestion externalities, they would need to raise wages more than the less specialized in order to increase employment in the concentrated sector by the same amount. As a consequence, equilibrium employment in the concentrated sector could grow relatively less in the more specialized cities, even if they undergo a relatively greater productivity shock.[6]

Rather than being exhaustive of the potential pitfalls of employment growth regressions, the foregoing discussion suggests that a number of forces other than pure agglomeration-effects are likely to affect local equilibrium employment determination. To estimate the strength of local externalities within the standard employment-based framework, one would need to construct a structural model in which agglomeration effects and local industrial structure are jointly determined. A more viable alternative is dismissing employment and using the correct empirical measure of dynamic externalities, i.e. TFP growth. That is our strategy here. As in the urban growth literature, the analysis is partial equilibrium and relates TFP growth to beginning of the period indicators of the local industrial structure. We

[6]Note that, from a statistical point of view, the negative effect of specialization on employment growth might simply signal mean reversion induced by random measurement error in the local employment data. In our empirical analysis we will be able to control for (and dismiss) this hypothesis.

therefore consider only the direction of the causality that runs from local structure to externalities, a partial but important step in jointly determining the two.

3 Measuring local TFP

3.1 Data description

As in most of the existing literature, the unit of observation here is sectoral activity at the local level. Our geographical units are the Italian local labor systems (LLS), defined as groups of municipalities characterized by a self-contained labor market, as determined by the National Statistical Institute (NSI) on the basis of the degree of work-day commuting by the resident population. Using 1991 census data, the NSI procedure identified 784 LLSs covering the whole national territory.[7] Sectorally, we restrict our attention to manufacturing, given the well-known problems of estimating productivity in services. Following NSI's territorial analysis, we use the 10-sector classification system reported in Table 1, which achieves a good compromise between the need for homogeneity within sectors and that for a sufficient number of observations for statistical reliability. Our unit of observation is the local labor system-sector (C-S for consistency with previous notation).

To obtain information on productivity and its determinants at C-S level, we combine data from three different sources. First, we exploit the earliest available wave (1986) of the National Social Security Institute (NSSI, *Istituto Nazionale Previdenza Sociale*) archives on the universe of Italian firms to compute precise measures of the local industrial structure. For all firms with at least one employee, the archives show the total number of employees, their average yearly earnings and some firm characteristics, such as the address (municipality and postal code) and the sector of activity. We use these data to compute the employment-based measures of the

[7] Even if defined using the same criteria (commuting ties), the concept of LLS differs from US Core Based Statistical Areas since its identification does not impose minimum population size. Hence, similarly to French "zones d'employ", they entirely and continuously cover the national territory. 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.

local industrial structure.[8]

The NSSI dataset has no information on production or capital stock. Hence we computed local TFP measures using information from the Company Accounts Data Service, CADS (*Centrale dei Bilanci*), a large dataset collected by a consortium of banks that in pool information on borrowers with 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 in granting loans, they are carefully quality controlled and contain actually reported (as opposed to imputed) figures. Firms in the sample account for approximately half of total manufacturing employment in Italy and for larger 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 Cingano and Schivardi (2003) for details) and employment) in 1991.

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

The second potential problem is that firms are not randomly chosen. Though

[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.

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 1999), the focus on the level of borrowing skews the sample towards larger firms. This can be seen 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 fewer account for 60% of the firm population but less than 10% of total employment) explains much of the observed difference. Moreover, since banks are most interested in firms that are creditworthy, firms in default are not in the dataset, so the sample is also tilted towards higher-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 spurious correlation between the estimated local TFP growth rates and our explanatory variables. We also include detailed sectoral and geographical controls in the growth regressions to account for error in measurement that is correlated across space or lines-of-work.

As to the precision of our productivity growth estimate, the average number of observations at the C-S level is 8.5 (Table 4, last row). 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 nevertheless think that this measure is sufficiently precise for our purposes. First, as we have seen, CADS firms account for a very large share of total output. Second, in order to account for the different precision with which TFP is computed, we use weighted least squares, the weights determined by the number of firm-level observations available. We also perform several further robustness checks.

The final data source is the Italian population census (Censimento generale della popolazione, 1981) used to calculate measures of human capital in the LLSs.

3.2 TFP Estimation: procedures and results

We exploit our detailed firm-level dataset to measure TFP at the C-S level. We postulate the usual Cobb-Douglas production 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 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 the perfect competition hypothesis is unrealistic. 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 of local externalities. Indeed, with Solow's method any effect of the scale of production would be attributed to TFP, potentially introducing significant 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 decision to shut down, consistent estimation of the production function parameters requires addressing problems of simultaneity and selection. We use the multi-step estimation algorithm proposed by Olley and Pakes (1996), which accounts for both problems, allowing for unbiased and unconstrained estimation of α_s and β_s.[9] To obtain our measure of TFP in C-Ss we first calculate productivity at the firm level as a residual and aggregate TFP at the C-S level as the employment-

[9] In summary, the procedure controls for endogeneity by approximating the unobserved productivity shocks with a nonparametric function of observable variables and for selection by introducing a Heckman-type correction term.

weighted average of firm-level TFP.[10] To control the reliability of the estimates, we also calculate the coefficients using Solow's assumptions. In this case, the C-S 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.[11] In terms of single coefficients, the Olley and Pakes procedure tends to result in a higher labor coefficient and a lower one for capital, 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. 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) for a sample of OECD countries. The bottom part of the table presents a standard growth accounting exercise. As the second column shows, between 1986 and 1998 TFP grew on average at a rate ranging between 1.2% and 4% and was generally lower in the traditional (textiles, footwear etc.) and food sectors than in basic metals and

[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.

[11] Given that the capital coefficient is estimated through a semi-parametric procedure, we obtained its standard errors through a bootstrapping exercise based on 150 replications. As for Olley and Pakes (1996), standard errors are relatively large and imply that the null of CRTS can never be rejected (see Table 2). Pakes and Olley (1995) discuss the asymptotic properties of the estimator, suggesting that the bootstrapping procedure might overestimate the true standard deviation of the capital coefficint, partially explaining the higher values when compared to those of the labor coefficient.

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 that is due to the change in the productive structure of the firms in the sample. In line with the previous discussion about the coefficients, these contributions are generally small. The most noticeable exception is basic metals and, to a lesser extent, transportation equipment, where a substantial contribution to labor productivity growth derived from the *decrease* (both sectors are characterized by decreasing returns to scale) 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.

4 Empirical specification and results

Our data allows us to parallel the empirical specification adopted so far in the urban-growth literature. We closely follow Combes (2000), who carefully discusses the empirical framework. The degree of sectoral specialization of a given C-S is measured by the share of sectoral city employment ($\text{Spec}_{c,s} = L_{c,s}/L_c$). Our measure of the scale of local economic activity is total manufacturing employment ($\text{Scale}_c = L_c$).[13] Externalities induced by the degree of productive variety outside sector s in the city are captured by a Hirschman-Herfindahl index defined as:

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

The index ranges between 1, when all other manufacturing employment in the city is concentrated in a single sector, and $1/(J_c - 1)$ if it is evenly distributed across

[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.

[13] As discussed by Combes (1999), such control allows to correctly interpret the coefficient on specialization as the effect of local relative concentration (sectoral employment share) holding total employment in the city constant.

other sectors in the city.[14]

In addition to the traditional effects discussed above, theories of innovation and technological diffusion suggest two additional channels through which the local industrial structure might affect growth. First, as suggested by Porter (1990), local competition stimulates the production of innovations, their rapid adoption and improvement. In our analysis local competition will be captured by an index of employment concentration within each C-S:

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

where $L_{c,s,i}$ is the employment level of firm i belonging to c, s. Low competition should result in a less uniform distribution of employment across firms (captured by a higher value of the index). Second, a debate dating back to Schumpeter (1950) focuses on the role of firm size in innovation and growth: large firms have the resources and the knowledge to undertake costly R&D projects, but small firms might be important in fostering competition and introducing new products.[15] Accordingly, we include the inverse (for comparability with previous studies) of average firm size in the C-S, $\mathrm{Size}_{c,s} = n_{c,s}/\Sigma_{i \in c,s} L_{c,s,i}$, where $n_{c,s}$ is the number of firms in the C-S. All indexes have been calculated using the NSSI archives of the universe of firms in 1986. Summary statistics of the main variables used in the empirical analysis are found in Table 4.

We will focus on the following estimating equation:

$$\widehat{A}_{c,s} = \beta_1 \mathrm{SPEC}_{c,s} + \beta_2 \mathrm{SCALE}_c + \beta_3 \mathrm{VAR}_{c,s} + \beta_4 \mathrm{COMP}_{c,s} + \beta_5 \mathrm{SIZE} + \beta_6 X_{c,s} + u_{c,s} \tag{1}$$

[14] This might be an imperfect measure of diversity, because our sectoral definition might be too coarse to precisely capture it; moreover, we exclude services, a potentially important source of externalities.

[15] According to this argument, the effects of average size on productivity growth cannot be signed a priori. Pagano and Schivardi (2001), using cross-country data at the sectoral level, find that productivity growth is positively correlated with average firm size, the more so the higher the R&D intensity of the sector, indicating that larger size facilitates the production and/or the diffusion of innovations.

where $\widehat{A}_{c,s}$ is the average TFP growth rate calculated over the 1986-98 period and capital letters on the right-hand side indicate log-transformation of the corresponding regressors. The vector $X_{c,s}$contains additional controls, i.e. human capital at the city level, measured by the average number of years of schooling of the city's working-age population in 1981, the initial level of C-S TFP and two sets of dummy variables accounting for sector and geographical location (macro-area).

Two other features of our estimation approach are worth mentioning before we discus the results. First, since the Centrale dei Bilanci sample is open (with entry and exit of firms over time), in principle we can compute C-S TFP growth rates with various sample selection rules. The results shown in the following section use the most restrictive rule, i.e. considering only those city-industries that are represented by at least one firm over the entire time-span. As we shall see later, our results are robust to alternative selection choices. Second, since TFP estimates in the C-S are averages of individual firms, their precision increases with the number of firms. To reduce the noise from potentially imprecise estimates, we use Weighted Least Squares. This implies that C-Ss with a larger number of firms will have greater weight in determining the coefficients.[16] To check that this does not affect the results, we also run the basic specification without weighting.

4.1 TFP results

The results from estimating the basic specification of (1) are reported in Column [1] of Table 5. First, the elasticity of TFP growth to sectoral specialization, holding total city-size constant, is positive and significant at the 5% level. Our point estimate ($\beta_1 = 0.23$) implies that raising our specialization index by one standard deviation (a three-fold increase in the share of sectoral employment in the city) would increase TFP growth in the corresponding sector by nearly 0.3% per year over the subsequent period. Second, TFP growth is positively affected by city size. Since

[16] 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.

we are holding the sectoral composition of production in the city constant, this can be interpreted as the effect of the size of the local market, which is consistent with modern theories in urban economics. According to our estimated coefficient, a one standard deviation increase in total manufacturing employment in the city would raise yearly productivity growth by 0.5%.

We do not find that other possible sources of externalities at the local level matter for our measure of TFP growth. According to our estimates, neither the initial range of productive variety nor the initial degree of competition, capturing Porter and Jacobs externalities respectively, are significantly different from zero (at 10% level). The same is true for our measure of average human capital in the LLS (not reported). 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 C-S is negative and highly significant, capturing convergence in the growth rates within sectors. In sum, the key result in Table 5, column [1] is that when local growth is properly measured, the main findings of the urban growth literature on specialization, city size and urbanization economies are overturned.

As our results conflict with most of the previous literature, we performed several robustness checks. First, 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, increasing the number of spatial controls included in our baseline regression[17]. The results are shown in column [2] (20 region controls) and [3] (95 province controls): our estimates are only slightly affected. Similar findings are obtained when running unweighted OLS (column [4]).

While the baseline specification uses only C-S that were continuously present in the sample, we also controlled for different selection criteria. In column [5] we

[17] As long as (at least part) of the variation in omitted determinants of TFP growth across C-S is picked up by these spatial controls, 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.

used those that are in the sample in the first and the last year and in column [6] we used all possible information, calculating average TFP growth using all available years, i.e. also C-S that were in the sample for just a few 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 the most 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 C-S level we also examined how localized these forces are by adding two variables to measure scale and own-industry specialization in the neighboring area, obtained by aggregating our C-S data at the province level.[18] 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, columns [2] and [3] (the first column replicates column [1] in Table 5). This result is in line with previous work based on patents (Jaffe, Trajtenberg and Henderson 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.

We performed additional robustness checks and extensions to the original specification (results are not reported for brevity). First, we restricted the analysis to larger LLSs, excluding from the baseline regression those observations falling in the bottom 10%, 25% and 50% of the distribution. By doing so, our geographical units become more directly comparable with US Metropolitan Statistical Areas, defined as LLSs containing one large urban cluster. Not surprisingly, given that our firm-level sample already excludes scarcely populated LLSs, the main results regarding specialization, scale and diversity externalities are unaffected. Second, we checked the robustness of our results using alternative measures of localization-MAR economies. Henderson (2003) argued that the count of own-industry plants would be a

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

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-agricultural land) rather than its level. Our results proved to be robust to both changes. All in all, at this stage we conclude that there is robust evidence that MAR externalities and scale effects in terms of city size are at work at the local geographical level in Italy, while other potential sources of dynamic externalities do not seem to matter for productivity growth.

4.2 Employment results

Our findings on the determinants of local productivity growth are at odds with most of the urban-growth literature, which has obtained robust evidence of negative MAR-specialization and scale externalities and less clear-cut evidence of positive Jacobs urbanization economies. These differences could be due to some specific feature of the Italian economy[19] or to the fact that, as noted in Section 2, employment growth regressions could be ill-suited to draw inference on local externalities. We can discriminate between these two explanations by running the same regressions as before using employment growth as the dependent variable:

$$\widehat{l}_{c,s} = \gamma_1 \mathrm{SPEC}_{c,s} + \gamma_2 \mathrm{SCALE}_c + \gamma_3 \mathrm{VAR}_{c,s} + \gamma_4 \mathrm{COMP}_{c,s} + \gamma_5 \mathrm{SIZE} + \gamma_6 X_{c,s} + \epsilon_{c,s} \tag{2}$$

where $\widehat{l}_{c,s}$ is average employment growth in c, s, as recovered from the NSSI dataset. For comparability, we estimated this equation using the same WLS scheme and the same sub-sample of C-S observations of the TFP regressions. The results (Table 7)

[19] 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 (1999) 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.

indicate that productive specialization is associated with slower employment growth at the C-S level, the opposite of what we found for TFP. Raising sectoral specialization in a given location by a one standard deviation will reduce average employment growth in that sector by nearly 0.9% per year. The partial elasticity of employment growth with respect 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, increasing initial employment in a city by one standard deviation would reduce the growth rate by more than 1.4% per year over the subsequent period. We also find that variety, size and competition, which apparently have no direct effect on TFP growth, do significantly affect local employment. In particular, in line with the findings of Combes (2000) for France, the impact of productive diversity is negative. As for France and US cities, we also find that smaller firm size is associated with faster employment growth.

We ran several robustness checks, as we did for the TFP specification. Controlling for the existence of spatially correlated omitted variables (columns [2] and [3]), most of the previous results are unaffected, but the variety coefficient becomes insignificant. Unweighted regressions (column [4]) showed no significant differences from the baseline. Finally, we also considered a version of our regression where the dependent variable was obtained from the CADS sample, not the whole 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. The three coefficients that are significant (specialization, city size and competition) are very similar to those in column [1], which we interpret as evidence of the representativeness of the CADS data. However, in contrast with the population-based regressions (NSSI data), the coefficients of firm size and of variety are not significantly different from zero. This, together with the substantially lower R^2 (.16 against .43), suggests that resorting to the CADS data creates noise and reduces precision of the estimates. However, there is no evidence of any systematic bias. This last regression also indicates that measurement error in the employment data is not the main driving force behind the negative coefficient of specialization. In fact, employment growth and the specialization index are computed from two different, independently collected datasets, so that any measurement error in the two is not likely to be correlated.

Wage growth has also been used in previous work as an alternative measure of agglomeration economies(Glaeser et al. 1992), based on the assumption that some productivity gains accrue to labor. Using firm-level average annual compensation of employees available in NSSI archives, we construct a measure of wage growth at the C-S level and regress it on the same indicators as before (including the initial wage level). The results are reported in Table 8. In general, the coefficients tend to be smaller and less precisely estimated. Apart from mean reversion, the only robust results are that city size and average firm size are conducive to a faster wage growth, while specialization has a positive but generally insignificant effect (except in the CADS sample, column [5], where it is significant at 5%). These findings are in line with those of Glaeser et al. (1992). Compared with the TFP regressions, results are in accordance for city size and, more weakly, specialization. More importantly, almost all the coefficients have the opposite sign with respect to the employment growth regressions. Hence, wage growth results are broadly consistent with our discussion on the role that labor supply shifts might play in determining equilibrium outcomes in the labor market; they also suggest that, although they are less problematic than employment growth, wage growth regressions are also a fairly unreliable measure of urbanization economies

4.3 Discussion

Our findings cast serious doubt on the use of employment changes as alternative indicators of dynamic externalities and hence on the conclusions of most of the previous literature. This reading is supported by other recent productivity studies. Henderson (2003) estimates a plant-level production function with plant-specific fixed effects on a panel of US firms in the capital goods and high-tech sectors. Unlike previous studies for the US, he finds no evidence of urbanization economies, and positive effects of specialization (measured here by the number of neighboring own-industry plants) on productivity in the high-tech sector. Though obtained using a different methodology and less directly comparable with those of the previous urban growth literature, results in Henderson (2003) are thus in line with our findings.[20] Similar conclusions about the inappropriateness of employment-based regressions are reached by Dekle (2002)'s work on growth in the Japanese prefectures, although he finds no evidence of dynamic externalities in manufacturing.[21]

All in all, in our view it should be quite clear by now that the only way to identify dynamic local externalities within this framework is the direct measurement of TFP.

5 Conclusions

Over the last ten years a number of empirical works have used employment growth to sort out whether local externalities are related to the concentration of an industry in a city or to its productive variety. In this paper we have argued that employment growth regressions are likely to be affected by serious identification problems, and shown that inference on agglomeration economies changes dramatically when local growth is properly measured with productivity. In particular, and contrary to what employment-based regressions indicate, we find that local TFP growth is enhanced by the scale of activity and by sectoral specialization, but not by urban diversity.

In terms of policy, our findings imply that fostering productivity could require different instruments then fostering employment, which has important bearings on

[20] The two works differ along several important dimensions, however. First, we estimate TFP growth regression that closely parallel the employment equations used in the literature, both regarding the explanatory variables (beginning of the period employment-based indicators of the local industrial structure) and the sectoral coverage (the entire manufacturing). Hence, comparison with previous results is straightforward. Second, while both exercises deal with production function estimation, by employing the Olley-Pakes procedure we carefully account for both endogeneity of inputs and firms selection, two issues neglected by Henderson. Finally, by using changes in the measures of the industrial structure to identify agglomeration effects, Henderson's analysis is vulnerable to unobserved innovations (for example local shocks caused by subsidies, improved infrastructures etc.) that drive changes in both the industrial structure and plant productivity.

[21] 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.

the debate on public intervention to promote growth in less developed areas.

In terms of future work, it will be important to develop models that, by explicitly considering labor supply and mobility choices, allow for differential effects of the local structure both on productivity and on employment. This will help provide a structural interpretation of the results of past employment-growth regressions and explain why productivity and employment may respond so differently to local conditions. At the same time, it will be interesting to extend the TFP analysis to other countries to check whether, as seems likely, the insights that we obtain here extend to other economies.

References

Arrow, K. (1962), 'The economic implications of learning by doing', *Review of Economic Studies* **29**, 155–73.

Bernard, A. B. and Jones, C. (1996), 'Comparing apples to oranges: Productivity convergence and measurement across industries and countries', *American Economic Review* **86**, 1216–1238.

Bradley, R. and Gans, J. (1996), 'Growth in australian cities', *The University of South Wales Working papers* **13**, 329–355.

Cainelli, G. and Leoncini, R. (1999), 'Externalities and long-term local industrial development. Some empirical evidence from Italy', *Revue d'economie industrielle* **90**, 25–40.

Chatterjee, S. and Carlino, G. A. (2001), 'Aggregate metropolitan employment growth and the deconcentration of metropolitan employment', *Journal of Monetary Economics* **48**, 549–583.

Ciccone, A. and Hall, R. E. (1996), 'Productivity and the density of economic activity', *American Economic Review* **86**, 54–70.

Cingano, F. and Schivardi, F. (2003), Sources of local productivity growth, Temi di Discussione della Banca d'Italia n. 474, http://www.bancaditalia.it/ricerca/consultazioni/temidi.

Combes, P. (1999), Marshall-Arrow-Romer externalities and city growth: A methodological note, CERAS working paper n.06.

Combes, P. (2000), 'Economic structure and local growth: France, 1984-1993', *Journal of Urban Economics* **47**, 329–355.

Combes, P., Magnac, T. and Robin, J. (2003), The dynamics of local employment in France, mimeo, CERAS, INRA-LEA and CREST.

Dekle, R. (2002), 'Industrial concentration and regional growth: evidence from the prefectures', *Review of economics and statistics* **84**, 310–315.

Duranton, G. and Puga, D. (2001), 'Nursery cities', *American Economic Review* **91**, 1454–75.

Duranton, G. and Puga, D. (2003), Micro-fundations of urban agglomeration ecomomies, Forthcoming in *Handbook of Urban and Regional Economics*, volume 4.

Eaton, J. and Eckstein, Z. (1997), 'Cities and growth, theory and evidence from France and Japan', *Regional Science and Urban Economics* **27**, 443–474.

Fujita, M. (1989), *Urban Economic Theory. Land Use and City Size*, Cambridge University Press.

Glaeser, E. L., Kallal, H. D., Scheinkman, J. A. and Shleifer, A. (1992), 'Growth in cities', *Journal of Political Economy* **100**, 1125–1152.

Guiso, L. and Schivardi, F. (1999), Information spillovers and factor adjustment, CEPR discussion paper n. 2289.

Henderson, V. (1974), 'The sizes and types of cities', *American Economic Review* **64**, 640–56.

Henderson, V. (2003), 'Marshall's scale economies', *Journal of Urban Economics* **53**, 1–28.

Henderson, V., Kuncoro, A. and Turner, M. (1995), 'Industrial development in cities', *Journal of Political Economy* **103**(5), 1067–1090.

Jacobs, J. (1969), *The Economy of Cities*, Vintage, New York.

Jaffe, A., Trajtenberg, M. and Henderson, R. (1993), 'Geographic localization of knowledge spillovers as evidenced by patent citations', *Quarterly Journal of Economics* **108**, 577–598.

Marshall, A. (1890), *Principles of Economics*, London:Macmillan.

Olley, S. and Pakes, A. (1996), 'The dynamics of productivity in the telecommunications equipment industry', *Econometrica* **64**, 1263–1297.

Pagano, P. and Schivardi, F. (2001), 'Firm size distribution and growth', *The Scandinavian Journal of Economics*. Forthcoming.

Pakes, A. and Olley, S. (1995), 'A limit theorem for a smooth class of semiparametric estimators', **65**, 295–332.

Porter, M. (1990), *The Competitive Advantage of Nations*, Free Press, New York.

Romer, P. (1986), 'Increasing returns and long run growth', *Journal of Political Economy* **98**, S71–S102.

Rosenthal, S. and Strange, W. (2000), Geography, industrial organization and agglomeration, UBC, mimeo.

Rosenthal, S. and Strange, W. (2003), Evidence on the nature and sources of agglomeration economies, Forthcoming in *Handbook of Urban and Regional Economics*, volume 4.

Schumpeter, J. (1950), *Capitalism, Socialism and Democracy*, Harper and Row, New York.

Segal, D. (1976), 'Are there returns to scale in city size', *Review of Economics and Statistics* **58**, 217–235.

Simon, C. J. (1988), 'Frictional unemployment and the role of industrial diversity', *Quarterly Journal of Economics* **103**, 715–728.

Soest, D. V., Gerking, S. and van Oort, F. (2002), Knowledge externalities, agglomeration economies, and employment growth in Dutch cities, CentER discussion paper n. 41.

Sveikauskas, K. (1975), 'Productivity of cities', *Quarterly Journal of Economics* **89**, 393–413.

Table 1: Firms' characteristics (Average values)

		CADS				NSSI	
Sector		Val.add.*	Cap stock*	Empl.	N. obs	Empl.	N. obs
1	F	4,617	9,596	92	1,516	10	25,819
2	T&C	2,769	4,287	82	2,335	13	43,784
3	L&F	1,637	1,634	53	820	12	13,254
4	W&C	1,756	3,086	55	1,167	7	27,830
5	T&Gl	4,017	9,912	88	1,260	15	14,001
6	BM	6,393	17,065	157	711	39	4,224
7	Mach	4,441	5,935	112	5,582	14	91,606
8	Chem	7,460	14,843	128	2,013	27	13,785
9	P&P	4,325	7,375	90	992	12	15,634
10	TEq	9,692	36,191	555	489	115	2,353
	Total	4,749	8,418	113	16,885	14	261,549

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

Table 2: Production function coefficients: factor share and direct estimates

Sector		Factor shares β	α	Direct estimates β	α	$\alpha+\beta$
		[1]	[2]	[3]	[4]	[5]
1	F	0.56	0.44	.63***	0.39***	1.02
				(.005)	(.066)	(.064)
2	T&C	0.60	0.40	0.58***	0.37***	0.95
				(.003)	(.035)	(.036)
3	L&F	0.61	0.39	0.62***	0.43***	1.05
				(.005)	(.091)	(.091)
4	W&C	0.63	0.37	0.70***	0.35***	1.05
				(.005)	(.077)	(.076)
5	T&Gl	0.58	0.42	0.67***	0.37***	1.04
				(.005)	(.080)	(.078)
6	BM	0.65	0.35	0.60***	0.33***	0.93
				(.007)	(.057)	(.054)
7	Mach	0.67	0.33	0.72***	0.28***	1.00
				(.002)	(.013)	(.012)
8	Chem	0.60	0.40	0.70***	0.29***	0.99
				(.004)	(.044)	(.043)
9	P&P	0.66	0.34	0.72***	0.32***	1.04
				(.005)	(.039)	(.035)
10	TEq	0.74	0.26	0.70***	0.26*	0.96
				(.008)	(.144)	(.144)

Note: α is the capital coefficient and β the labor 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. Standard errors in parenthesis. Standard errors for the capital coefficient and for the sum of the coefficients computed by a bootstrapping procedure based on 150 replications. In column 4 and 5, *** indicates significance at 1%, ** at 5% and * at 10% (assuming normality for the bootstrapped standard errors). In column 6, the null $\mathrm{H}_0 : \alpha + \beta = 1$ is never rejected at standard significance levels. 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 labor 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	Descriptive 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)
Initial TFP	-5.93***	-6.05***	-6.08***	-6.81***	-6.12***	-9.02***
	(.303)	(.310)	(.311)	(.312)	(.280)	(.566)
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 C-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%, ** at 5% and * at 10%.

Table 6: City-industry productivity growth: neighborhood externalities

	[1]	[2]	[3]
Specialization	.230**	.262**	.219*
	(.111)	(.124)	(.126)
Neighborhood'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)
Initial TFP	-5.93***	-5.29***	-6.06***
	(.303)	(.304)	(.310)
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 C-S level. All regressions include sector dummies. Spatial controls are macro areas, regions and Provinces. *** indicates significance at 1%, ** at 5% and * at 10%.

Table 7: 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 C-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%, ** at 5% and * at 10%.

Table 8: 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)
Initial wage	-3.120	-3.518	-3.787	-4.391	-5.081
	(.235)	(.226)	(.243)	(.255)	(.334)
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 C-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%, ** at 5% and * at 10%.